Machine Learning for Healthcare
6.7930 [6.871], HST.956

Lecture 14: Dataset Shift

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Slides credit:
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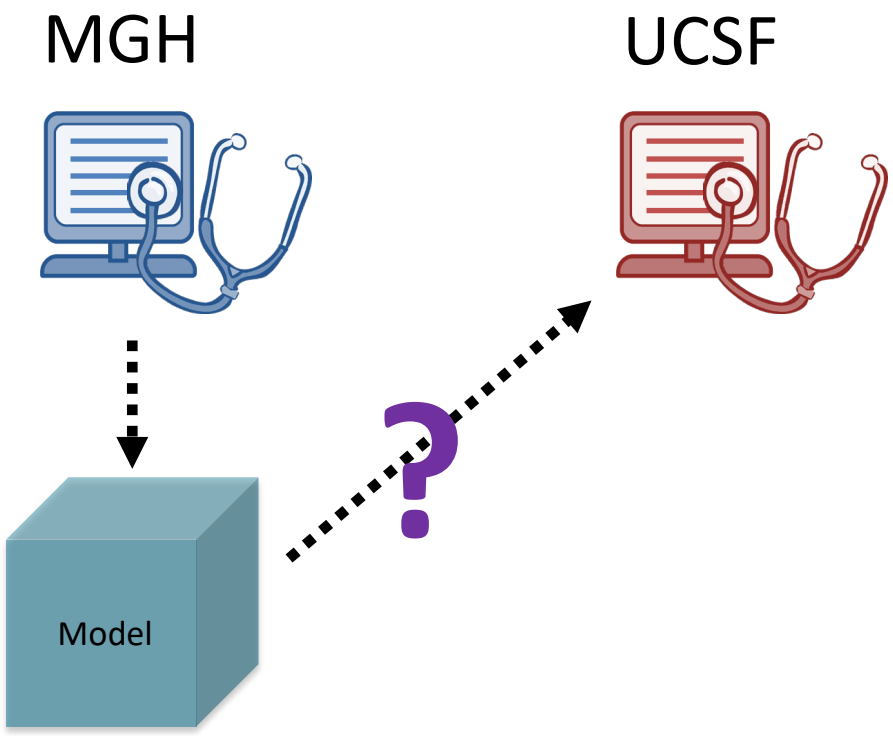
Dataset shift / non-stationarity:

Models often do not generalize



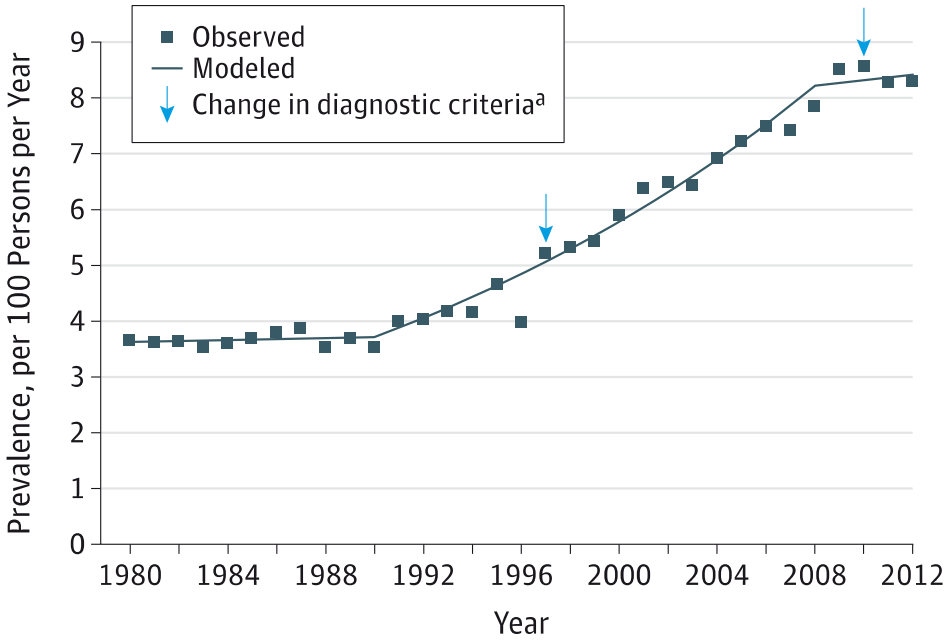
What kinds of dataset shift might this have, and why?

Imagine machine biases
Population age/health
Treatment patterns
Treatment selection
Past history of treatments
Environmental factors
Socioeconomic factors

[Figure adopted from Jen Gong and Tristan Naumann]

Dataset shift / non-stationarity:

Diabetes Onset After 2009



→ Automatically derived labels may change meaning

Better diagnosis

Insulin/glucose biomarkers

Obesity rates

Definition of disease

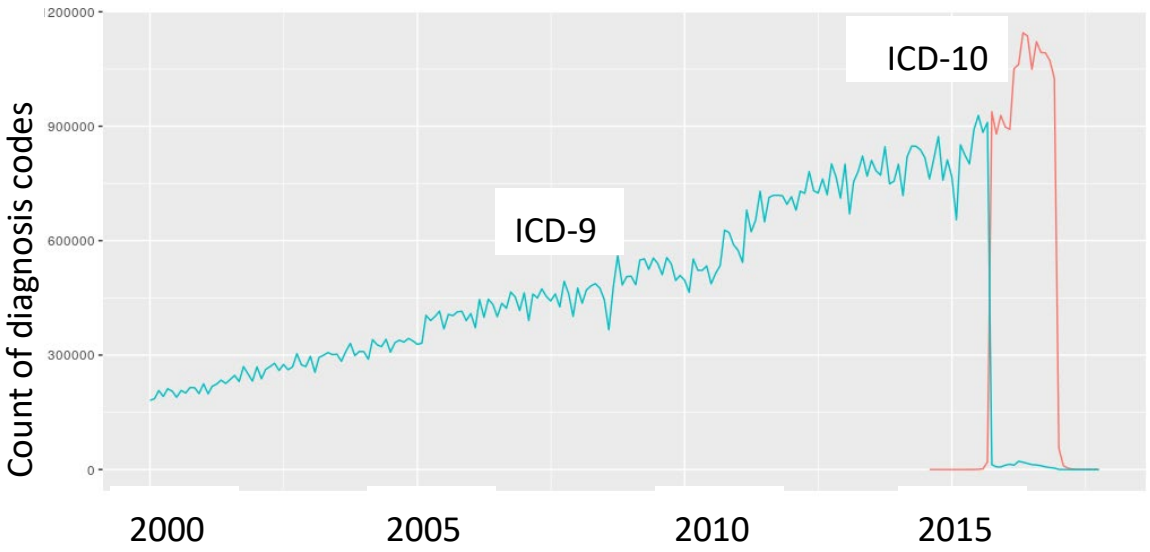
Meaning of label

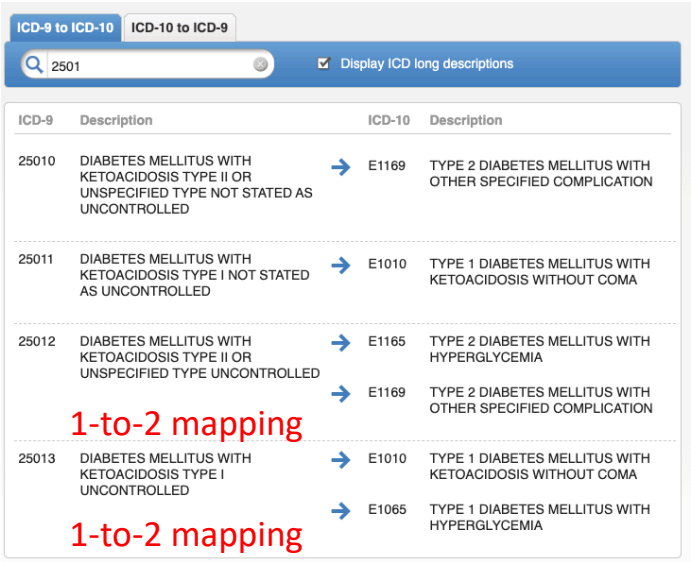
T1D vs. T2D

[Geiss LS, Wang J, Cheng YJ, et al. Prevalence and Incidence Trends for Diagnosed Diabetes Among Adults Aged 20 to 79 Years, United States, 1980-2012. JAMA, 2014.]

Dataset shift / non-stationarity:

ICD-9 to ICD-10 shift





→ Significance of features may change over time

(note, map from ICD10 to ICD9 isn't 1-1)

One approach: Map each to a common vocabulary

[Figure credits: (Left) Mike Oberst, (Right) http://www.icd10codesearch.com/]

Outline for today's class

- **Examples & formalization of dataset shift**
- Testing for dataset shift
- Mitigating dataset shift

Formalizing Dataset Shift

- General Task: Perform well on a “target domain” Q

  Train: Population **P** (e.g. MGH)
  Apply: Population **Q** (e.g. UCSF)

- Assumptions: What is changing vs. what is stable?
  - Covariate Shift / Label Shift / more general shifts

Formalizing Dataset Shift

- General Task: Perform well on a “target domain” Q
- Assumptions: What is changing vs. what is stable?
  - Covariate Shift / Label Shift / more general shifts

An Impossible Problem

Given $\{X_i, Y_i\}_{i=1}^n$ from a *source domain* $\boldsymbol{P}(X, Y)$, find a model that performs well on some *target domain* $\boldsymbol{Q}(X, Y)$

$$\min_{f \in \mathcal{F}} \mathbb{E}_{\boldsymbol{Q}}[\ell(Y, f(X)]$$

Minimize the expected loss between truth Y and prediction *f*(X) in domain Q
Find the function *f* that minimizes this

Examples:
- P and Q are two different hospital systems
- P is the past, Q is the future
- …

Not well-posed without further assumptions or information about Q!

Worst-case scenario

Learning algorithm doesn't know q. Outputs h.

$\forall x$, set $q(y|x) = 1[y = \hat{y}(x)]$

where $\hat{y}(x) = \underset{y}{\operatorname{argmax}}\ \ell(y, h(x))$

i.e. choose the opposite label of what h would output.

Then, set $p(x) = 1[x = \hat{x}]$

where $\hat{x} = \underset{x}{\operatorname{argmax}}\ \ell(\hat{y}(x), h(x))$.

concentrate on worst-case data point.

Worst case scenario of P⇔Q discrepancy: flip all of the labels: exactly opposite diagnosis

Easy to reason about, but we learn something about the problem

Learn: ➔ Need to infer relationships between distributions

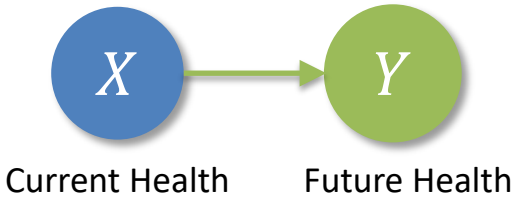
Formalizing Dataset Shift

- General Task: Perform well on a “target domain” Q
- Assumptions: What is changing vs. what is stable?
  - Covariate Shift / Label Shift / more general shifts

Example: Covariate Shift Assumption

$$P(X) \neq Q(X)$$
$$P(Y \mid X) = Q(Y \mid X)$$

Why might this be true? One rationale: $P(Y \mid X)$ encodes some "causal" mechanism



Example: Risk stratification for different patient populations

Common assumption: distribution of future health will be the same. But doesn't usually hold

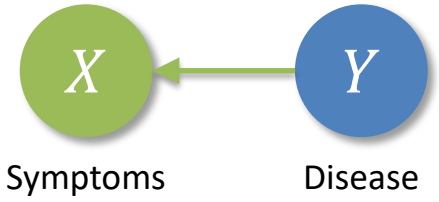
Example: Label Shift Assumption

$$P(Y) \neq Q(Y)$$

$$P(X \mid Y) = Q(X \mid Y)$$

(flip directionality from previous slide)

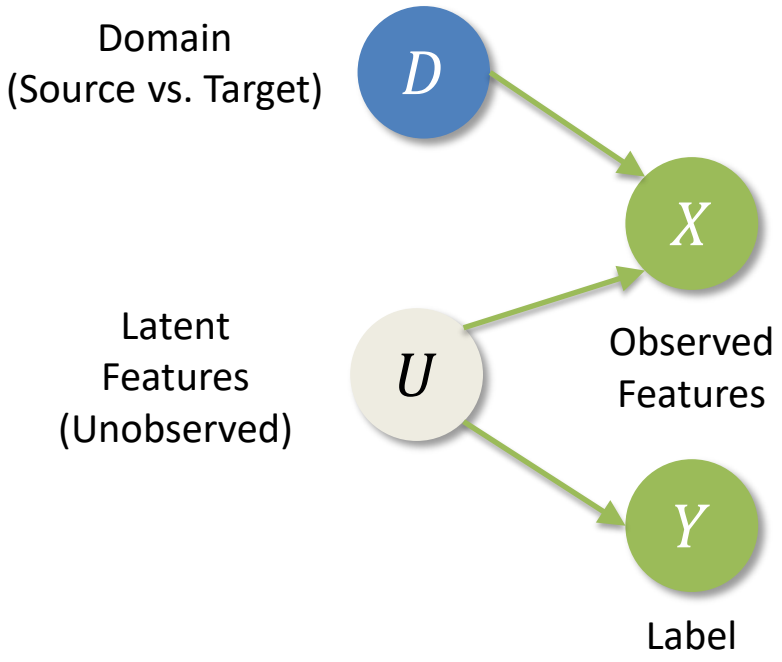
Why might this be true? One rationale: $P(X \mid Y)$ encodes some "causal" mechanism



Example: Diagnostic testing under changes in disease prevalence.

Disease informative of symptoms. Prior vs. posterior probability.
Generative model vs. data-conditional posterior-probability inference

Example: "Domain Shift"



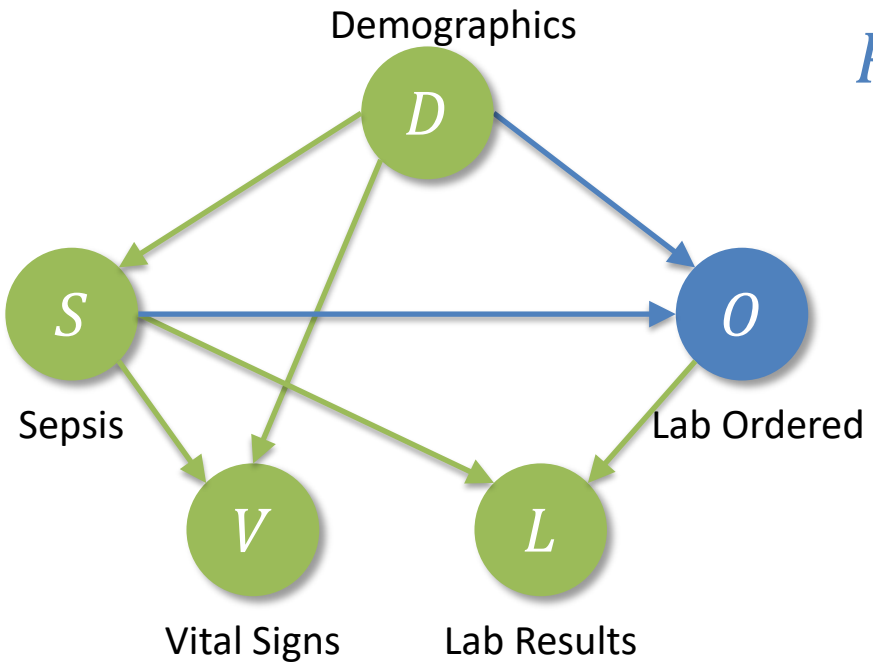
Example: Changes in how features are derived (e.g., ICD-9 versus ICD-10)

We can also view the domain itself as a variable that influences others

Note: So far, we have not discussed how to mitigate these shifts. In this example, more information is required!

Quinonero-Candela et al., (2008). *Dataset Shift in Machine Learning*, MIT Press.

Example: Using causal graphs to reason about shift



$$P(O \mid D, S) \neq Q(\mathrm{O} \mid \mathrm{D}, \mathrm{S})$$

More fine-grained shifts can be reasoned about as changes in marginal/conditional distributions

Example: Changes in lab ordering patterns across hospitals

$$P(D, S, O, V, L) = P(D)P(S|D)P(V \mid D, S)P(O|D, S)P(L|O, S)$$

Example from Subbaswany et al. (2021). *Evaluating Model Robustness and Stability to Dataset Shift.* AISTATS

Outline for today's class

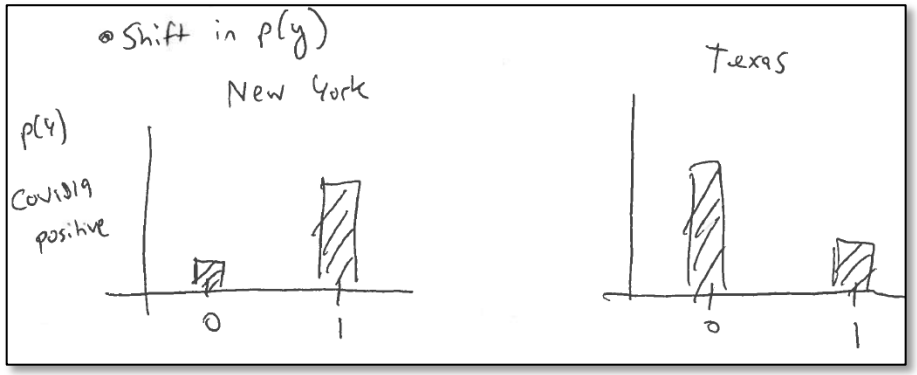
- Examples & formalization of dataset shift
- **Testing for dataset shift**
- Mitigating dataset shift

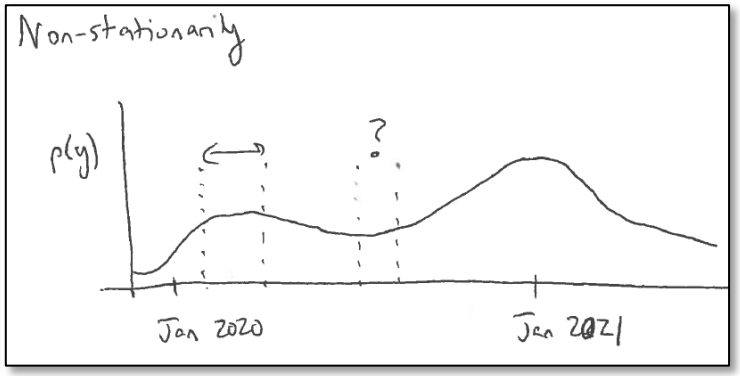
Testing for dataset shift

- Shift in p(y):
  - Plot distributions (across data sets, across time)

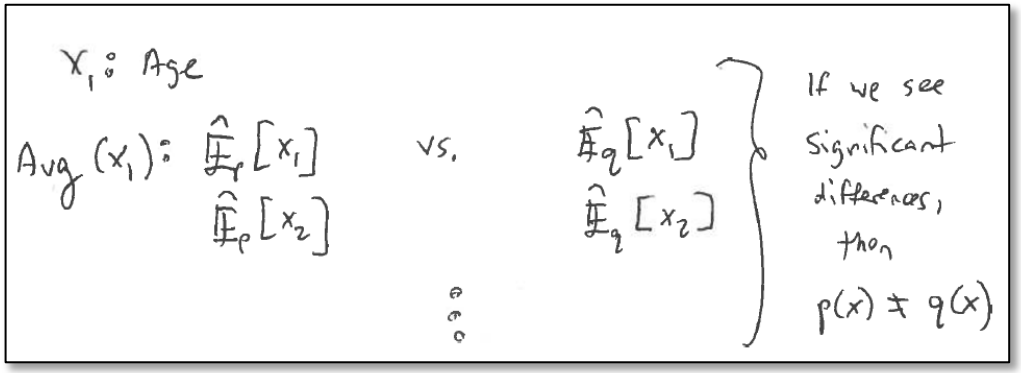
Testing for dataset shift

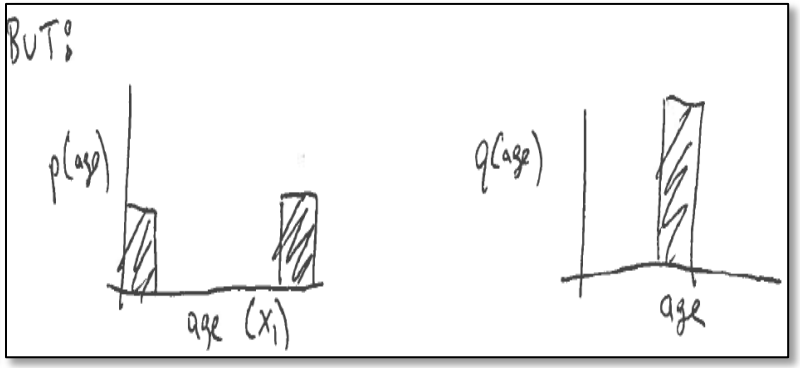
- Shift in p(y):
  - "Label shift". e.g. 'diabetes' now means something different
  - Plot distributions (across data sets, across time)





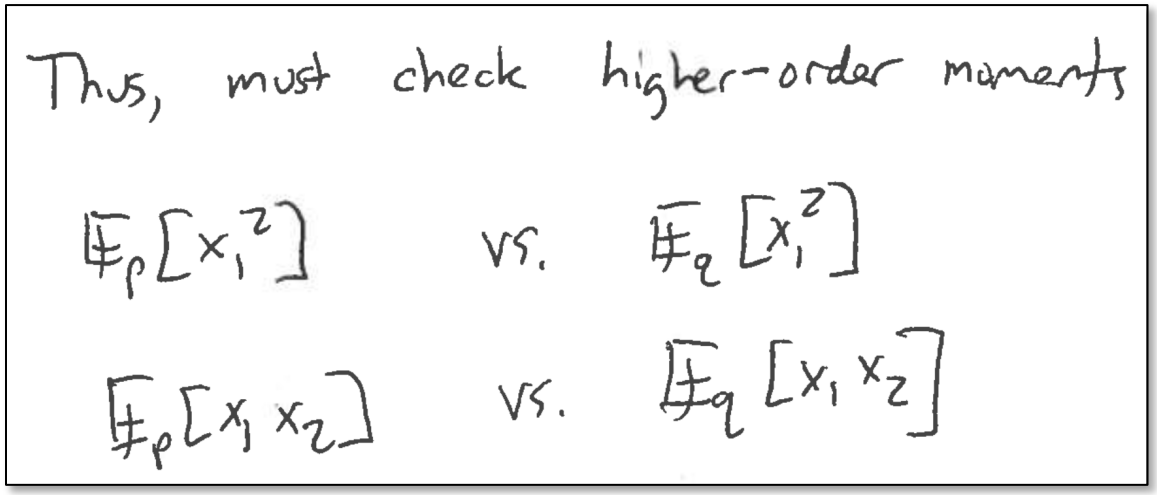
- Shift in p(x) or p(x|y):
  - Different: x is multidimentional
  - E.g. Compare feature means ➔ but could miss bi-modal vs. unimodal
  - Could look for additional moments.





Testing for dataset shift

- Shift in p(y):
  - Plot distributions (across data sets, across time)
- Shift in p(x) or p(x|y):
  - Compare feature means (repeat for each value of Y, assuming discrete)
  - However: means can be identical even if two distributions are different!
  - E.g. variance, co-variance

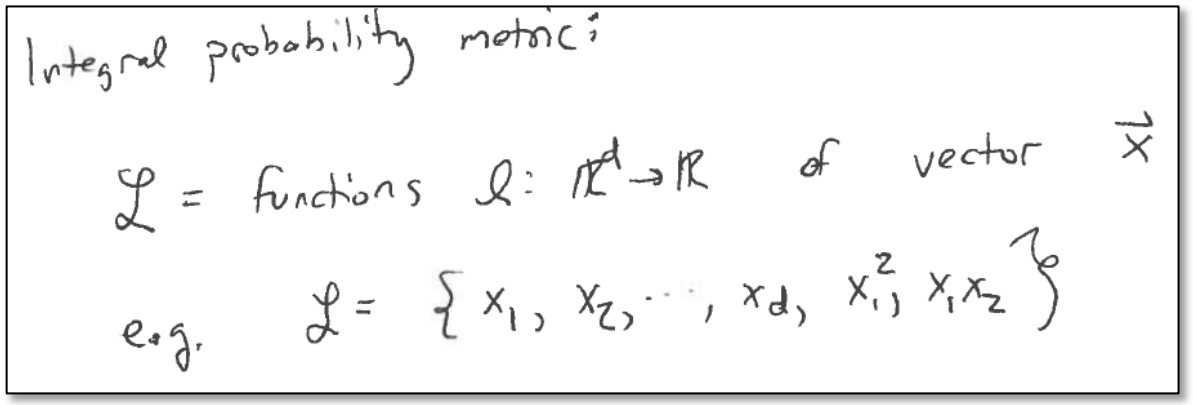


Testing for dataset shift

- Shift in p(y):
  - Plot distributions (across data sets, across time)
- Shift in p(x) or p(x|y):
  - Compare feature means
  - Use kernel two-sample test (Gretton et al., JMLR '12)

Integral probability metric:
(Muller, 1997)

$$\mathrm{IPM}_{\mathcal{L}}(p, q) := \sup_{\ell \in \mathcal{L}} |\mathbb{E}_p[\ell(x)] - \mathbb{E}_q[\ell(x)]|$$



l(x): generalization of mean/variance (all possible functions)

Testing for dataset shift

- Shift in p(y):
  - Plot distributions (across data sets, across time)
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Integral probability metric:
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Maximum mean discrepancy (MMD): L are functions with norm 1 in a RKHS:
(Gretton et al., 2012)

$$\text{samples } x_1, ..., x_m \sim p,\ x'_1, ..., x'_n \sim q$$

$$\hat{\mathrm{MMD}}^2_k(p,q) := \frac{1}{m(m-1)} \sum_{i=1}^{m} \sum_{j=1}^{m} k(x_i, x_j) - \frac{2}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} k(x_i, x'_j) + \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} k(x'_i, x'_j)$$

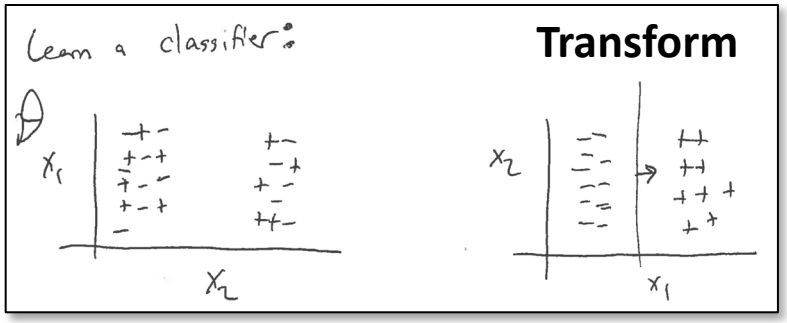
Testing for dataset shift

- Shift in p(y):
  - Plot distributions (across data sets, across time)
- Shift in p(x) or p(x|y):
  - Compare feature means
  - Use kernel two-sample test such as maximum mean discrepancy/MMD (Gretton et al., JMLR '12)
  - (Attempt to) learn a classifier to distinguish one dataset from the other

samples $x_1, ..., x_m \sim p$, $x'_1, ..., x'_n \sim q$

Binary classification (0 vs. 1)

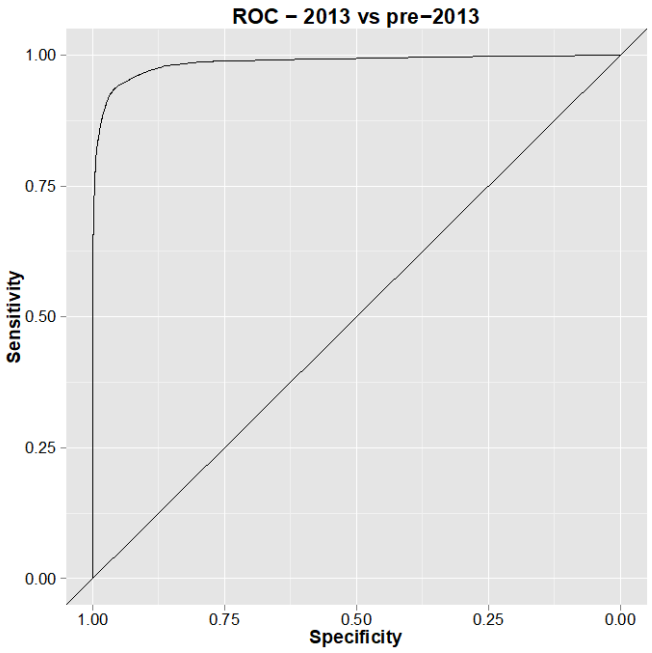
$$\mathcal{D} = \{(x_1, 1), \ldots, (x_m, 1), (x'_1, 0), \ldots, (x'_n, 0)\}$$



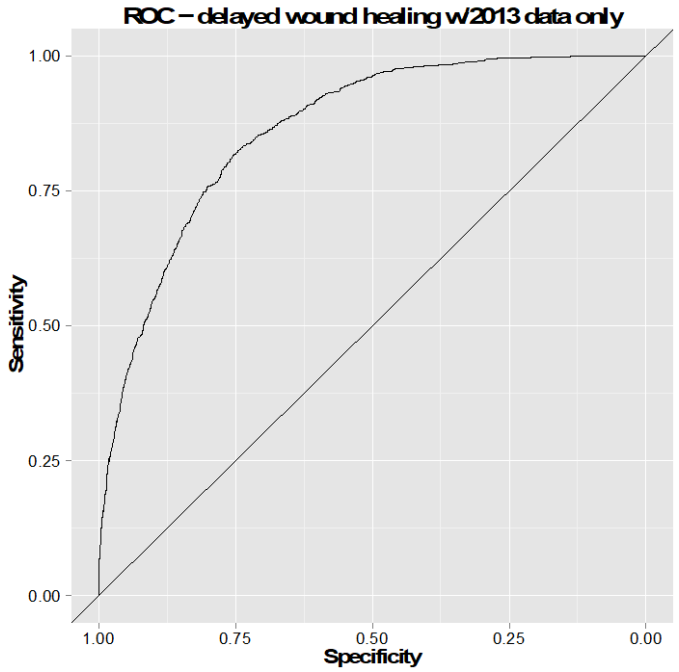
Could find *any* non-linear transformation (kernel) that makes the data separable

Testing for dataset shift

- Testing for covariate shift (wound healing):



Distinguish 2013 from pre-2013



Distinguish first 2/3 of 2013 from last 1/3 of 2013

(Figures from Ken Jung. See also Jung & Shah, Implications of non-stationarity on predictive modeling using EHRs, Journal of Biomedical Informatics, 2015)

Outline for today's class

- Examples & formalization of dataset shift
- Testing for dataset shift
- **Mitigating dataset shift**

Some practical answers

- **Domain shift** – transform features
  - imputation of missing values
  - artificially introduce noise/missingness during training
  - reprocess images
  - map to a common space
  - drop features that do not transfer
- **Concept drift / non-stationarity**
  - eg, p(y|x) changes because of new medical treatments
  - Retrain the model with most recent data
  - Research question: how to automate the above?
- ***Covariate shift***
  - When the underlying demographics / metadata is shifted
  - Application to different population: younger, healthier, etc
  - Next slide

Covariate shift: nonparametric regression just "works"

When can we expect training on p(x,y) and testing on q(x,y) to give good results, for $\mathrm{p} \neq q$?

Theorem: If $\mathrm{p(x)} > 0$ whenever $\mathrm{q(x)} > 0$ and $p(\, y \mid x \,) = q(\, y \mid x \,)$, then in the limit of infinite data from *p*, can achieve Bayes' error on *q*

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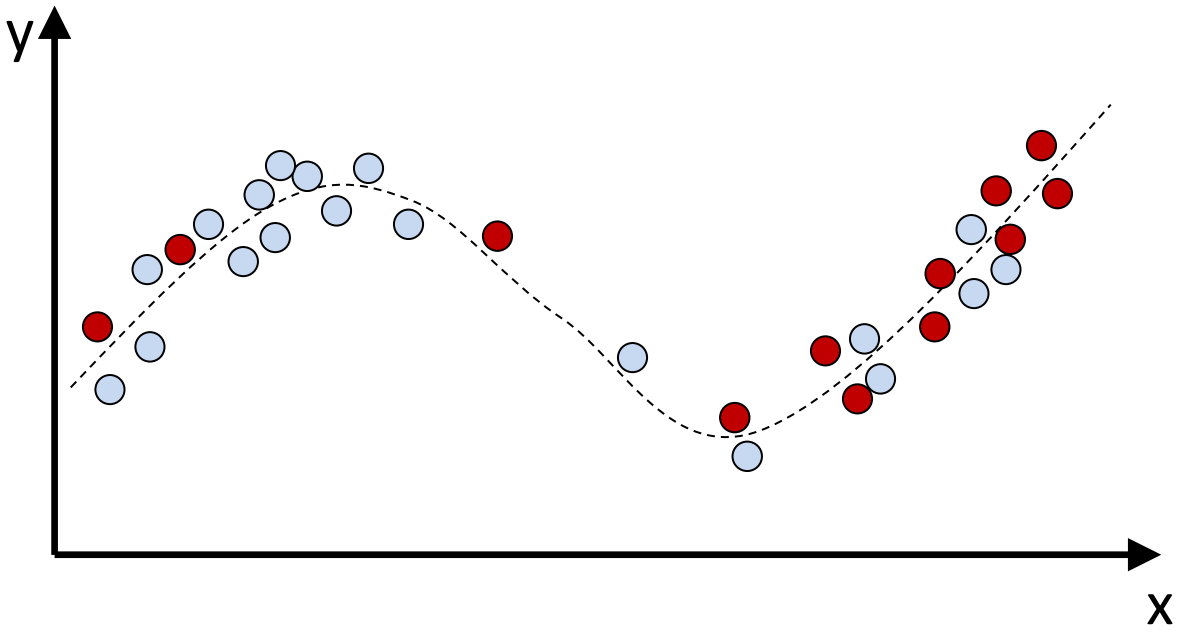
We never have infinite data!

May have to use a more restricted model to prevent overfitting
(e.g. a linear model despite true one being non-linear)

Effect of covariate shift when (naively) learning with misspecified models

- Training data p(x,y)= and test data q(x,y)=



[Storkey, “When Training and Test Sets are Different”, Dataset in Machine Learning, MIT Press 2009]

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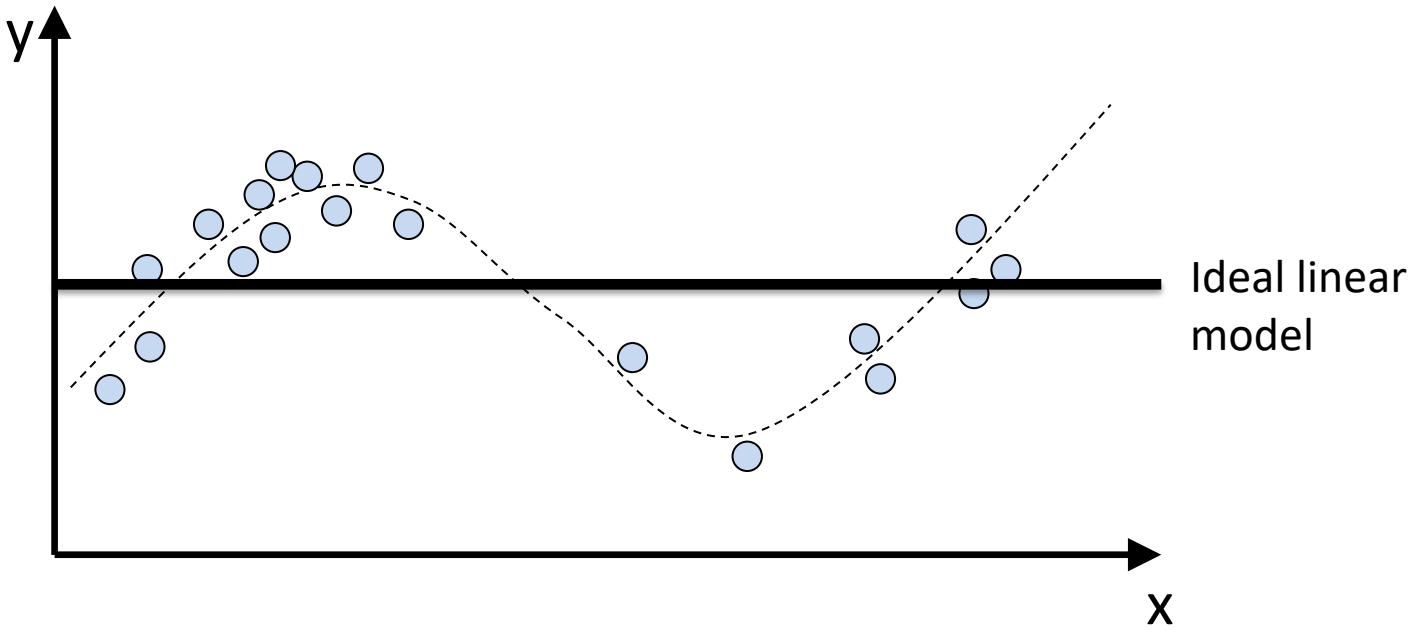

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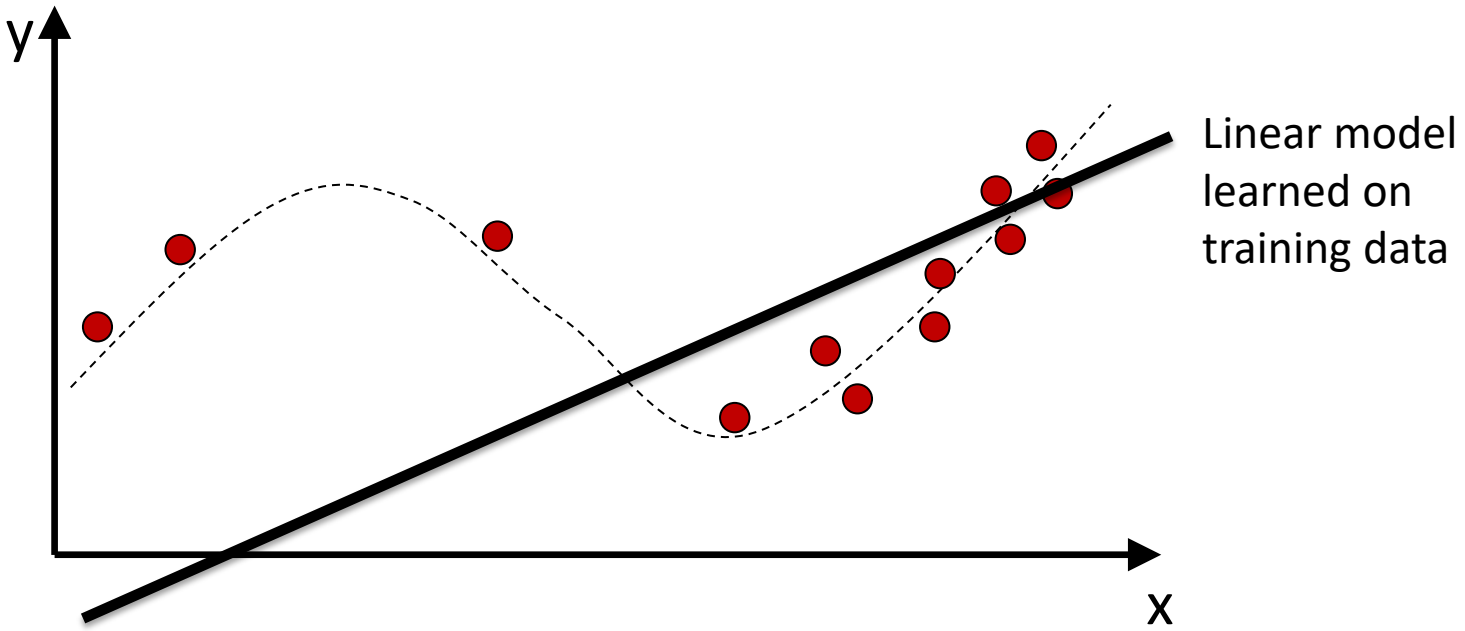
Effect of covariate shift when (naively) learning with misspecified models

- Training data p(x,y)= ● and test data q(x,y)= ○



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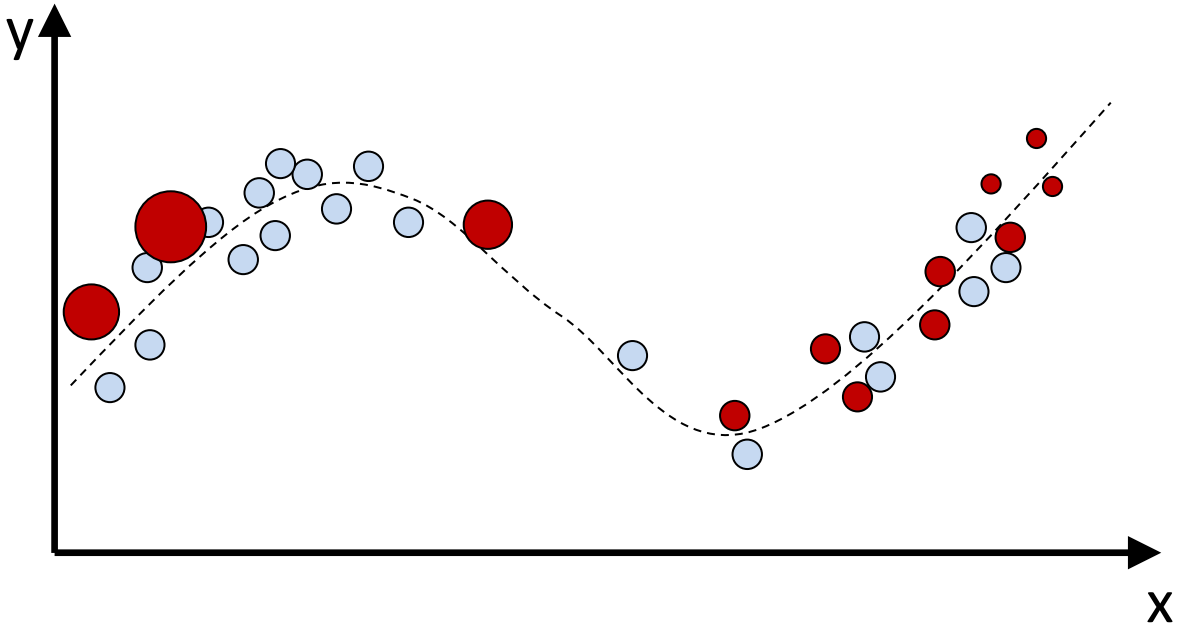
Learning using importance reweighting under covariate shift

- Training data p(x,y)= ● and test data q(x,y)= ○



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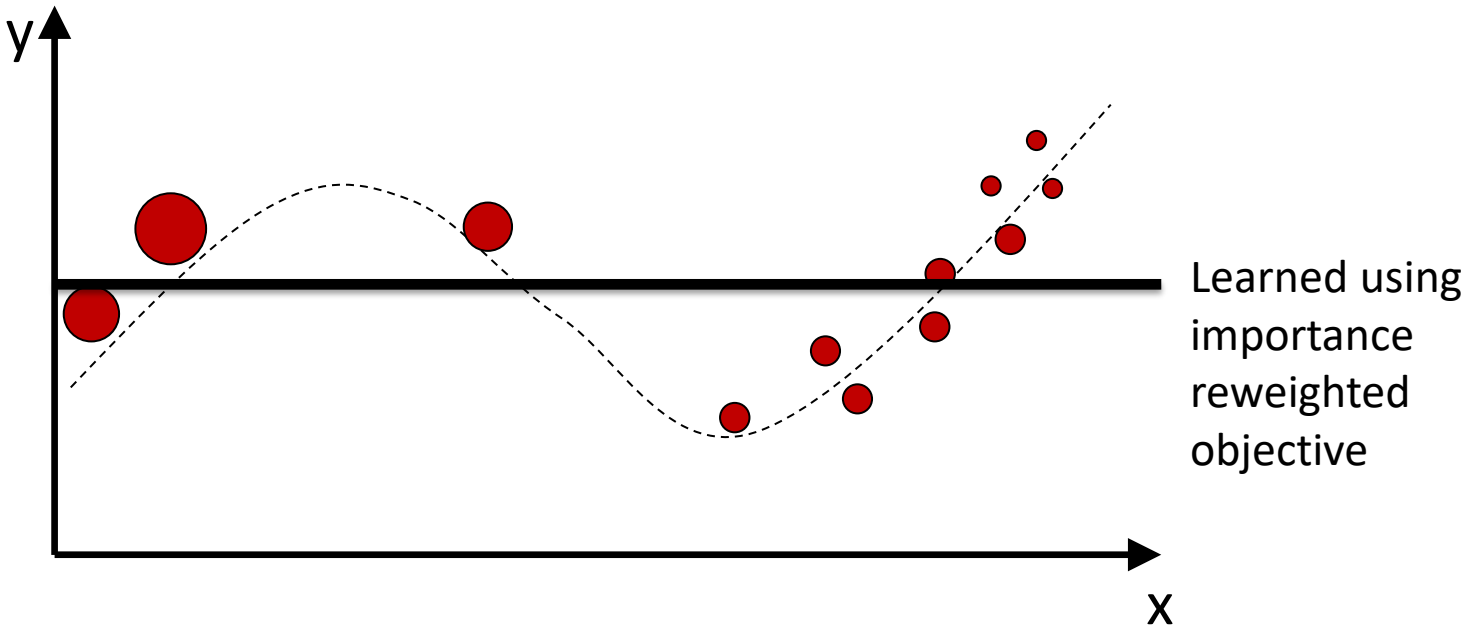

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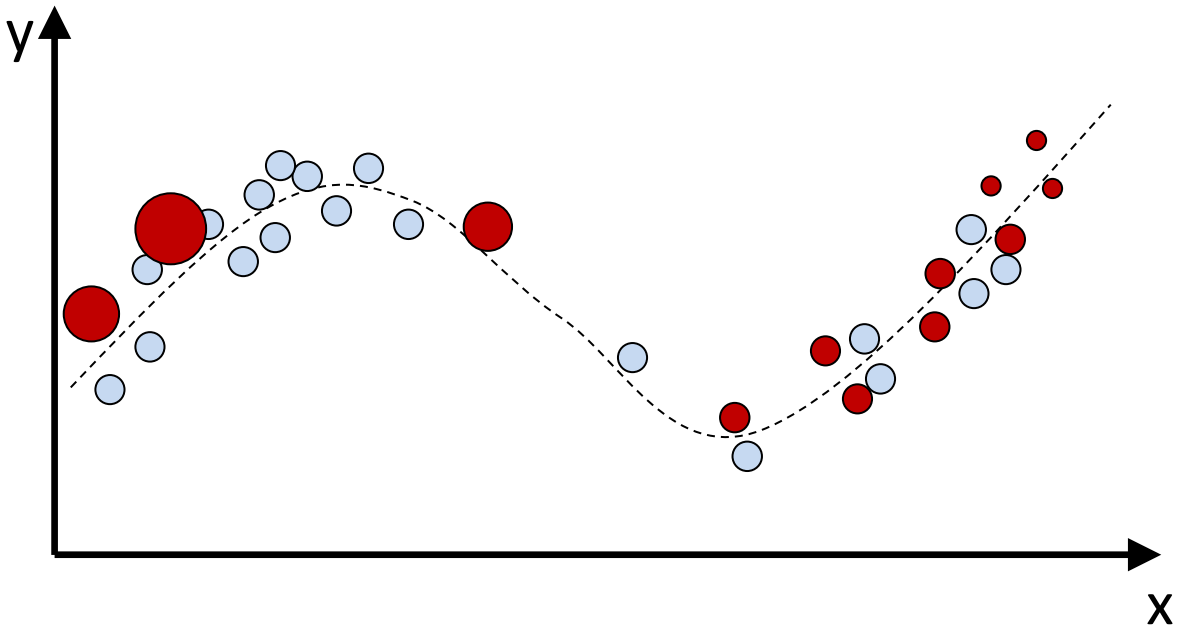

Key insight: We only need to know q(**x**) to reweight the training data!

Example of *unsupervised* domain adaptation. *No need for y values!*

Learning using importance reweighting under covariate shift

Goal of learning:

$$\min_\theta \mathbb{E}_{(x,y)\sim q} L(x, y; \theta)$$

Example – squared loss, linear model

$$L(x, y; \theta) = (y - \theta \cdot x)^2$$

But, suppose all we have are samples $(x_1, y_1), \ldots, (x_m, y_m) \sim p(x, y)$

Learn using: $\frac{1}{m} \sum_{i=1}^{m} \frac{q(x_i)}{p(x_i)} L(x_i, y_i; \theta)$

Importance reweighting

Recall $p(y|x) = q(y|x)$

$$\mathbb{E}_p\left[\frac{q(x)}{p(x)} L(x, y; \theta)\right] = \int_{x,y} \cancel{p(x)} p(y|x) \frac{q(x)}{\cancel{p(x)}} L(x, y; \theta)\, dx\, dy$$

$$= \int_{x,y} q(x, y) L(x, y; \theta)\, dx\, dy = \mathbb{E}_q[L(x, y; \theta)].$$

Learning using importance reweighting under covariate shift

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How do we obtain q(x)/p(x)?

Approach 1:

Data (*x*, *d*), where *d* denotes the dataset

samples $x_1, \ldots, x_m \sim p$, $x'_1, \ldots, x'_n \sim q$ → $\mathcal{D} = \{(x_1, 1), \ldots, (x_m, 1), (x'_1, 0), \ldots, (x'_n, 0)\}$

$$\frac{q(x)}{p(x)} \leftarrow \frac{\Pr(d = 1 \mid x)}{1 - \Pr(d = 1 \mid x)} \frac{n}{m}$$

Learning using importance reweighting under covariate shift

Goal of learning:

$$\min_\theta \mathbb{E}_{(x,y)\sim q} L(x, y; \theta)$$

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$$\frac{q(x)}{p(x)} \leftarrow \frac{\Pr(d = 1 \mid x)}{1 - \Pr(d = 1 \mid x)} \frac{n}{m}$$

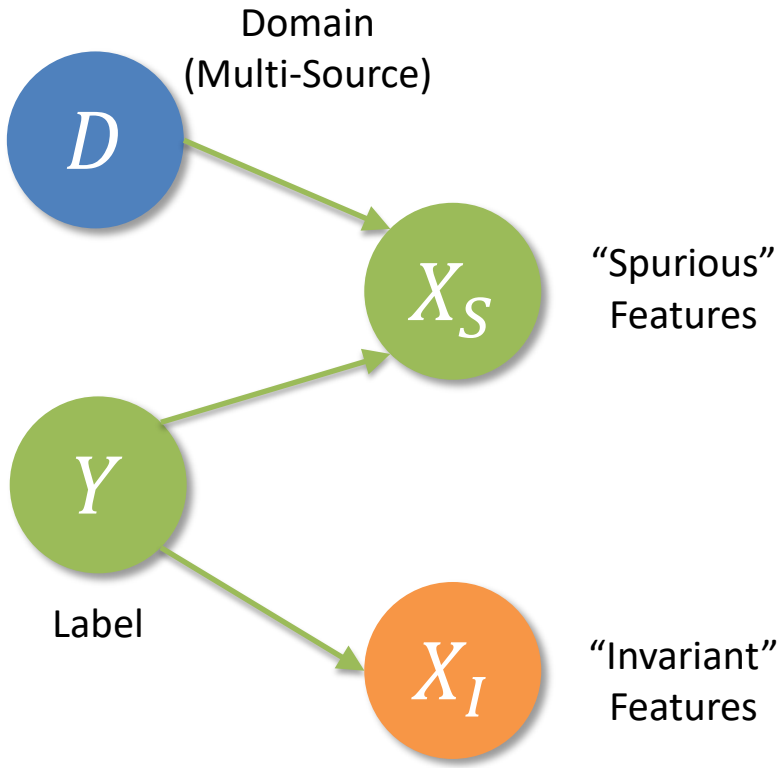
Approach 2: density estimation of *q* and *p*

When importance reweighting is not enough

- Importance reweighted estimator can be high variance
- If there is no *overlap*, then in general impossible – even with infinite data

Current state of research on dataset shift

- Seek "invariant" representations that will work well even after dataset shift



What properties should a representation have?

Here, the domain only influences (some) features.

Learn only on those features. Lower performance, but better translation between domains

But, how do we know which ones?

➔ We just saw several methods to do so

Observe: The distribution $P(Y \mid X_I)$ does not depend on D. Can we encourage our representation to recover X_I?

Potential approach: Given multiple source environments, learn a representation such that

$$\boldsymbol{\phi}(\boldsymbol{X}) \perp \boldsymbol{D}$$

Caveat: The right "invariance" depends on the generative structure, and how D impacts X, Y

Current state of research on dataset shift

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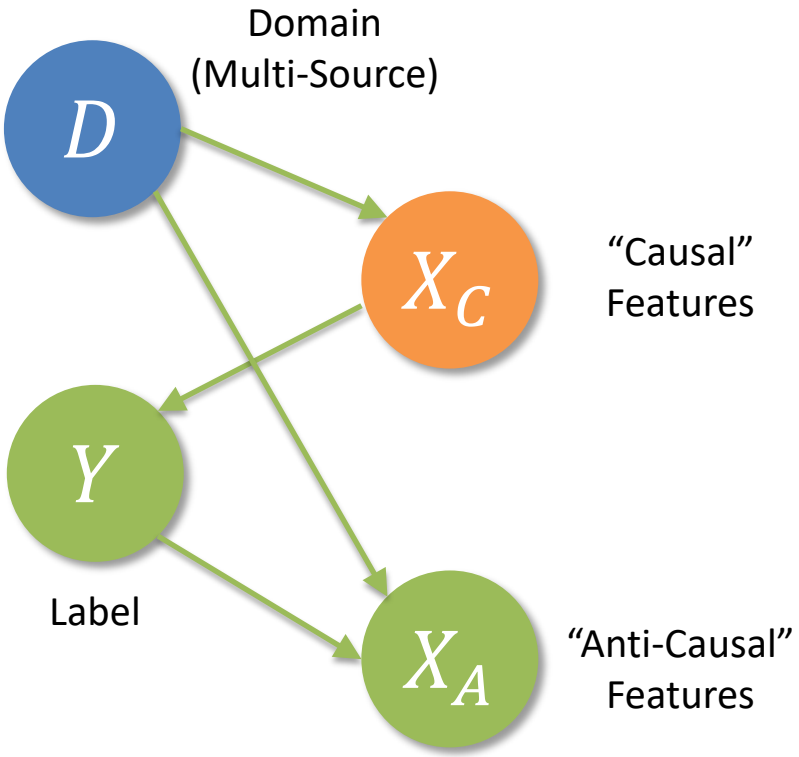


What properties should a representation have?

Here, the domain influences all features.

Observe: The distribution $P(Y \mid X_C)$ does not depend on D. Can we encourage our representation to recover X_C?

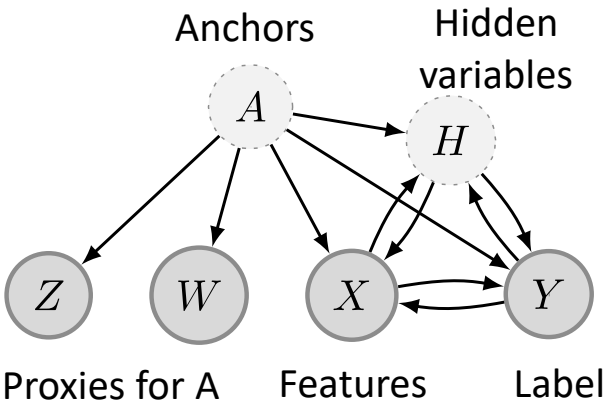
Potential approach: Given multiple source environments, learn a representation such that

$$\boldsymbol{Y \perp D \mid \phi(X)}$$

Note: Under this generative structure, it no longer makes sense to seek $\boldsymbol{\phi(X) \perp D}$

Current state of research on dataset shift

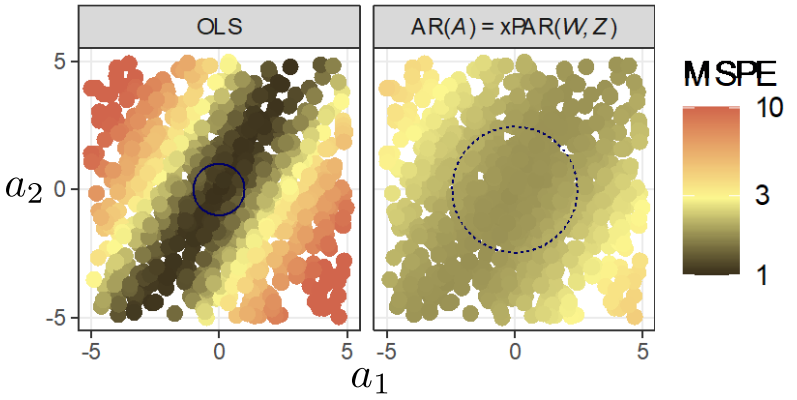
- Assume knowledge of ‘anchors’ that tell you what can change; learn to extrapolate



Assume p(*A*) will change in test distribution, and use distributionally robust training

$$f^* = \arg\min_{f \in \mathcal{F}} \sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}_{\mathbb{P}}[\ell(Y, f(X))]$$

Change in A is assumed to be *bounded*.



[Rothenhausler et al., Anchor regression: heterogeneous data meets causality. *J. of the Royal Statistical Society: Series B*, ‘18]
[Oberst, Thams, Peters, Sontag. Regularizing towards Causal Invariance: Linear Models with Proxies, ICML, ‘21]

Current state of research on dataset shift: benchmarking

WILDS: A Benchmark of in-the-Wild Distribution Shifts

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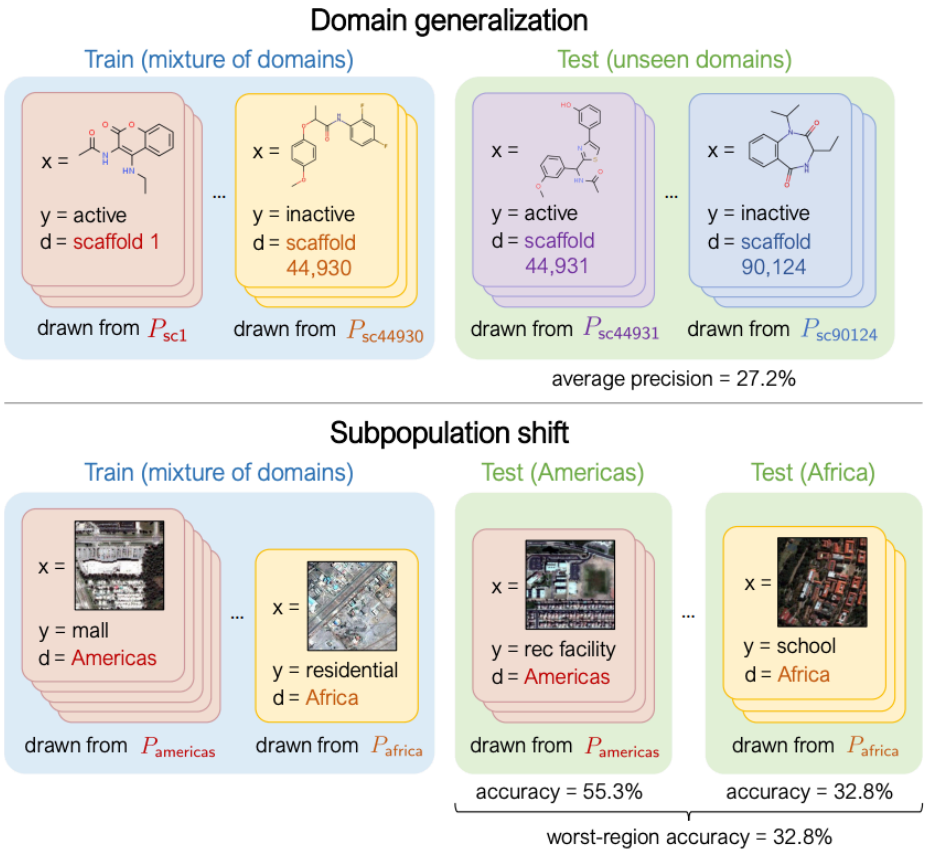
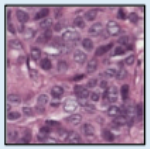
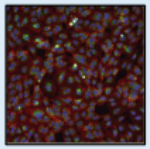
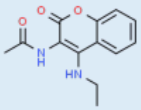
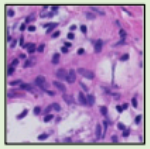
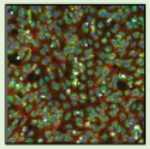
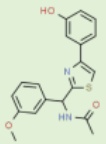
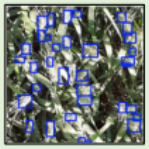


	Domain generalization					Subpopulation shift	Domain generalization + subpopulation shift			
Dataset	**iWildCam**	**Camelyon17**	**RxRx1**	**OGB-MolPCBA**	**GlobalWheat**	**CivilComments**	**FMoW**	**PovertyMap**	**Amazon**	**Py150**
Input (x)	camera trap photo	tissue slide	cell image	molecular graph	wheat image	online comment	satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat head bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	country, rural-urban	user	git repository
# domains	323	5	51	120,084	47	16	16 x 5	23 x 2	2,586	8,421
# examples	203,029	455,954	125,510	437,929	6,515	448,000	523,846	19,669	539,502	150,000
Train example						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						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!	`import subprocess as sp p=sp.Popen() stdout=p.___`
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

[Koh et al., WILDS: A Benchmark of in-the-Wild Distribution Shifts. arXiv:2012.07421, 2021.]

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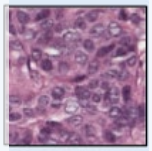
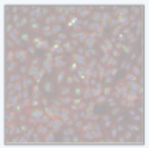
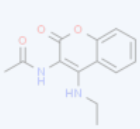
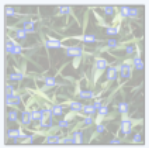
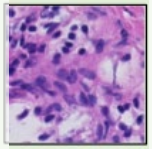
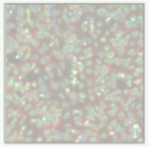
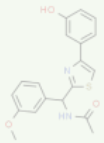
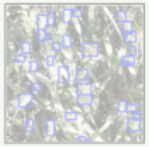
Train example						What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	`import numpy as np … norm=np.___`
Test example						As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	`import subprocess as sp p=sp.Popen() stdout=p.___`
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TL;DR: Existing algorithms don't substantially improve over Empirical Risk Minimization (ERM)

ERM = estimate risk empirically on training data, cuz we don't know all possible distributions of datasets

Table 2: The out-of-distribution test performance of models trained with different baseline algorithms: CORAL, originally designed for unsupervised domain adaptation; IRM, for domain generalization; and Group DRO, for subpopulation shifts. Evaluation metrics for each dataset are the same as in Table 1; higher is better. Overall, these algorithms did not improve over empirical risk minimization (ERM), and sometimes made performance significantly worse, except on CivilComments-WILDS where they perform better but still do not close the in-distribution gap in Table 1. For GlobalWheat-WILDS, we omit CORAL and IRM as those methods do not port straightforwardly to detection settings; its ERM number also differs from Table 1 as its ID comparison required a slight change to the OOD test set. Parentheses show standard deviation across 3+ replicates.

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.	**51.2 (1.8)**	—	—	47.9 (2.0)
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)

Note: These are *blind* implementations (with no domain knowledge injected) that do not attempt to understand the causal nature of the dataset shifts.

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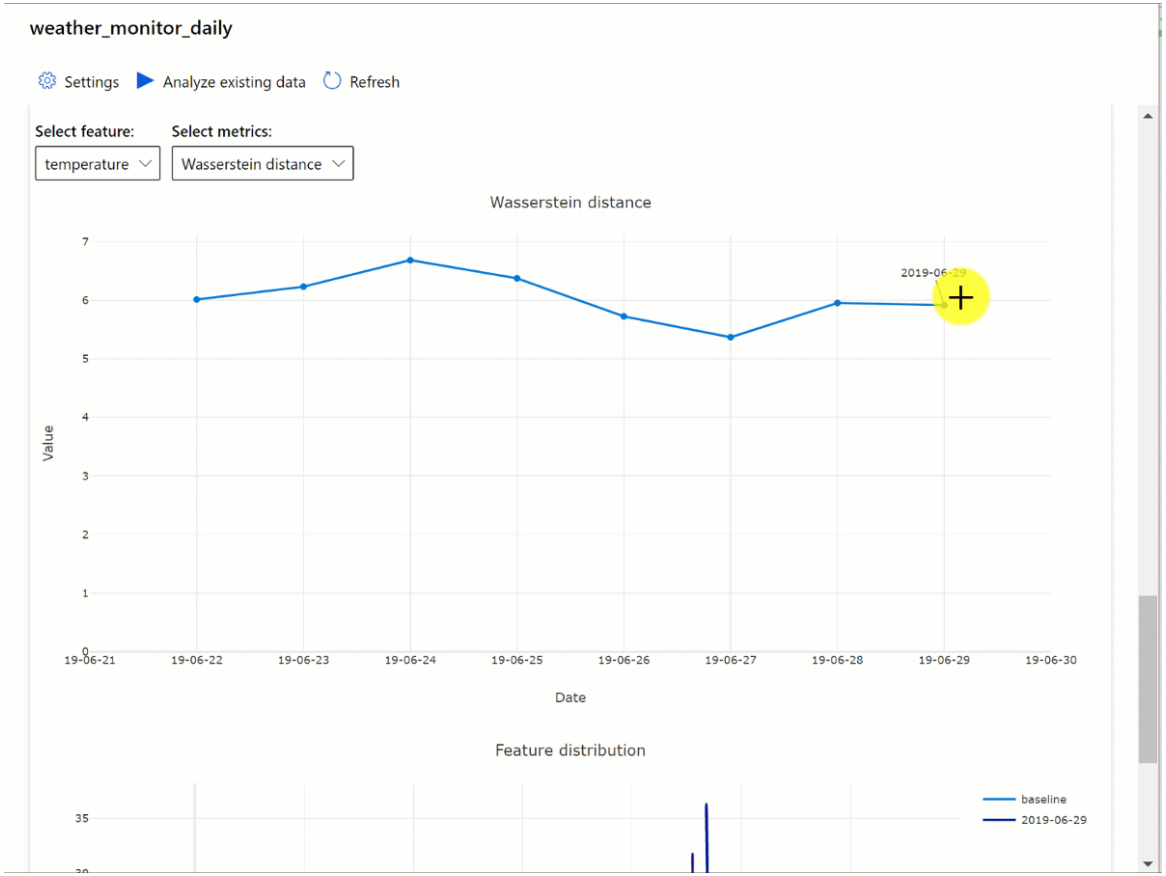
Current state of industry on dataset shift



Source: https://docs.microsoft.com/en-us/azure/machine-learning/how-to-monitor-datasets

See also: https://cloud.google.com/solutions/machine-learning/ml-modeling-monitoring-identifying-training-server-skew-with-novelty-detection & https://docs.seldon.io/projects/alibi-detect/en/latest/

Conclusion

- Dataset shift happens all the time with healthcare data
- It doesn’t always hurt performance
- Interpretability methods can help with detecting and mitigating dataset shift
- Safe deployments should include automated checks for dataset shift
- Active area of research in ML

Additional references

- The Clinician and Dataset Shift in Artificial Intelligence. Finlayson et al., *NEJM* 2021
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