

hutom AI Research Introduction

- Data Playground @ 7 -

hutom AI
2019.09.27



hutom



BEFORE

Artificial 3D modeling and surgery rehearsal based on patient specific CT

Planning / Practice



DURING

Patient's anatomy view anytime and anywhere with tips on tool direction, contact alarm, scene playback

Optimal Decision Making

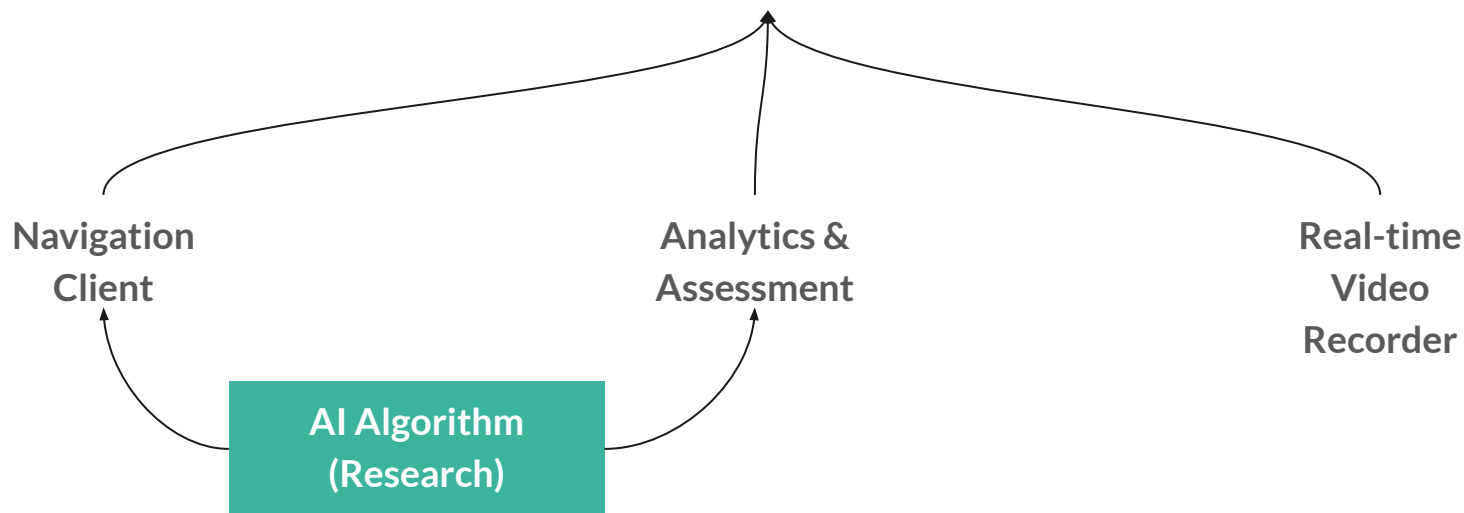


AFTER

AI driven customized reports on data analysis, surgical performance evaluation and review

Post Care / Review

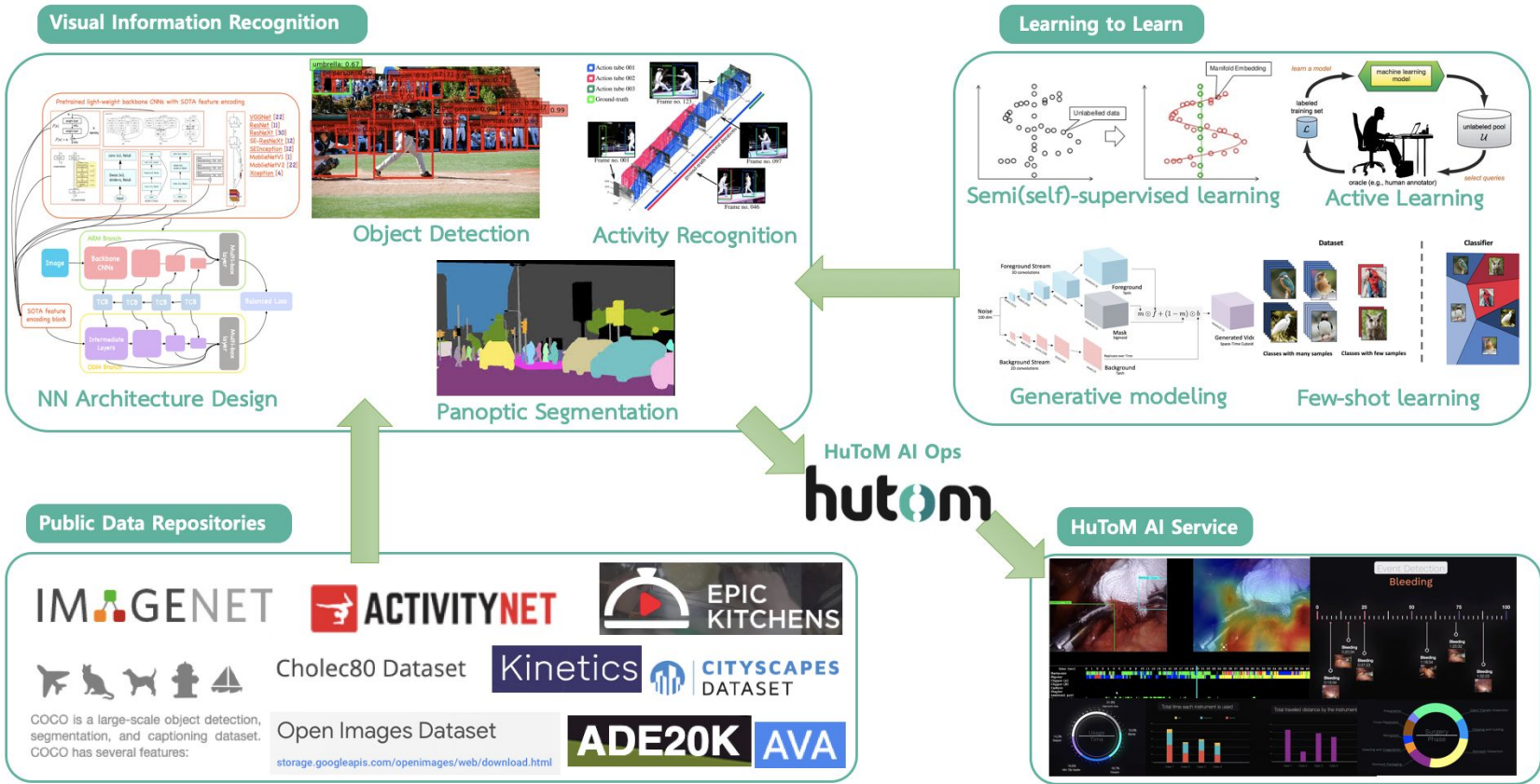
Surgical (Guidance) Platform



hutom AI Research



Research Objectives

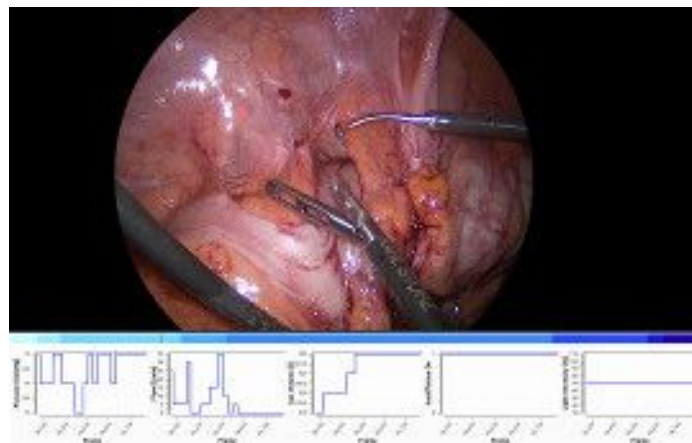


Surgical Workflow Analysis



Surgical Workflow And Skill Analysis

- Cholecystectomy [1]
- Annotations
 - Action
 - Instrument
 - Phase
 - Skill



Action ID	Action
0	Grasp
1	Hold
2	Cut
3	Clip

Phase ID	Phase
0	Preparation
1	Calot triangle dissection
2	Clipping and cutting
3	Galbladder dissection
4	Galbladder packaging
5	Cleaning and coagulation
6	Galbladder retraction

Tool Category ID	Tool Category
0	Grasper
1	Clipper
2	Coagulation instruments
3	Scissors
4	Suction-irrigation
5	Specimen bag
6	Stapler
7-20	Reserved for future additions

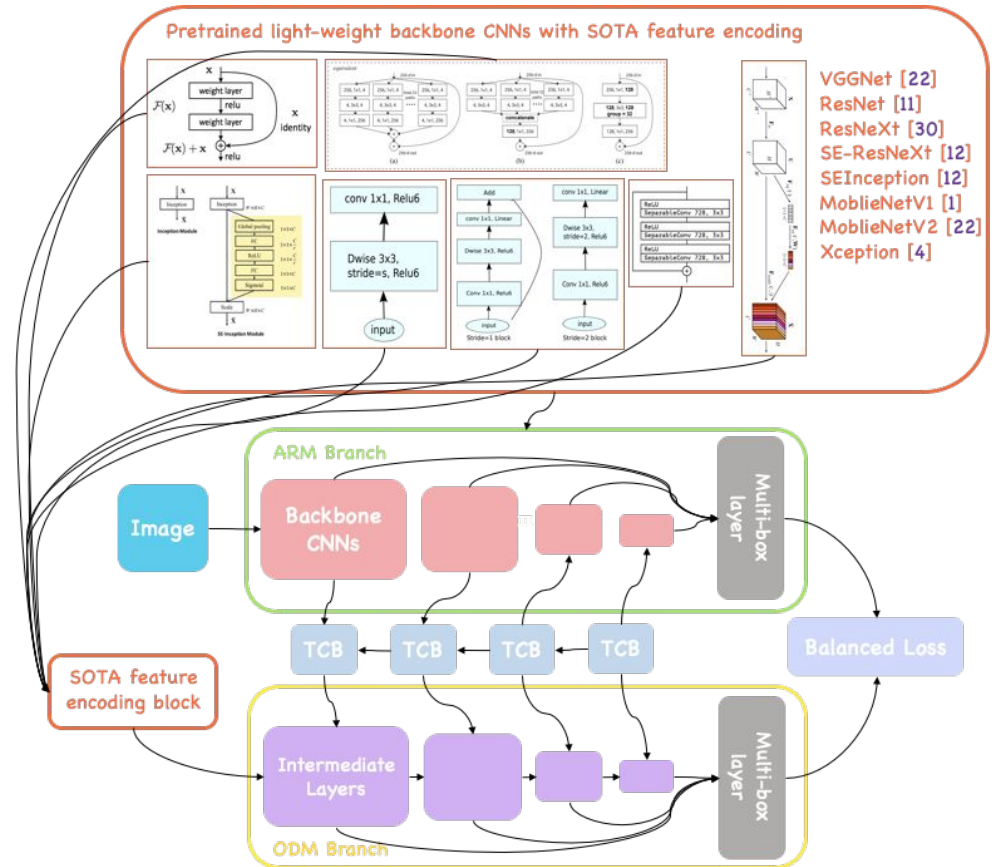
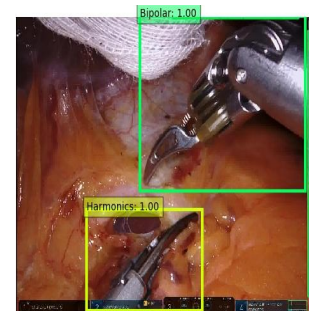
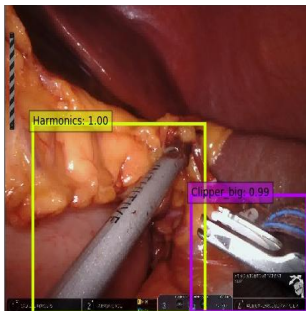
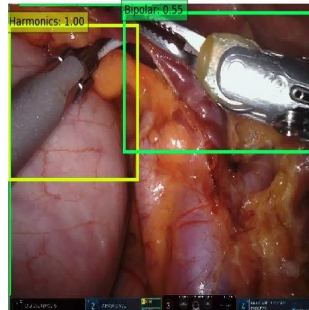
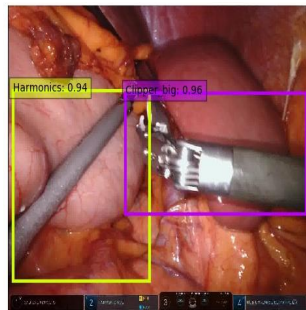
Tool Category ID	Tool ID	Instrument
0	0	Curved atraumatic grasper
0	1	Toothed grasper
0	2	Fenestrated toothed grasper
0	3	Atraumatic grasper
0	4	Overholt
2	5	LigaSure
2	6	Electric hook
3	7	Scissors
1	8	Clip-applier (metal)
1	9	Clip-applier (Hem-O-Lok)
0	10	Swab grasper
2	11	Argon beamer
4	12	Suction-irrigation
5	13	Specimen bag
0	14	Tiger mouth forceps
0	15	Claw forceps
0	16	Atraumatic grasper short
0	17	Crocodile forceps
0	18	Flat grasper
0	19	Pointed forceps
6	20	Stapler
7-19	21-29	Reserved for future additions
20	30	Undefined instrument shaft

Ranking Component	Depth perception	Bimanual dexterity	Efficiency	Tissue handling	Case difficulty
Range	1-5	1-5	1-5	1-5	1-5

[1] Endoscopic Vision Challenge, <https://endovissub-workflowandskill.grand-challenge.org/>

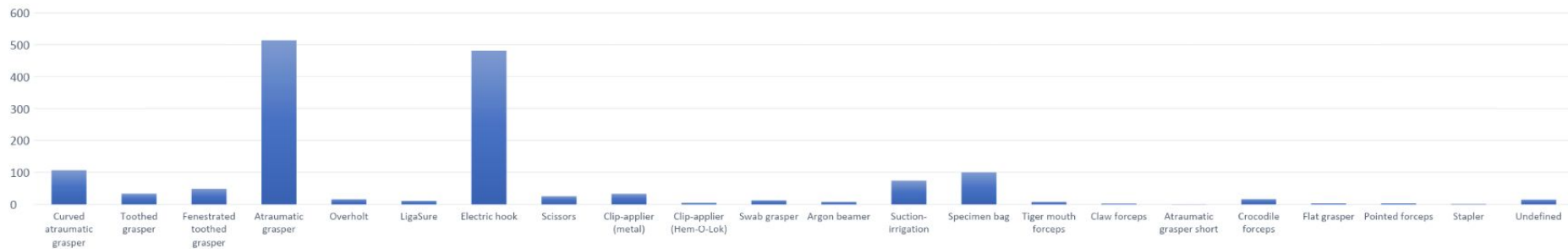
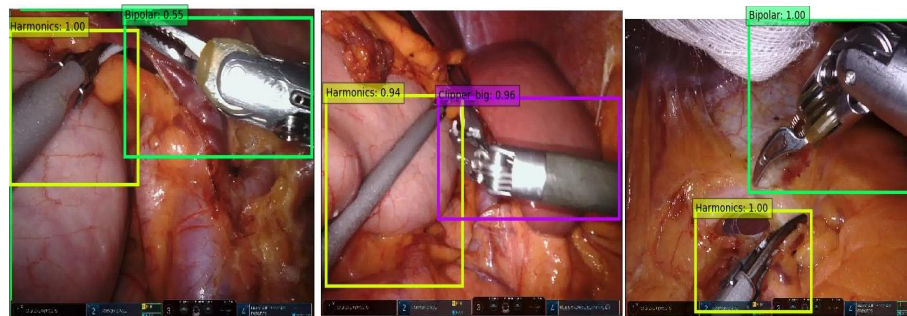
Instrument Detection

- RefineDet [1]
- Modern encoding blocks [2]



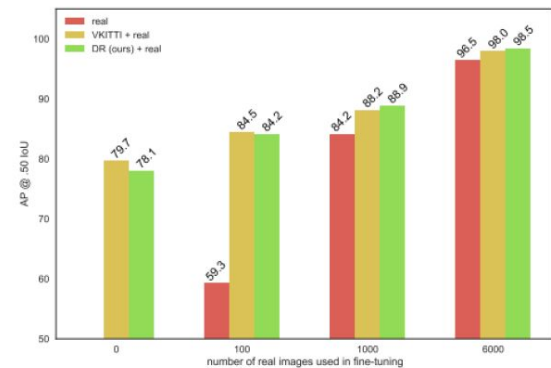
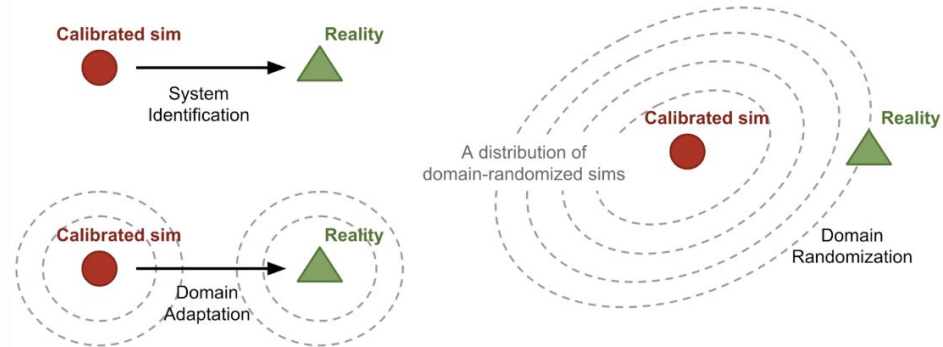
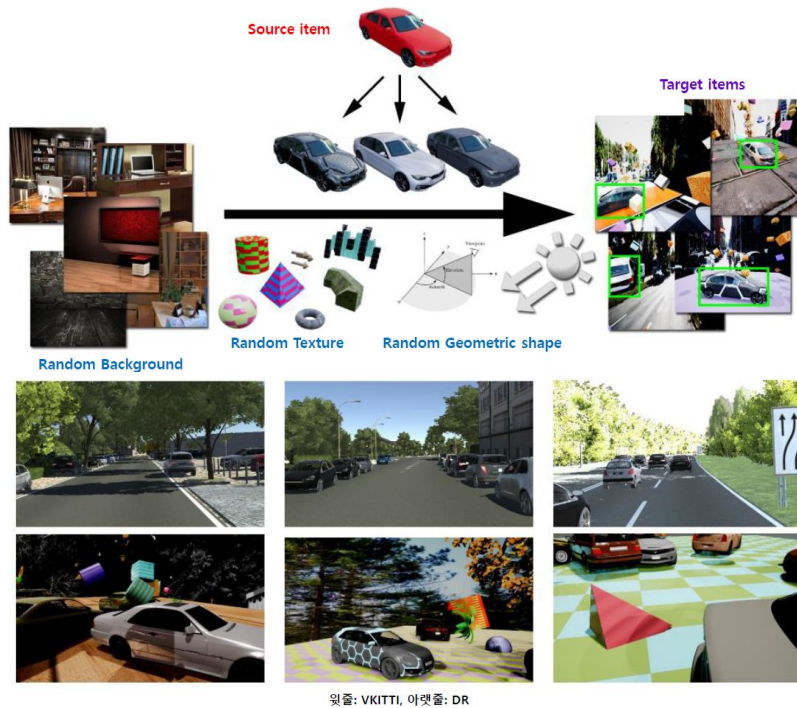
Class Imbalance Problem

- Surgical Video
 - Severe class imbalance

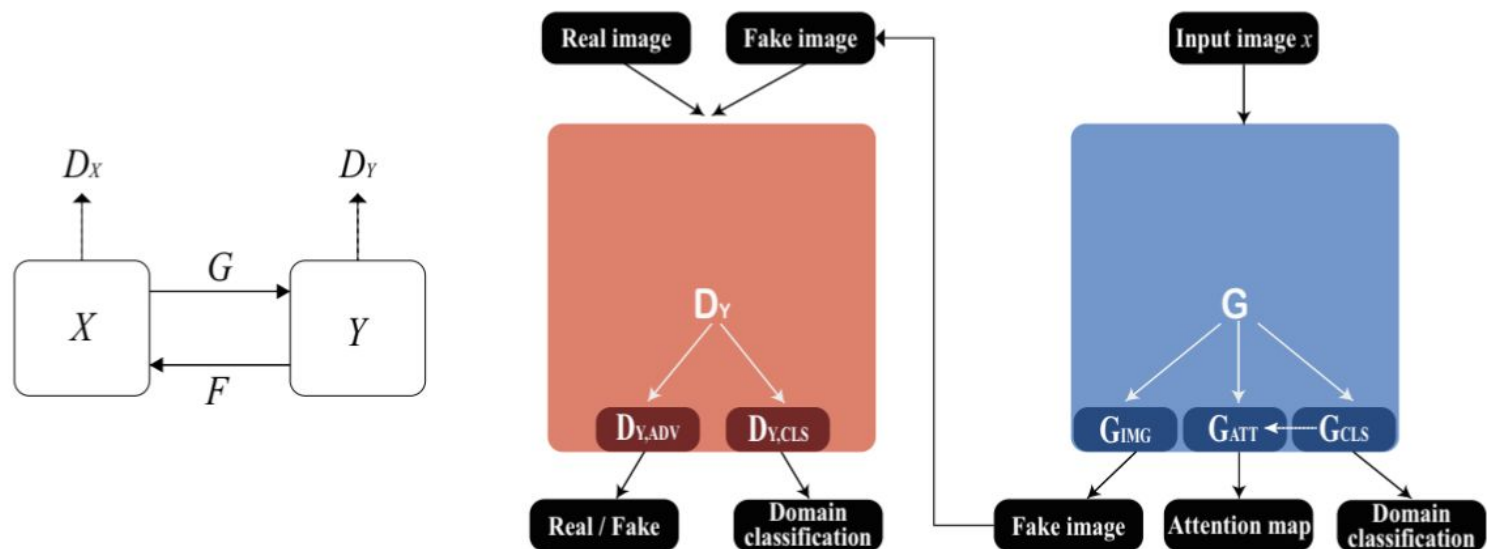


citation

- Self-annotation by synthesized modeling [1]



- DavinciGAN: Surgical Instrument Translation for Data Augmentation



$$L_D = L_{adv} + \lambda_{CLS} * (L_{D,CLS} + L_{CLS-ADV})$$

$$L_G = -L_{adv} + \lambda_{CLS}(L_{G,CLS} - L_{CLS-ADV}) + \lambda_{BG}L_{BG-CONSIST} + \lambda_{CYC}L_{CYC-CONSIST}$$

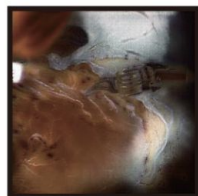
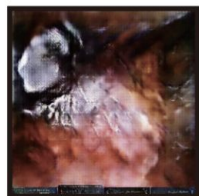
- DavinciGAN: Surgical Instrument Translation for Data Augmentation

Input

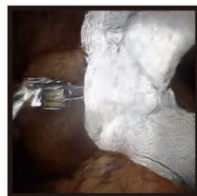
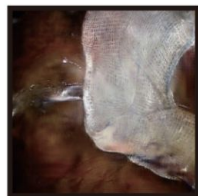
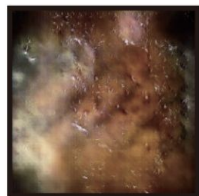
DiscoGAN

CycleGAN

Ours



(a) bipolar→cadere



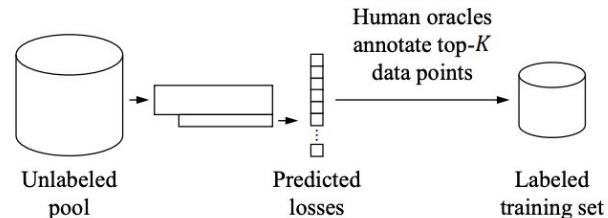
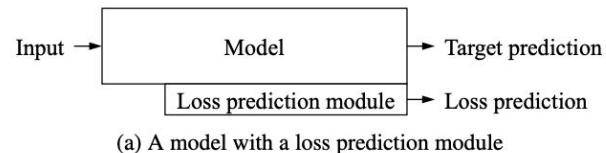
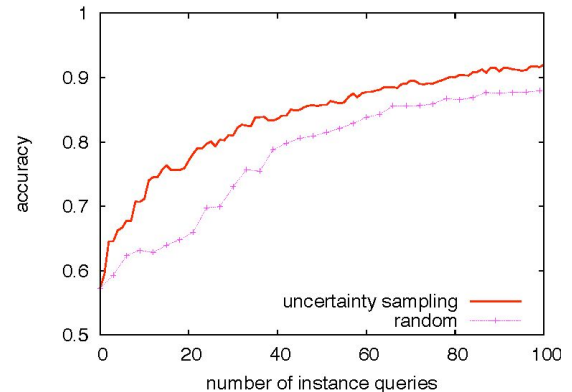
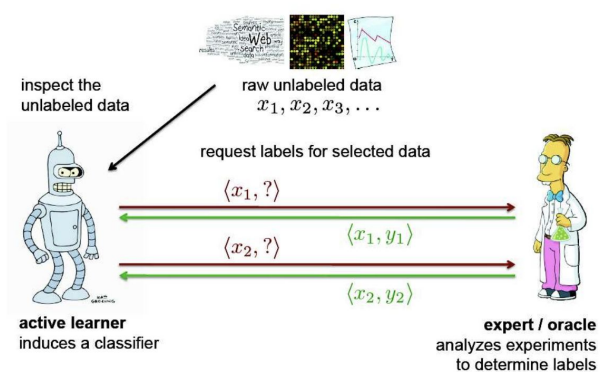
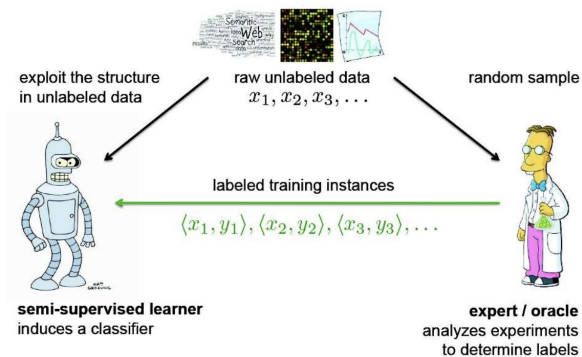
(b) cadere→bipolar

Dataset	Method	# of parameters	Accuracy (%)
Real 1000	-	-	58.84
Real 1000 + Synthetic 1000	DiscoGAN	67M	57.91
Real 1000 + Synthetic 1000	CycleGAN	56M	58.61
Real 1000 + Synthetic 1000	DavinciGAN	31M	61.34
Real 2000	-	-	62.31

Active Learning Using Analytic Learning Theory

Active Learning

- What teach first?

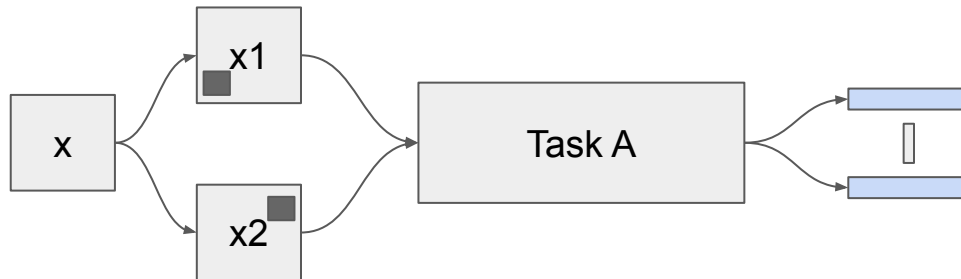


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- The graph illustrates the bias-variance tradeoff. The blue dashed line (training error) decreases as model capacity increases. The red solid line (generalization error) initially decreases, reaching a minimum at the 'optimal capacity', and then increases as capacity continues to grow. This increase in generalization error in the 'Overfitting zone' is due to the model fitting noise in the training data. The 'generalization gap' is the difference between the training and generalization errors.

-
- Diagram illustrating the generalization error bound formula, with annotations for each term:
- Generalization Error**: Points to $R(f)$.
 - Training Error**: Points to $\hat{R}_{S,\rho}(f)$.
 - Weights connected to layer k**: Points to $\|\mathbf{w}_k\|_1$.
 - Complexity of layer k**: Points to $\mathfrak{N}_m(\tilde{\mathcal{H}}_k)$.
 - Number of layers in NN**: Points to l .
 - Size of training data**: Points to m .
- $$R(f) \leq \hat{R}_{S,\rho}(f) + \frac{4}{\rho} \sum_{k=1}^l \|\mathbf{w}_k\|_1 \mathfrak{N}_m(\tilde{\mathcal{H}}_k) + \frac{2}{\rho} \sqrt{\frac{\log l}{m}} + C(\rho, l, m, \delta),$$

- Perturbations of a data point should not change the output of a model as if the true label is invariant under the perturbation

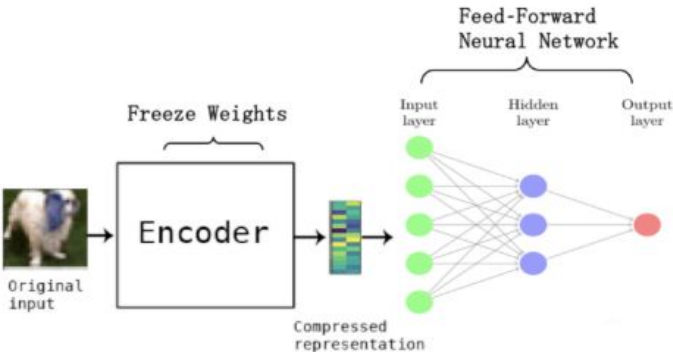
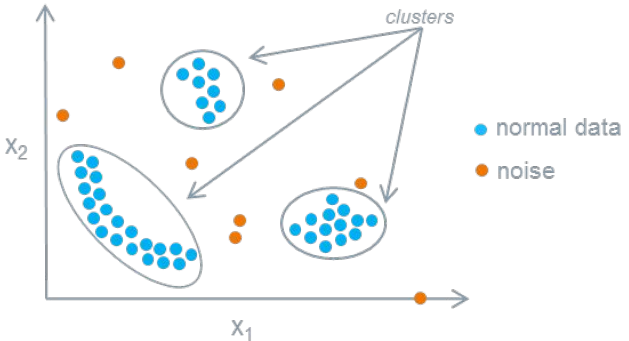
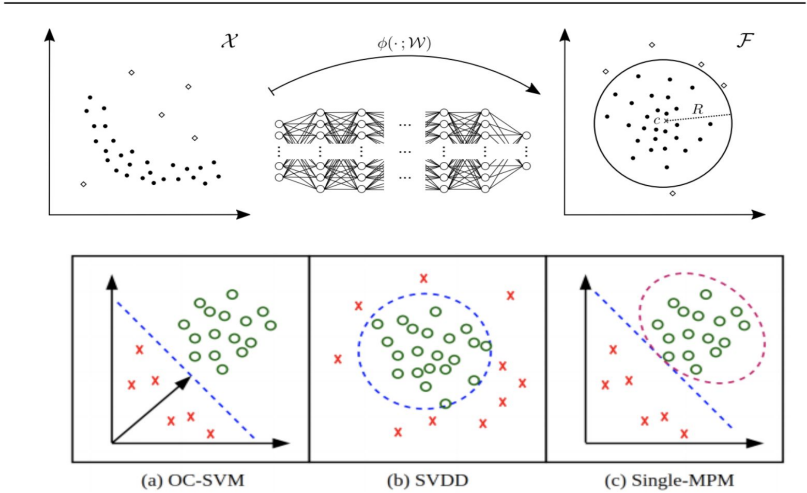
$$\ell_{\text{reg}}(x, \theta) = \int_{(x_1, x_2)} \|h(x_1, \theta) - h(x_2, \theta)\|_2^2 dP(x_1, x_2 | x),$$



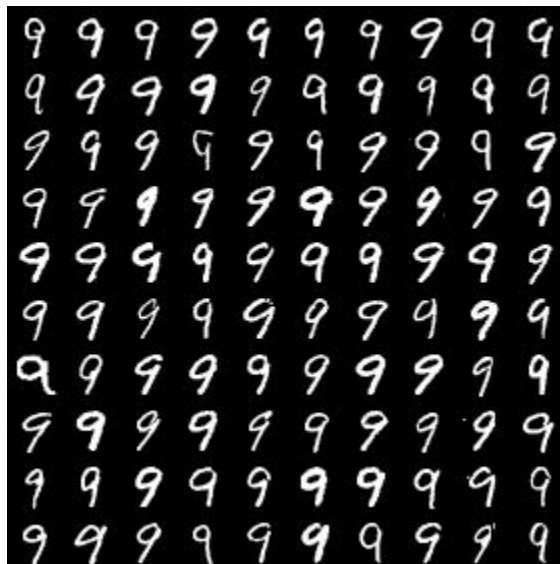
Method	CIFAR-10	CIFAR-100	SVHN
Standard	3.79 ± 0.07	19.85 ± 0.14	2.47 ± 0.04
Single-cutout	3.19 ± 0.09	18.13 ± 0.28	2.23 ± 0.03
Dual-cutout	2.61 ± 0.04	17.54 ± 0.09	2.06 ± 0.06

Anomaly Detection for Guided Annotation

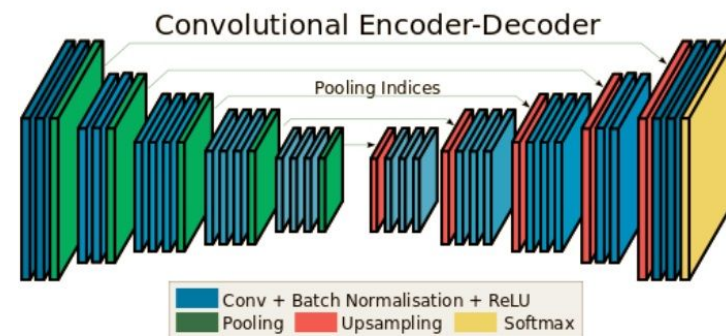
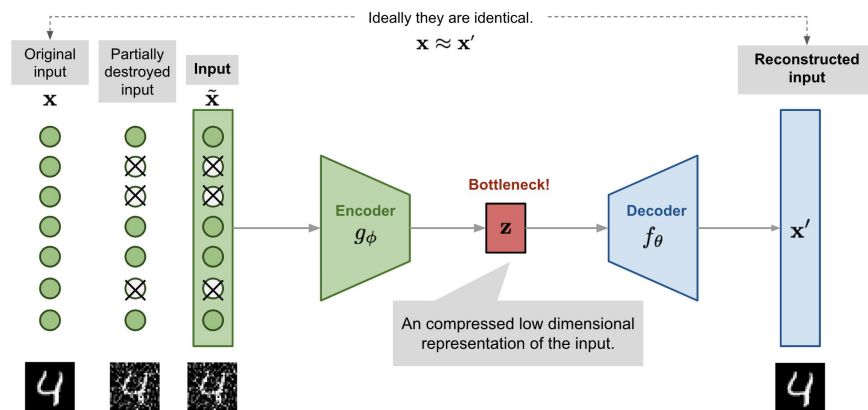
- Anomaly detection



- MNIST



- Surgery video



Thank You!

Q & A