Low-Resource Neural Adaptation

Beibin Li
beibin@uw.edu
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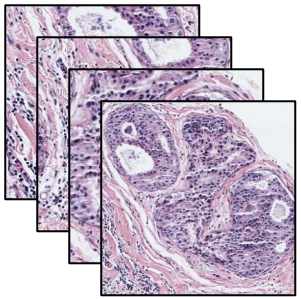
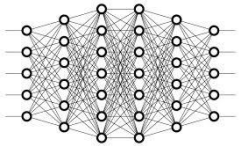
PAUL G. ALLEN SCHOOL

Traditional Machine Learning

Define the Problem → Collect Data → Train Model → Evaluate → Deploy

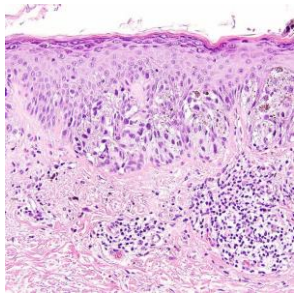
Breast Cancer



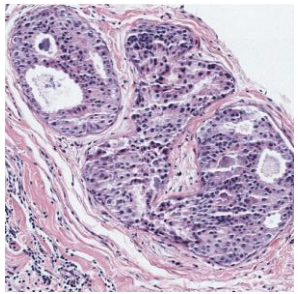


Opportunities and Challenges

During Training



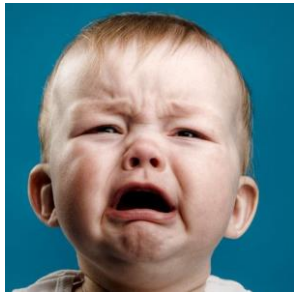
Melanoma



Breast Cancer

During Deployment

Adults



Children

Adaptation in Humans

During Learning

Skate

Snowboard

During Using

Drive car

Drive U-Haul Truck

How about Machines?

Can we do **better** and improve **machine**'s adaptation?

Learning

Utilize Prior Knowledge

Practice Different Tasks

Learn from Failure

Inference

Recognize Novel Samples

Estimate Confidence

Adjust Behavior

Adaptation

Adapting Knowledge

Big Data

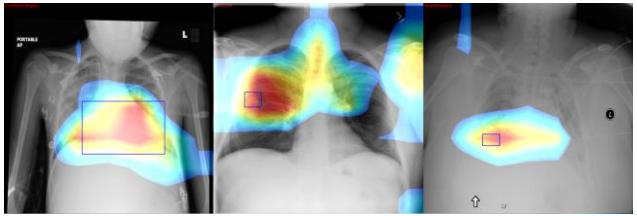
14+ Million Images

WikiText-103: 100+ Million Tokens

Foundation Models

(Large, Powerful)
(Centralized, Federated)

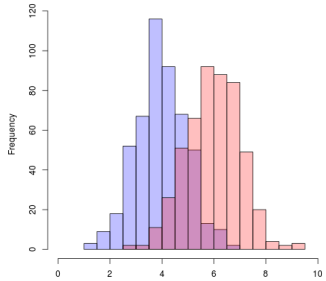
Small Datasets



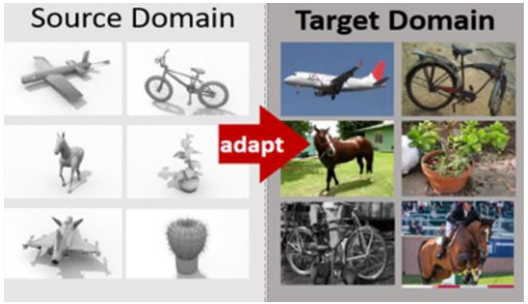
Medical Imaging

Private Documents

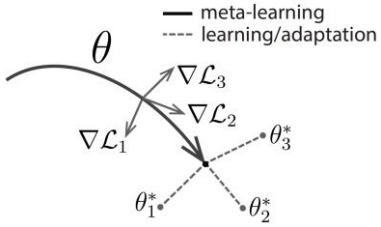
Prior Studies



Stats Analysis

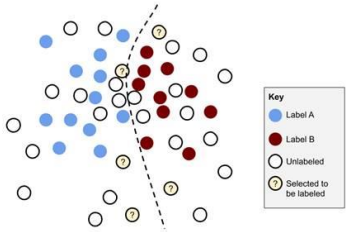


Domain Adaptation

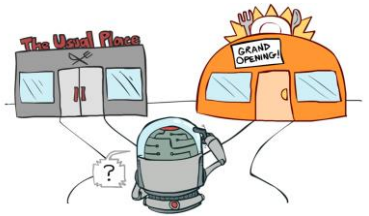


Meta Learning

Self-Supervision



Active Learning



$$R(T) \leq \beta n T + \gamma T + (1+\beta)\eta n T + \frac{\log(n\delta^{-1})}{\beta} + \frac{\log(n)}{\eta}$$

Exploration v.s. Exploitation

They are Powerful, But...

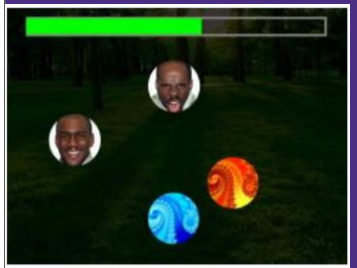
Unified Framework in Human Brain!

Prefrontal Cortex

Executive Functioning Skills
- Shifting
- Inhibitory
- Short-Term Memory

Confidence in Problem-Solving

Language Generation



- Social Influences on Executive Functioning in Autism: Design of a Mobile Gaming Platform. **Li, B.**, et al. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (p. 443) (ACM SIGCHI 2018).
- Memory Deficit in Patients with Temporal Lobe Epilepsy: Evidence from Eye Tracking Technology Zhu, G., et al. Frontiers in Neuroscience 2021

Translate DL for Real World

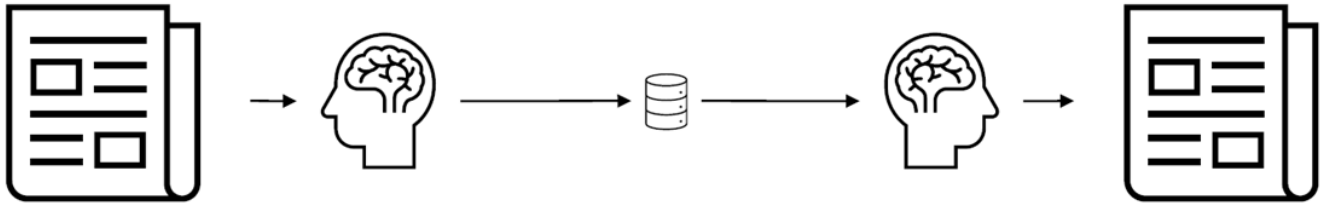
Bringing state-of-the-art adaptation techniques into real-world applications for private entities (e.g., due to HIPAA, privacy, labeling cost, etc.).

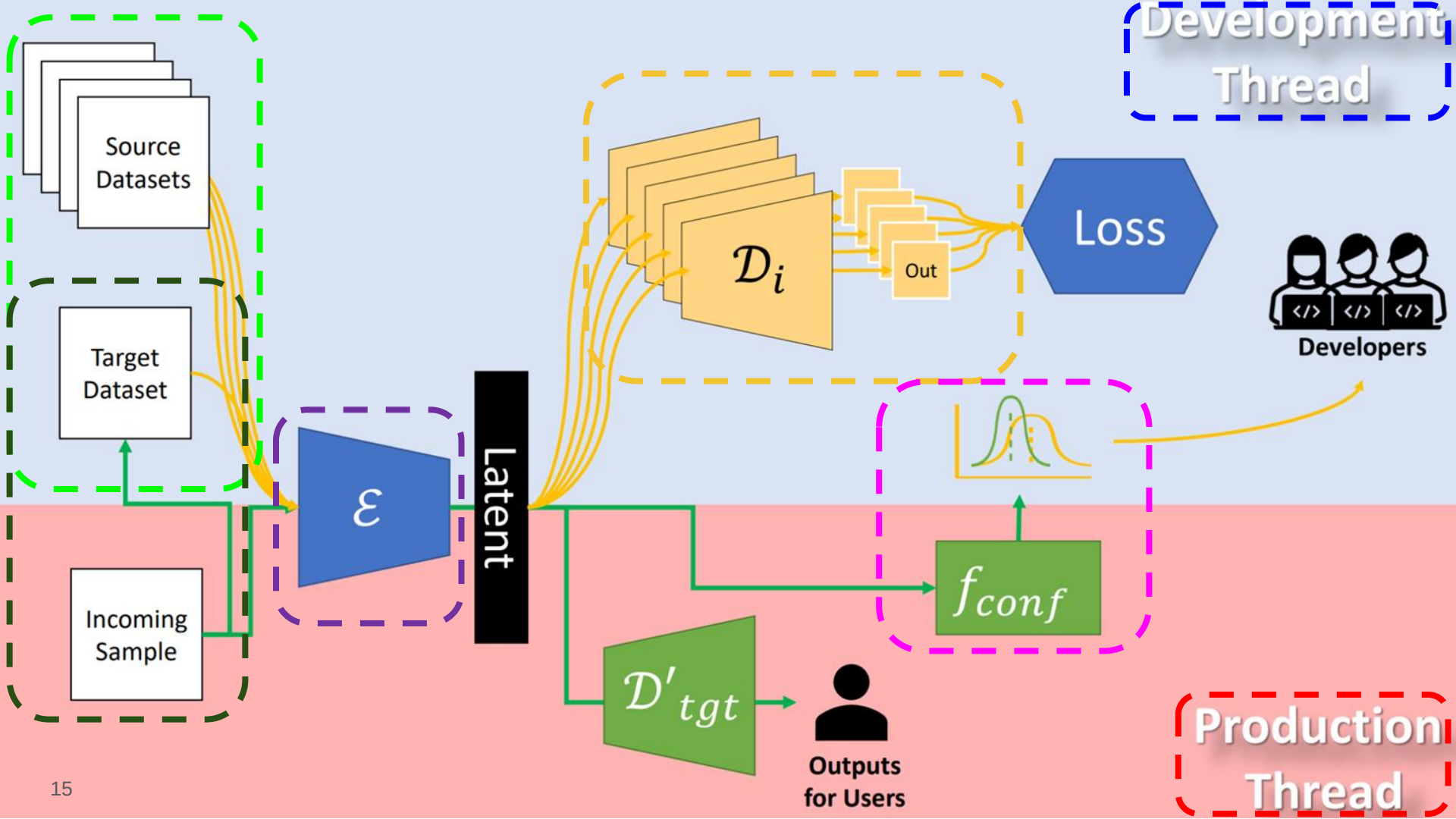
Motivation

We need a **unified** paradigm for these various ML tasks

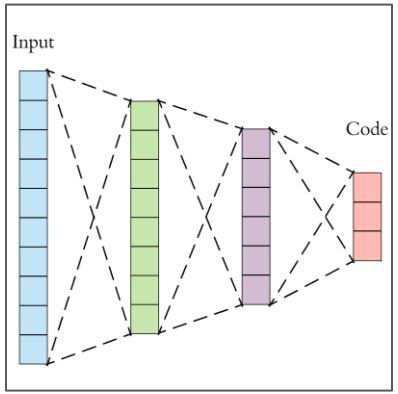
Build **in-house** private models for **low-resource** data

Method

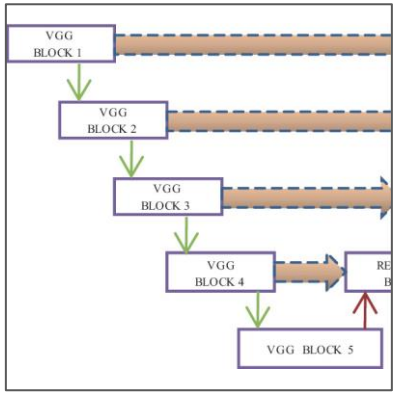



Development Thread
Source Datasets
Target Dataset
Incoming Sample
$\mathcal{E}$
Latent
$\mathcal{D}_i$
Out
Loss
Developers
f_{conf}
$\mathcal{D}'_{tgt}$
Outputs for Users
Production Thread

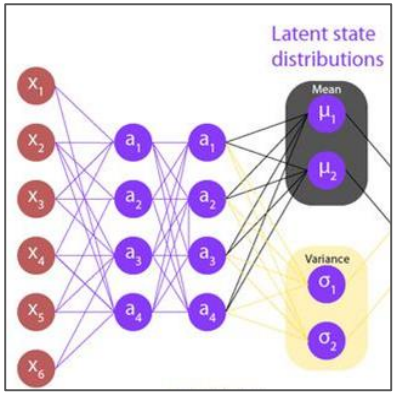
Encoder



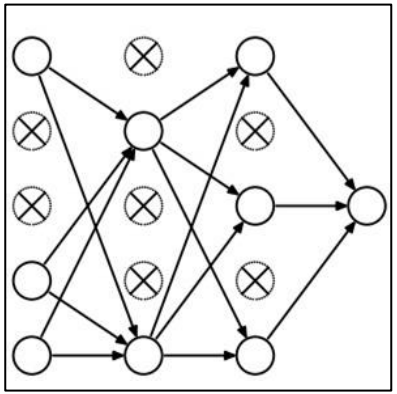
Standard



Skip Connections (Residuals)

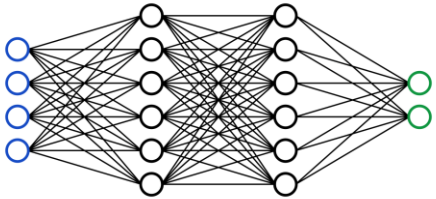


Variational Bayes

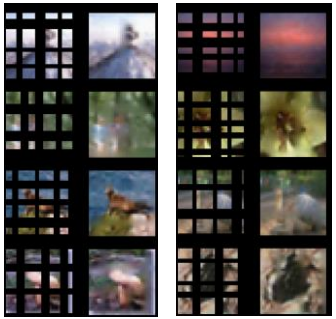


Monte Carlo Dropout

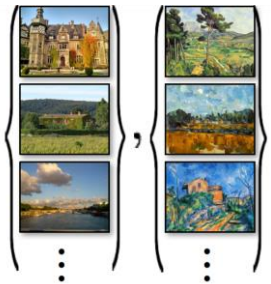
Decoders



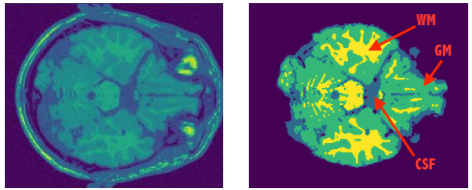
Classify, Regress



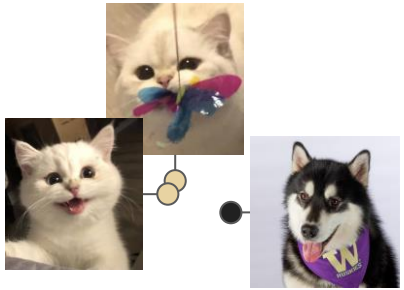
Reconst, Recover



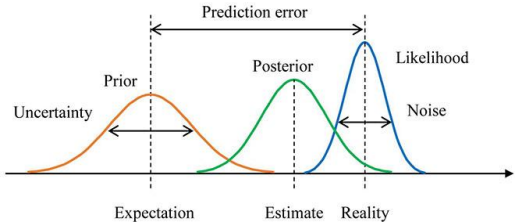
Generate



Segment, Detect



Contrastive

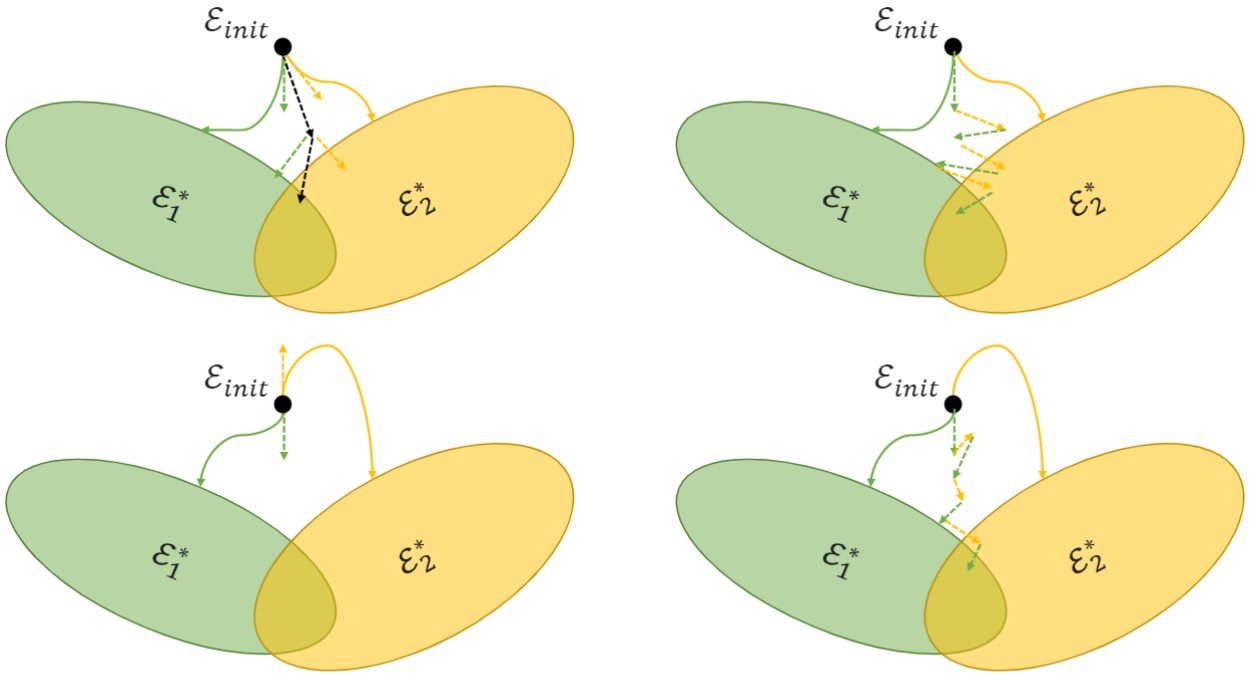


f(Confidence Esti.)

Learning Algorithms

Case 1

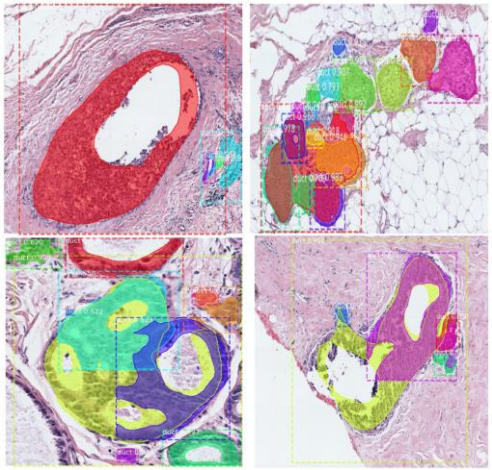
Case 2

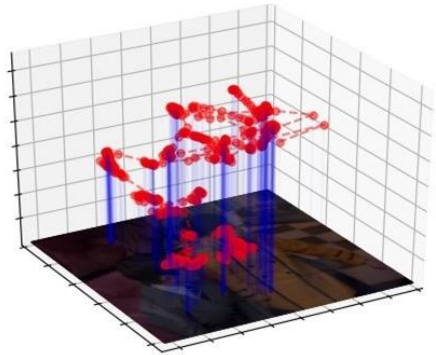


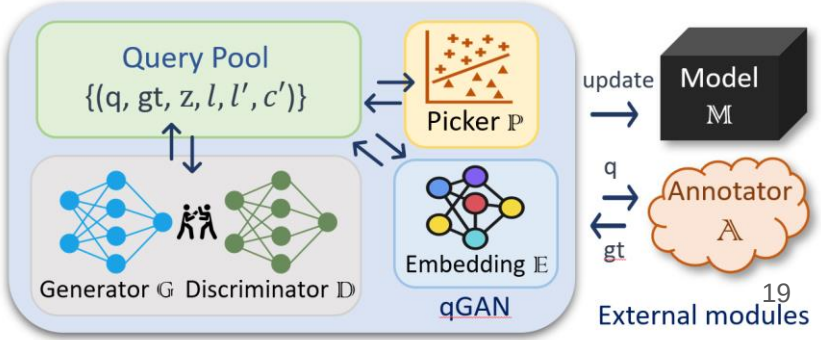
(a) MTL (b) Reptile

Applications

- Histopathological Medical Image
- Facial Expression for Autism
- Eye-tracking Analysis
- Database Optimization







Data and Consents

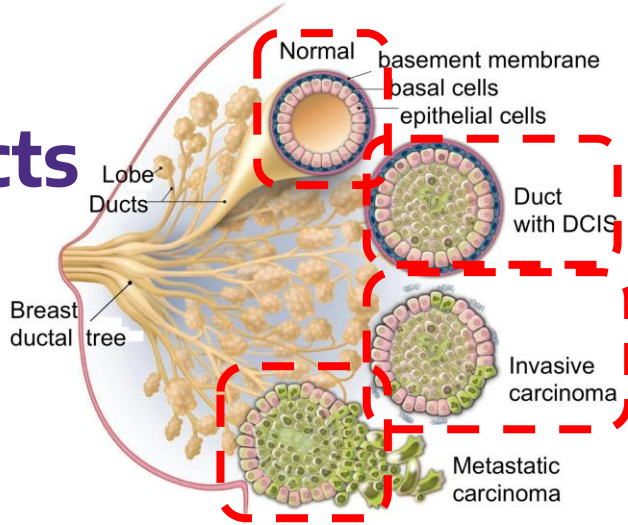
During our experiments, **informed consent** was obtained from all patients, participants, and parents of all children.

Study procedures were designed in accordance with:

- World Medical Association **Declaration of Helsinki**
- Ethical Principles for Medical Research Involving **Human Subjects**
- Health Insurance Portability and Accountability Act (**HIPAA**) to preserve privacy.
- **Institutional Review Board**
  - Yale University
  - Seattle Children's Research Institute
  - University of Washington
  - University of California

Medical Imaging

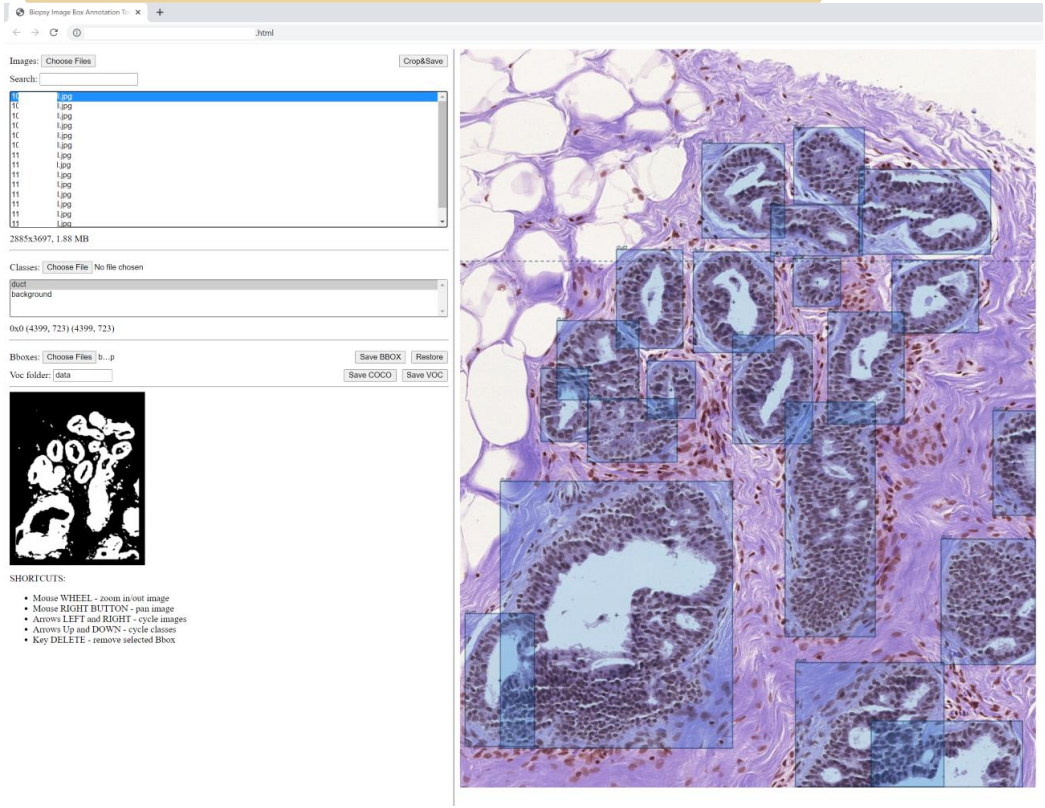
Breast Cancer Diagnosis: with Ducts



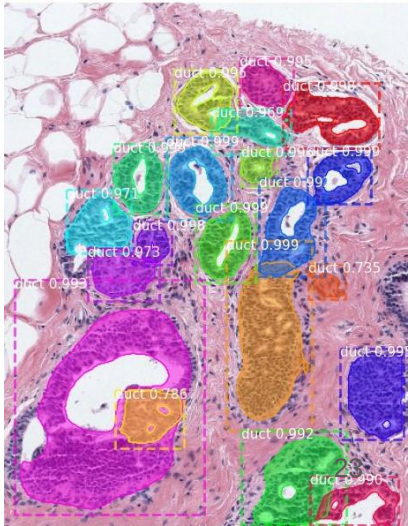
- **Important** Region for Diagnosis
- **Interpretable** Intermediate Results
- Only **240** Images (Biopsies) in the Dataset
- **No** Duct **Label**

Classifying Breast Histopathology Images with a Ductal Instance-Oriented Pipeline
Li, B.; Mercan, E.; Mehta, S.; Knezevich, S.; Arnold, C.; Weaver, D.; Elmore, J.; Shapiro, L.
In 2020 25th International Conference on Pattern Recognition. IEEE.

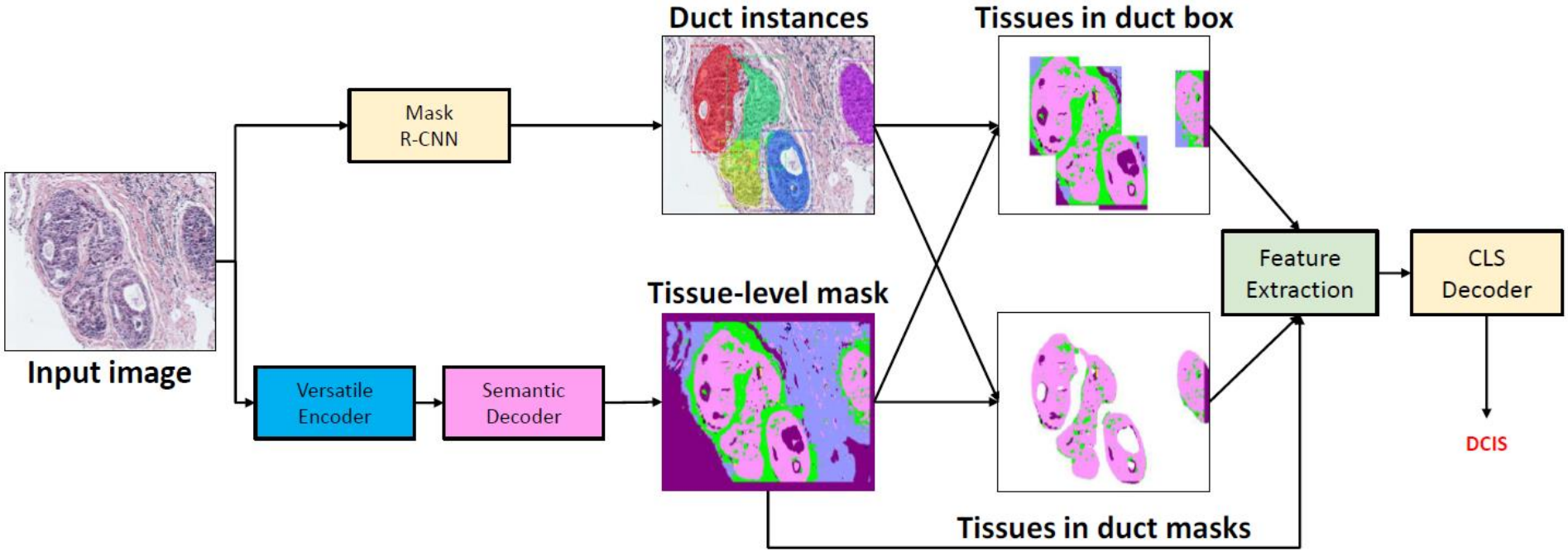
Weakly Supervised Annotation



- Human-AI Collaboration
- Weakly Supervised Labeling
- Combines
  - Machine's Semantic Prediction
  - Human Box Annotation
- Instance Segmentation Labels
- Silver Standard



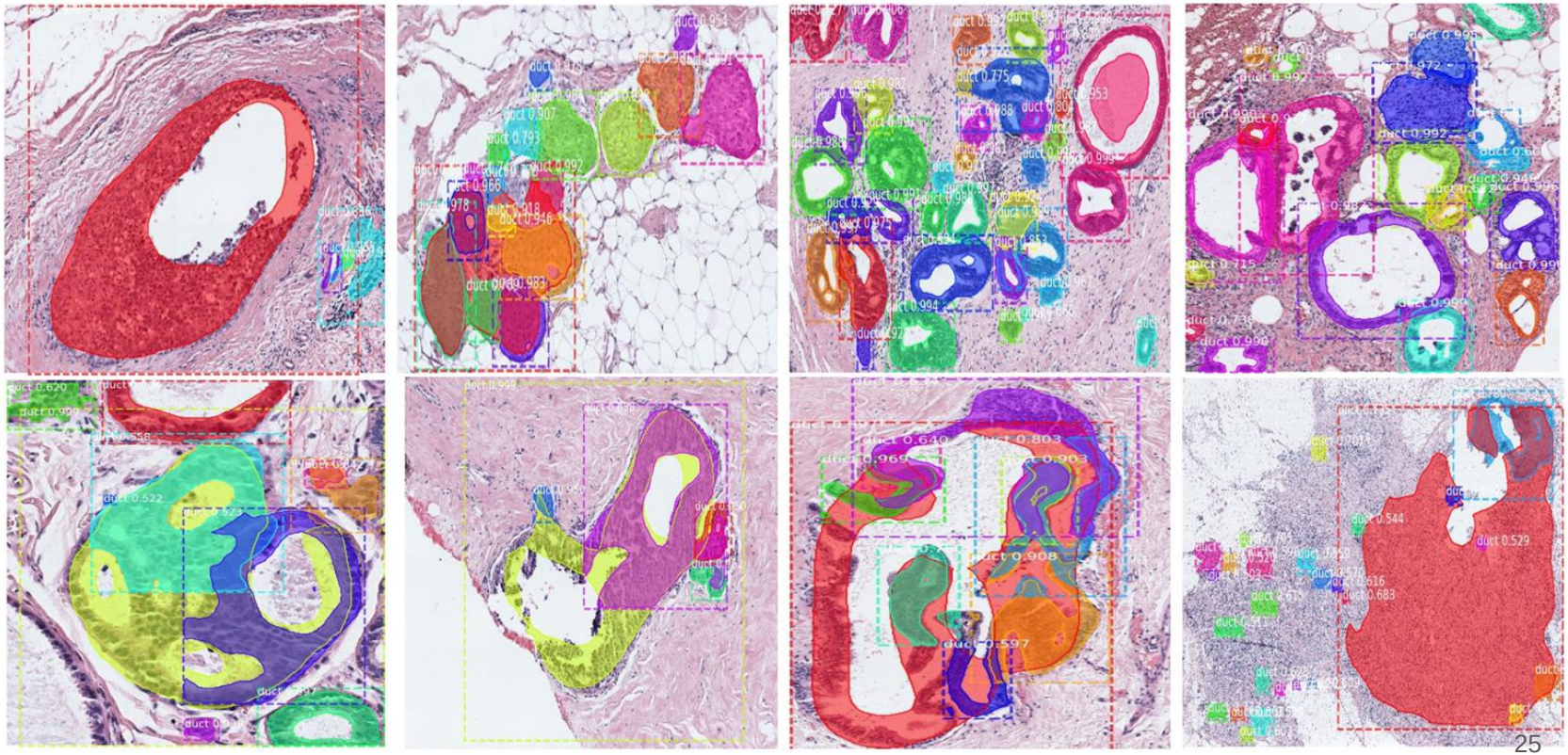
Diagnostic Performance



Instance Segmentation Results

Good

Imperfect



Diagnostic Results

Task	Features	Sensitivity	Specificity	Accuracy	F_1
Invasive vs Non-invasive	*Pathologists*	*0.84*	*0.99*	*0.98*	*0.86*
	Superpixel Features	**0.70**	0.95	0.94	0.62
	Structure Features	0.49	0.96	0.91	0.51
	Ours	0.62	**0.98**	**0.95**	**0.73**
Atypia and DCIS vs Benign	*Pathologists*	*0.72*	*0.62*	*0.81*	*0.51*
	Superpixel Features	0.79	0.41	0.70	0.46
	Structure Features	**0.85**	0.45	0.70	0.50
	Ours	**0.85**	**0.63**	**0.79**	**0.59**
DCIS vs Atypia	*Pathologists*	*0.70*	*0.82*	*0.80*	*0.76*
	Superpixel Features	0.88	0.78	0.83	0.86
	Structure Features	0.89	0.80	0.85	0.87
	Ours	**0.91**	**0.89**	**0.90**	**0.92**

Method	Accuracy
Pathologists	0.70
MIL with max-pooling	0.55
MIL with learned fusion	0.67
Semantic Learning	0.55
Y-Net	0.63
Ours	**0.70** $\pm$ 0.02

Interpretability

Malignant Epithelium (BE) and Necrosis (NC) co-occurs

Benign Epithelium (BE) near Boundary (BD)

Rank	DIOP (ours)	Tissue-level model
1	BD & BE in duct mask	ME & NC in ROI
2	ME & NC in duct mask	BG & NC in ROI
3	BD & NC in duct mask	SC freq in ROI
4	BE & NS in bounding box	BE freq in ROI
5	BG & NC in duct mask	BE & SC in ROI
6	BE & SC in ROI	ME & NS in ROI
7	ME & SC in bounding box	BE & NS in ROI
8	NC freq in bounding box	NC freq in ROI
9	BE & SC in bounding box	NS & NC in ROI
10	DS freq in duct mask	SC & NC in ROI

Necrosis (NC) near Boundary (BD)

MLCD: A Unified Software Package for Cancer Diagnosis
Wu, W.; **Li, B.**; Ezgi, M.; Mehta, S.; Bartlett, J.; Weaver, D.; Elmore, J.; Shapiro, L.
In Journal of Clinical Oncology (JCO). 2020

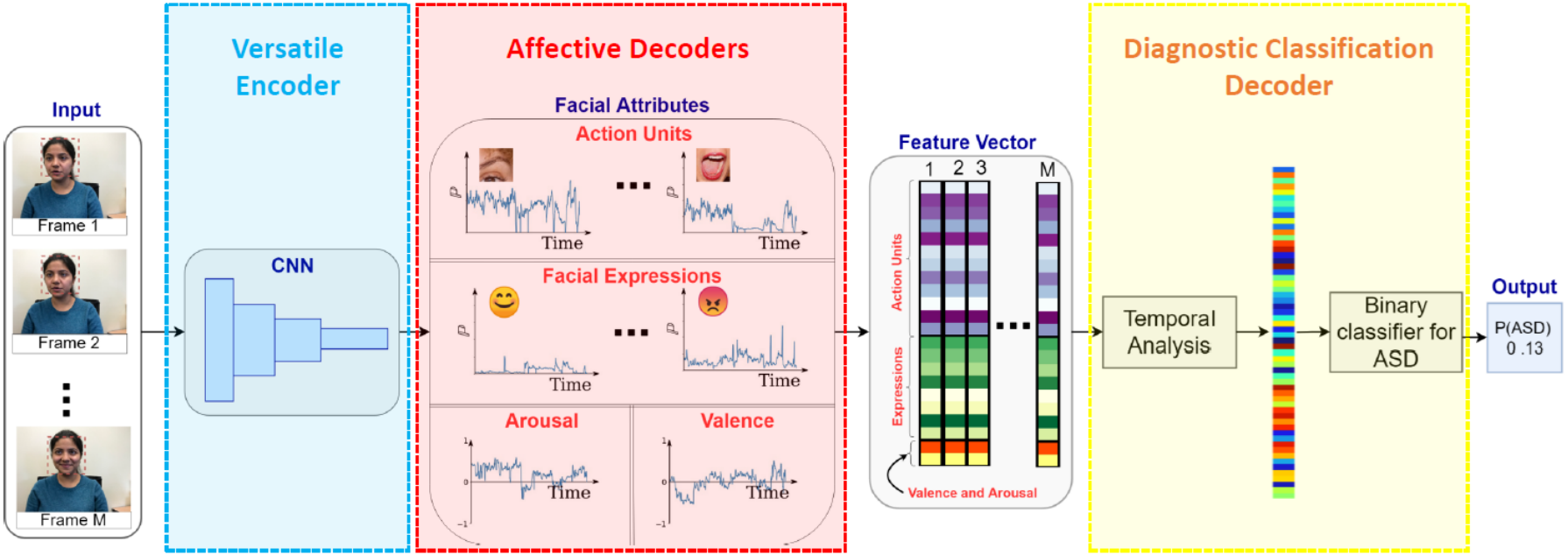
Learning Melanocytic Proliferation Segmentation in Histopathology Images from Imperfect Annotations
Liu, K.; Mokhtari, M.; **Li, B.**; Nofallah, S.; May, C.; Chang, O.; Knezevich, Stevan.; Elmore, J.; Shapiro, L. In 2021 Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)

Affective Computing

Data Collection

- From iPad Air 2 or iPad 5th Generation
- 88 participants
  - 49 children with ASD
  - 39 typically developing (TD) peers
- Auxiliary Data (> 1 million images)
  - AffectNet
  - EmotioNet

Model



A Facial Affect Analysis System for Autism Spectrum Disorder
Li, B.; Mehta, S.; Aneja, D.; Foster, C.; Ventola, P.; Shic, F.; Shapiro, L.
In Proceedings of the IEEE International Conference on Image Processing (ICIP 2019)

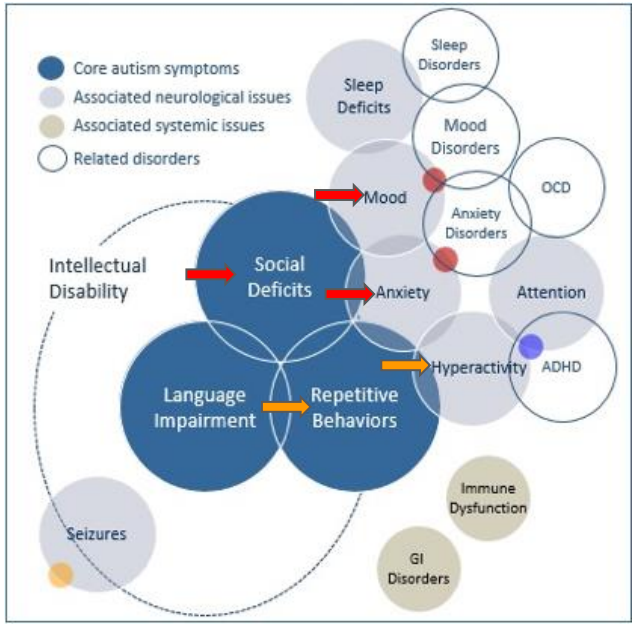
Results

CNN Unit	# Params	FLOPs	Expression (F1)	AU (mF1Acc)	Valence (CC)	Arousal (CC)
			Single-task			
Bottleneck	25.9 M	3.4 B	0.56	**0.78**	0.63	0.54
MobileNet	24.8 M	3.1 B	0.57	0.77	0.64	0.52
EESP	9.7 M	1.2 B	0.57	0.76	0.64	0.52
			Multi-task			
Bottleneck	6.5 M	0.85 B	**0.58**	0.75	0.68	0.61
MobileNet	6.2 M	0.78 B	**0.58**	0.75	0.68	**0.62**
EESP	**2.4 M**	**0.29 B**	**0.58**	0.75	**0.69**	0.61
			Literature			
SOTA	-	-	0.58	-	0.66	0.54
Human Performance	-	-	0.61	*	0.82	0.57

Autism Classification

Facial attributes				F1	Sensitivity	Specificity
AU	Aro	Val	Expr			
✓				0.69	0.69	0.62
✓	✓			0.72	0.71	0.67
✓	✓	✓		0.69	0.67	0.67
✓	✓	✓	✓	**0.76**	**0.76**	**0.69**

- Compared to peers, children with autism have
  - more joy
  - less neutral
- Expression/Arousal/Valence/Head movements are more various for children with autism.



Eye Tracking
(Gaze Estimation)

Eye Tracking

Lots of Applications

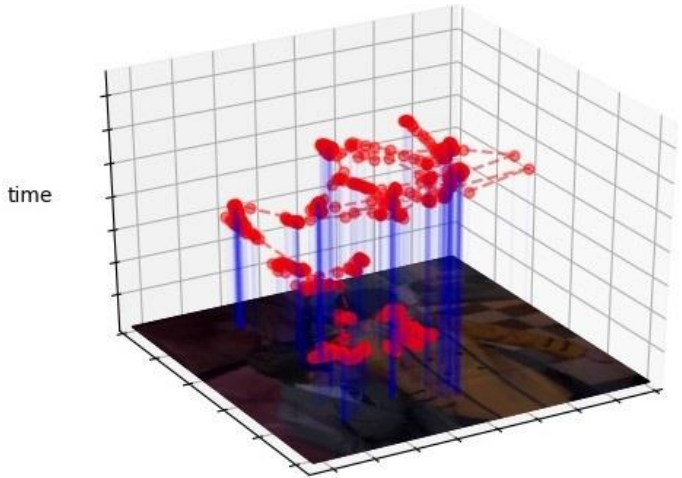
Few Public Datasets

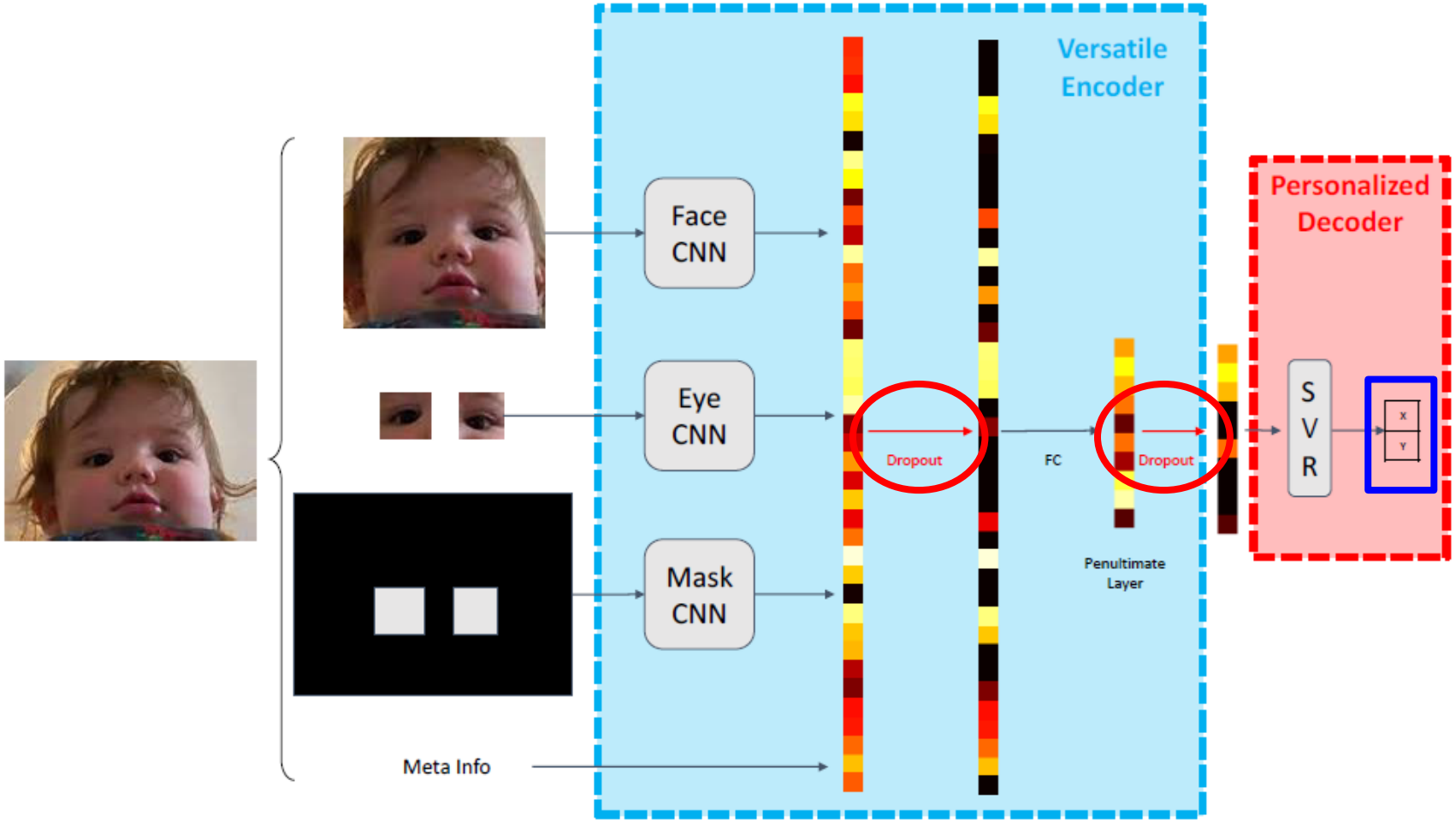
Small Sample Size

Large Feature Space

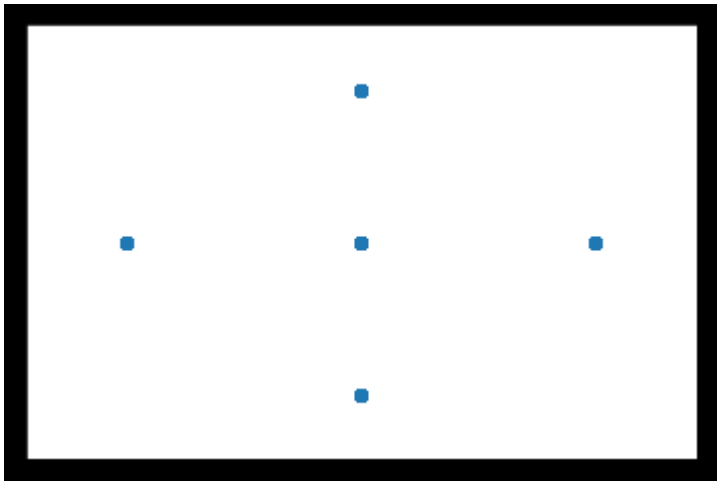
Eye-Tracking: Spatio-Temporal

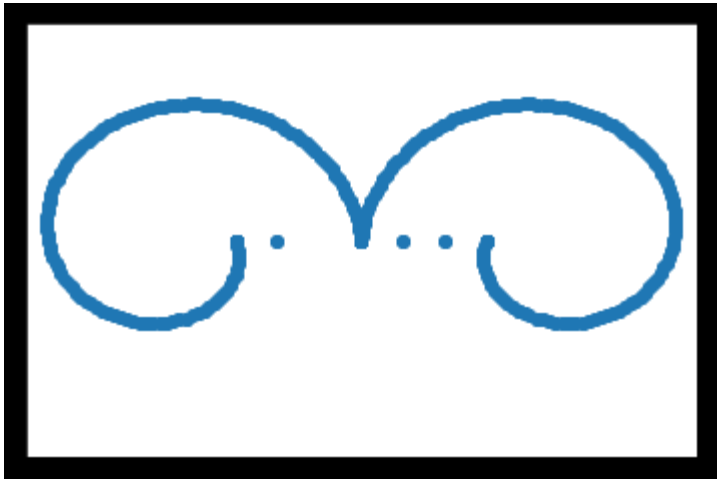
- Combines
  - Spatial Locations
  - Time-series
- A Special Case of Video Analysis
- No Known Foundation Models




Versatile Encoder
Face CNN
Eye CNN
Mask CNN
Meta Info
Dropout
FC
Dropout
Penultimate Layer
Personalized Decoder
S V R
x
y

Calibration for Labeling





Severity of Data Shift (Post-Hoc)

Population	Data Source	Euclidean Error	L/R Accuracy	U/D Accuracy
Adults	GazeCapture	3.53	0.86	0.82
TD Children	Lab	4.65	0.82	0.74
Children with ASD	Lab	4.86	0.81	0.68
Children with ASD	Home	4.96	0.74	0.65
		+ 1.43cm	**-12%**	**-17%**

worsen

Detect Shift and Errors

Feature	r	Adj. p
Face Size	-0.29	$< 10^{-3}$
43 (Eyes Closed)	0.21	$< 10^{-3}$
1 (Inner Brow Raiser)	-0.20	$< 10^{-3}$
17 (Chin Raiser)	-0.15	$< 10^{-3}$
5 (Upper Lid Raiser)	-0.15	0.001
2 (Outer Brow Raiser)	-0.11	0.001
Joy	0.10	0.019

σ of MC Dropout	r	Adj. p
Euclidean	0.41	$< 10^{-3}$
x-axis	0.35	$< 10^{-3}$
y-axis	0.31	$< 10^{-3}$

Features	RMSE (cm)
Facial	1.03
MC Dropout	0.86
Both	**0.81**

Adaptation (Calibration) Performance

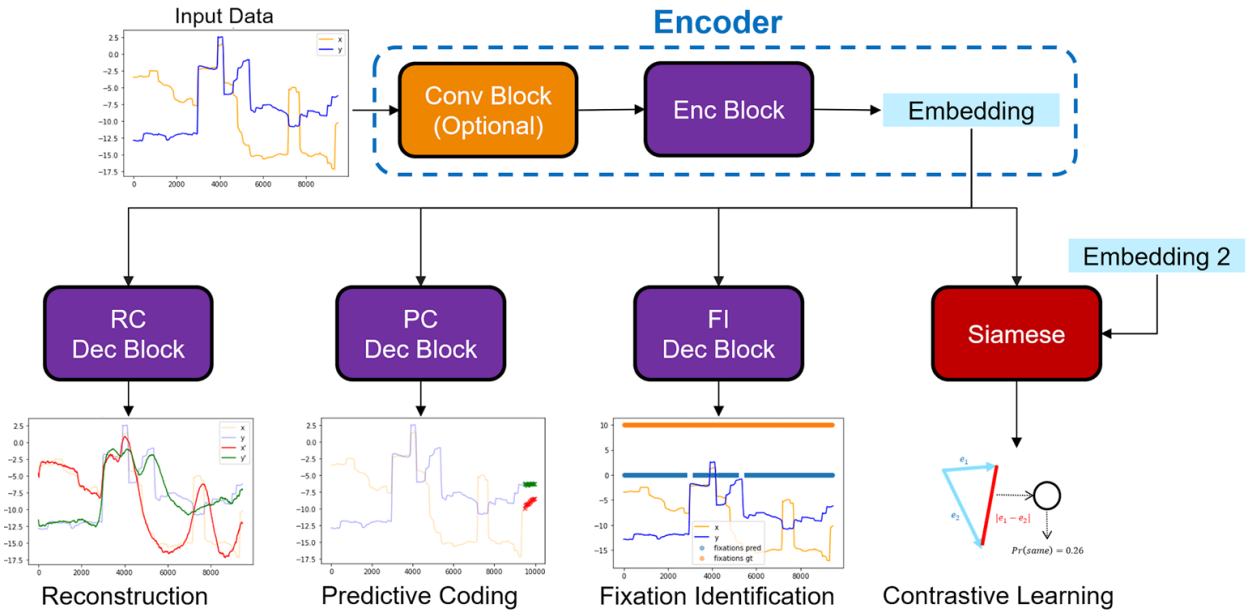
Calibrate On	Euclidean Error	L/R Accuracy	U/D Accuracy
None	4.80	0.81	0.71
5-point	4.59	0.81	0.74
Smooth Pursuit	4.47	0.82	0.69
Both	4.32	0.82	0.72

Using 5-10 seconds calibration

- 0.5cm **+1%** **+1%** **improvements**

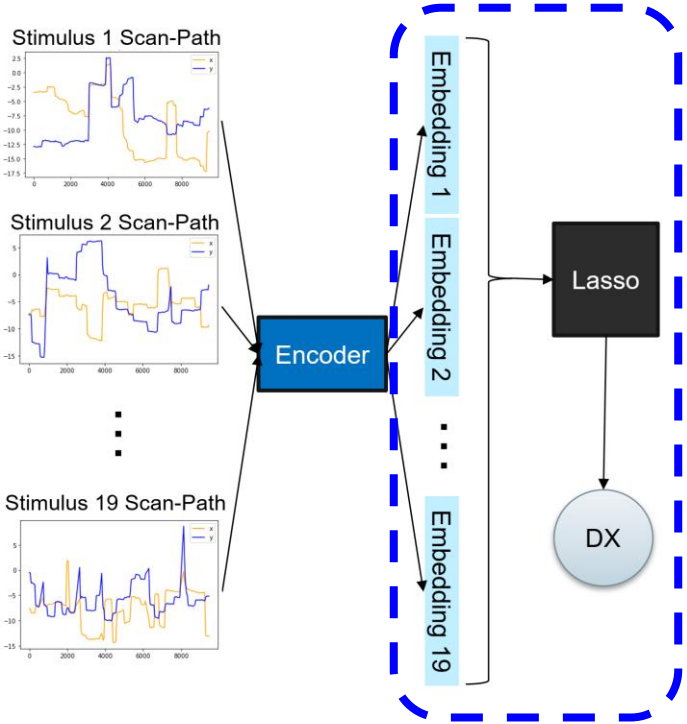
Eye Tracking
(Signal Analysis)

Learning Oculomotor Behaviors



Learning Oculomotor Behaviors from Scanpath Data. **Li, B.**; Nuechterlein, N.; Barney, E.; Foster, C.; Kim, M.; Mahony, M.; Atyabi, A.; Feng, L.; Wang, Q.; Ventola, P.; Shapiro, L.; Shic, F. In 2021 *ACM International Conference In Multi-modal Interaction (ICMI).*

Application Group Classification



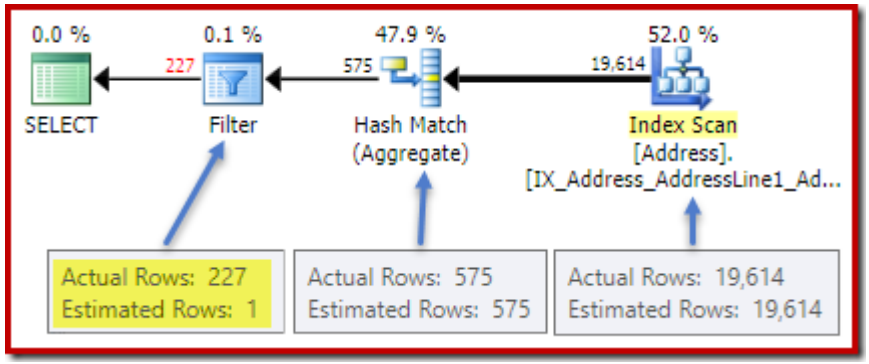
Method	Accuracy	AUC	F_1
Expert Features	0.74	0.68	0.82
SGIN (with more data)	0.78	**0.83**	0.83
Ours (UDA)	**0.80**	**0.83**	**0.88**

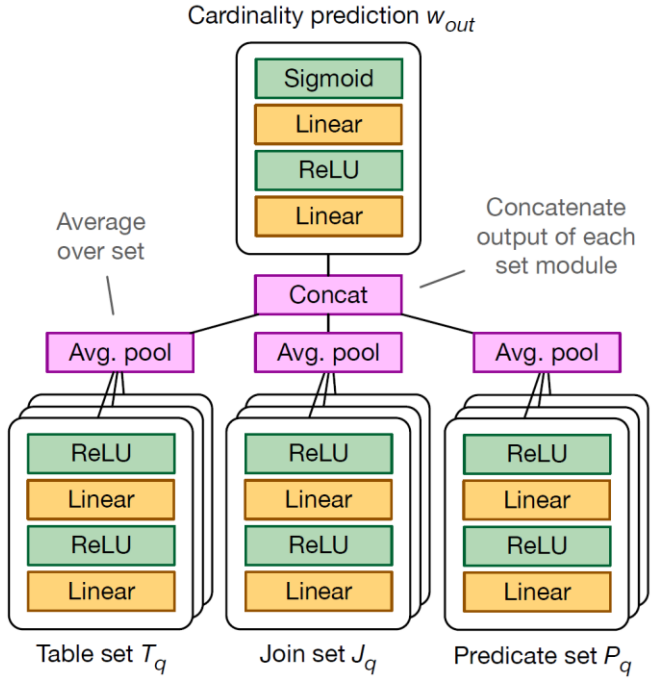
Selection of Eye-Tracking Stimuli for Prediction by Sparsely Grouped Input Variables for Neural Networks: towards Biomarker Refinement for Autism. **Li, B.**; Barney, E.; Hudac, C.; Nuechterlein, N.; Ventola, P.; Shapiro, L.; Shic, F. In Proceedings of ACM ETRA 2020.

Query Optimization in DBMS

Cardinality Estimation

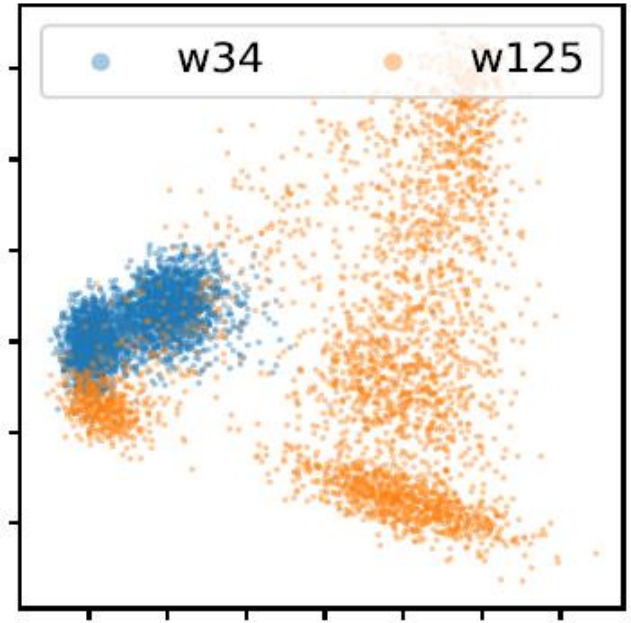
```
SELECT p.Name AS ProductName,
NonDiscountSales = (OrderQty * UnitPrice),
Discounts = ((OrderQty * UnitPrice) *
UnitPriceDiscount)
FROM Production.Product AS p
JOIN Sales.SalesOrderDetail AS sod
ON p.ProductID = sod.ProductID
ORDER BY ProductName DESC;
```

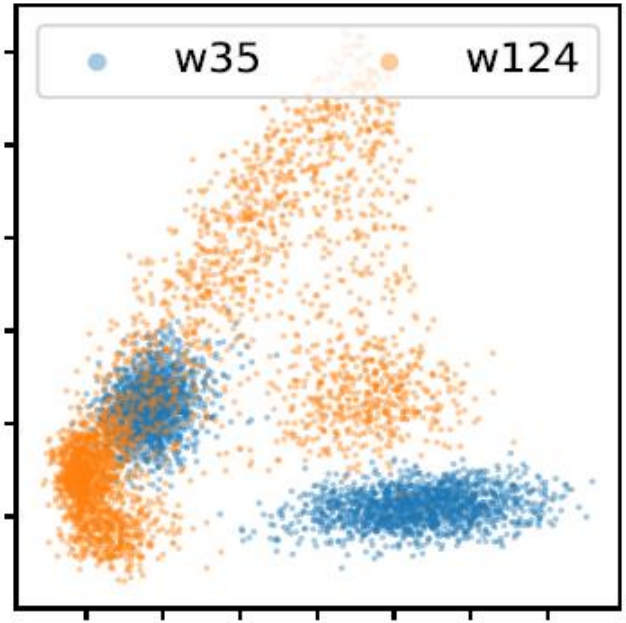


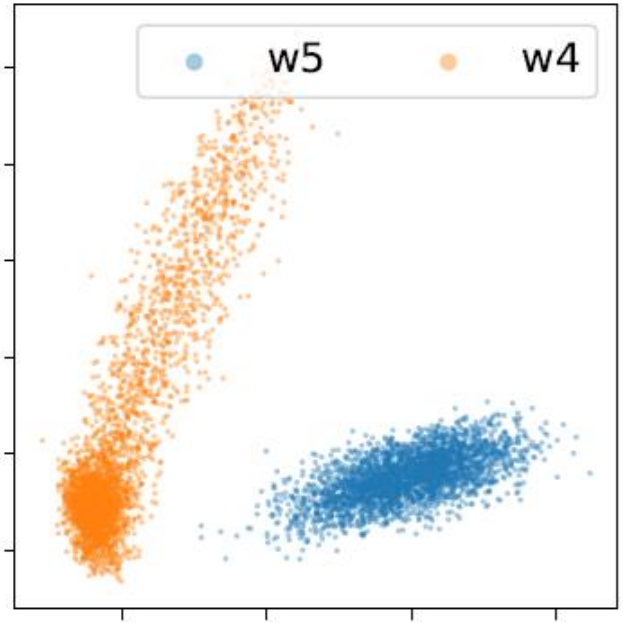


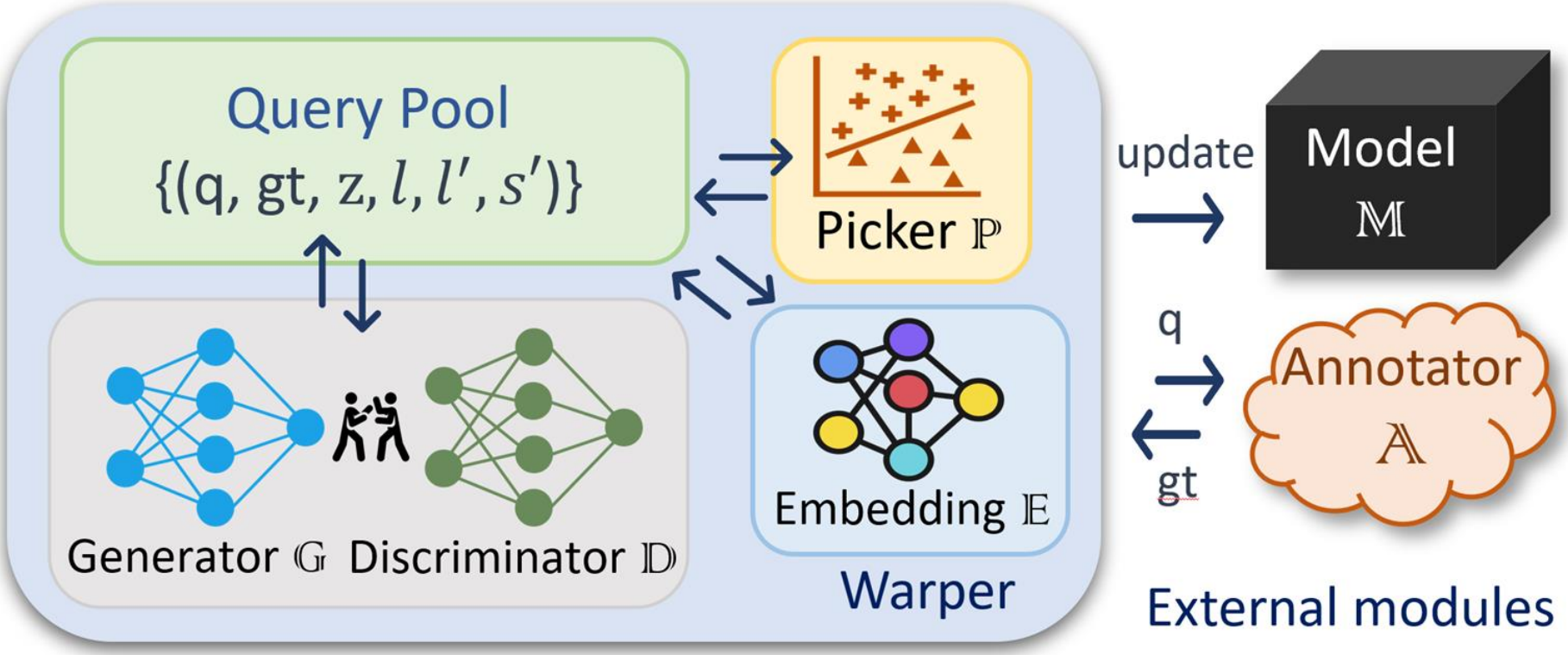
- Cardinality Estimation: Is Machine Learning a Silver Bullet? **Li, B.**; Lu, Y.; Wang, C.; Kandula, S.. The 3rd International Workshop on Applied AI for Database Systems and Applications (AIDB).
- Q-error Bounds of Random Uniform Sampling for Cardinality Estimation. **Li, B.**; Lu, Y.; Wang, C.; Kandula, S..
- Warper: Efficiently Adapting Learned Cardinality Estimators to Data and Workload Drifts. **Li, B.**; Lu, Y.; Wang, C.; Kandula, S. Proceedings of the 2022 International Conference on Management of Data (ACM SIGMOD).

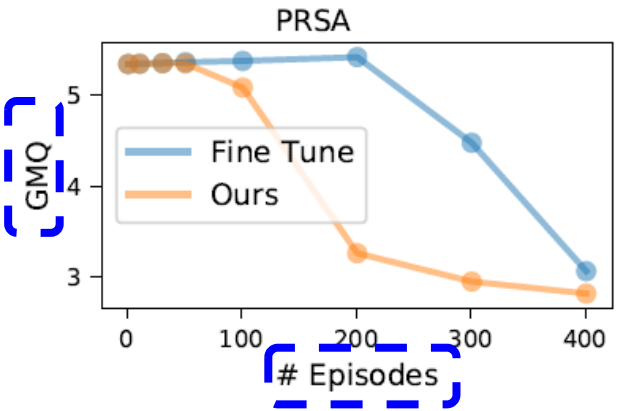
Data Shift After Deployment

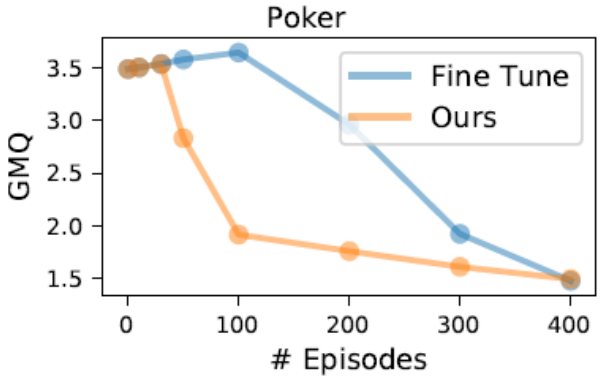


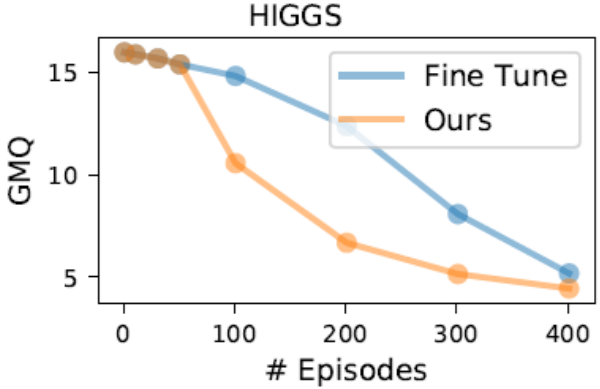


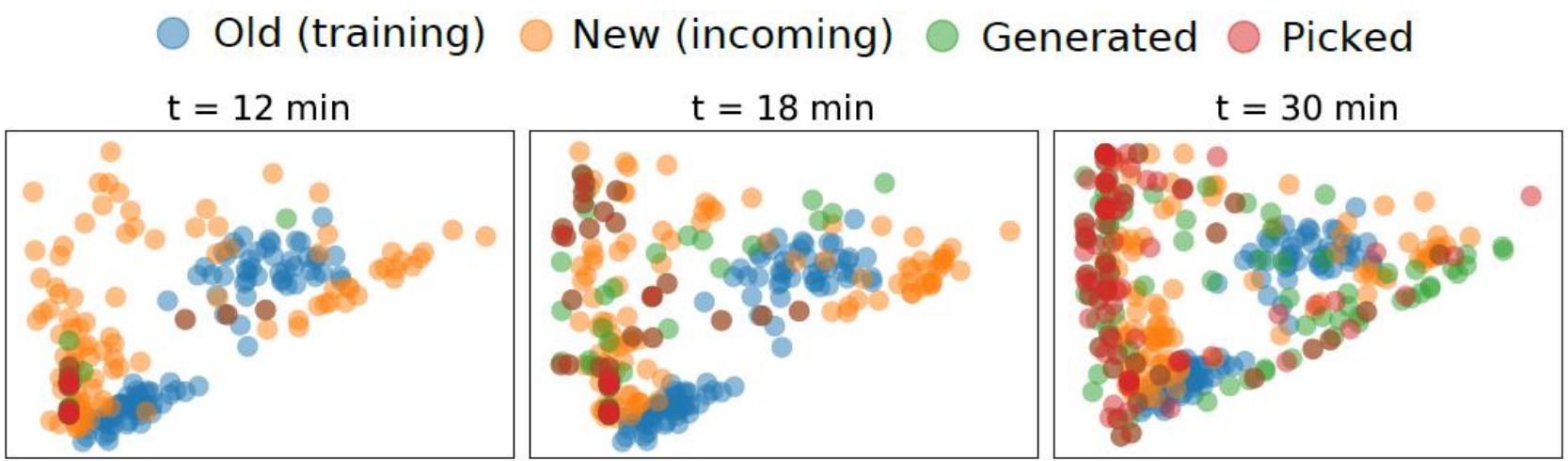



Query Pool
{(q, gt, z, l, l', s')}
Picker ℙ
Generator 𝔾
Discriminator 𝔻
Embedding 𝔼
Warper
update
Model
𝕄
q
gt
Annotator
𝔸
External modules


PRSA
GMQ
5
4
3
Fine Tune
Ours
0
100
200
300
400
Episodes


Poker
GMQ
3.5
3.0
2.5
2.0
1.5
Fine Tune
Ours
0
100
200
300
400
Episodes


HIGGS
GMQ
15
10
5
Fine Tune
Ours
0
100
200
300
400
Episodes

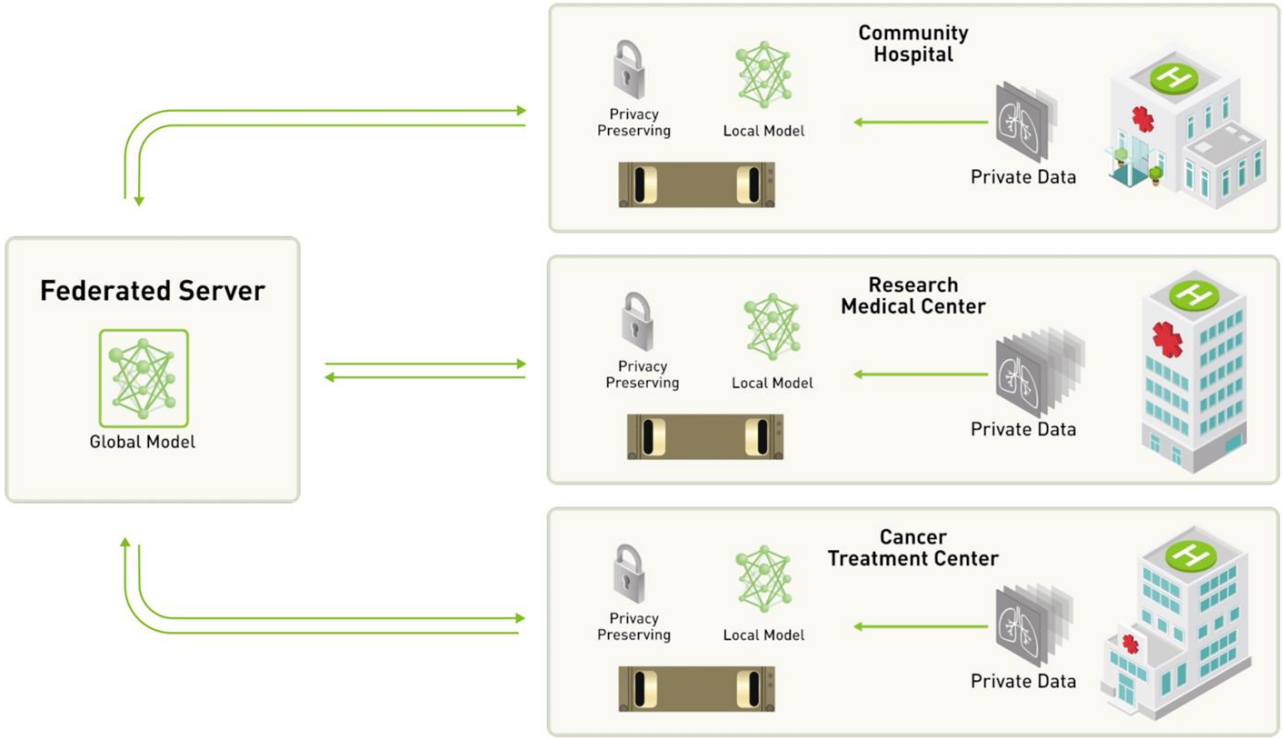

Old (training)
New (incoming)
Generated
Picked
t = 12 min
t = 18 min
t = 30 min

Discussion

Future Work

- Apply and Test on More Modalities (NLP, DNA, ...)
- More Theoretical Analyses
- Multi-Encoder
- User Interface and AutoML

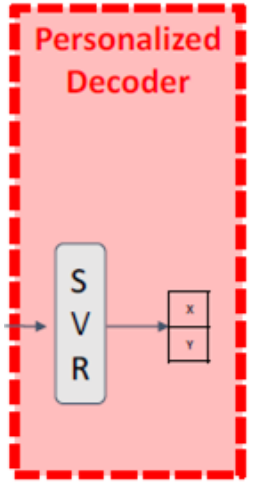
Federated and Decentralized Learning



https://blogs.nvidia.com/blog/**2019/10/13**/what-is-federated-learning/

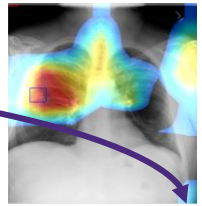
Diversity, Equality, Fairness, and Bias

- Minorities
- Special Population
- Underrepresented in Public Datasets
- Low-Resource Learning



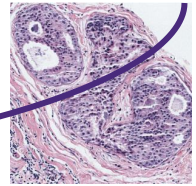
Next …

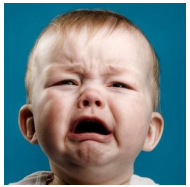
Ours



Big Data

Small Data





Improve

Thank You!


UCLA
PA
FACEBOOK REALITY LABS
Adobe Research
Seattle Children's
HOSPITAL • RESEARCH • FOUNDATION
Carnegie Mellon University
Microsoft Research
UNIVERSITY of VIRGINIA
MIAMI
YALE
COGSTATE
CENTRAL SOUTH UNIVERSITY
NIH
NSF
SIMONS FOUNDATION


Happy International Women's Day
March 8th 2022