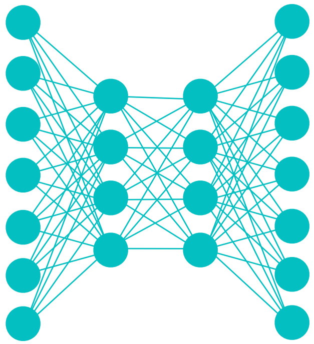
Lecture Notes for

Neural Networks and Machine Learning

Semi-supervised Loss Incorporation



Logistics and Agenda

- Logistics
  - Lab one due soon!!
- Agenda
  - Consistency Loss
  - Temporal Output Discrepancy
  - Student Paper Presentation
- Next Time
  - Multi-modal and Multi-Task
  - Multi-task demo and Town Hall
  - Finish Demos

Last Time

$$\min_{\mathbf{w}} \overbrace{\mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}}(y\,|\,\mathbf{x})]}^{\text{cross entropy}} + \lambda \overbrace{\mathscr{D}_{KL}\left(p_{\mathbf{w}}(y\,|\,\mathbf{x})\,||\,p_{\mathbf{w}}(y\,|\,\hat{\mathbf{x}})\right)}^{\text{consistency in augmentation}}$$

$$\mathscr{D}_{KL}(f\,||\,g) = -\sum f(x)\cdot\log\frac{g(x)}{f(x)}$$ definition of Kullback-Leibler (KL) Divergence

$$\mathscr{D}_{KL}(p(y\,|\,\mathbf{x})\,||\,p(y\,|\,\hat{\mathbf{x}})) = -\sum p(y\,|\,\mathbf{x})\cdot\log\frac{p(y\,|\,\hat{\mathbf{x}})}{p(y\,|\,\mathbf{x})} = -\sum p(y\,|\,\mathbf{x})\cdot\left(\log p(y\,|\,\hat{\mathbf{x}}) - \log p(y\,|\,\mathbf{x})\right)$$

$$= -\sum p(y\,|\,\mathbf{x})\cdot\log p(y\,|\,\hat{\mathbf{x}}) + \sum p(y\,|\,\mathbf{x})\cdot\log p(y\,|\,\mathbf{x})$$

$$= \mathbf{E}_{\mathbf{x}\in U,\hat{\mathbf{x}}\leftarrow q(\hat{\mathbf{x}}|\mathbf{x})}\left[-\log p(y\,|\,\hat{\mathbf{x}})\right] + \cancel{\mathbf{E}_{\mathbf{x}\in U}\left[\log p(y\,|\,\mathbf{x})\right]}_{\text{ignore}}$$

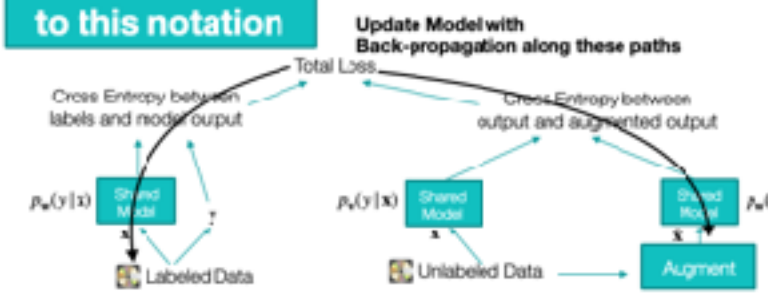
cross entropy of unsupervised labels after augmentation

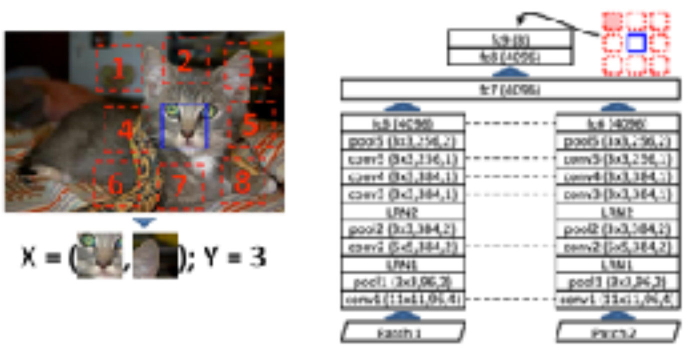
entropy of unsupervised labels ***constant***

Neural Network approximates $p(y|\mathbf{x})$ by $\mathbf{w}$
Use labeled data to minimize network

Sample new $\mathbf{x}$ from unlabeled pool with function q
function q is augmentation procedure
Minimize cross entropy of two models

Get accustomed to this notation





Unsupervised Visual Representation Learning by Context Prediction

Unsupervised Consistency Loss (review)

$$\min_{\mathbf{w}} \overbrace{\mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}}(y\,|\,\mathbf{x})]}^{\text{cross entropy}} + \lambda \overbrace{\mathcal{D}_{KL}\left(\underset{\textbf{no}\text{ back prop}}{p_{\mathbf{w}}(y\,|\,\mathbf{x})}\,||\,\underset{\textbf{yes}\text{ back prop}}{p_{\mathbf{w}}(y\,|\,\hat{\mathbf{x}})}\right)}^{\text{consistency in augmentation}}$$

Neural Network approximates $p(y|\mathbf{x})$ by $\mathbf{w}$
Use labeled data to minimize network

Sample new $\mathbf{x}$ from unlabeled pool with function q
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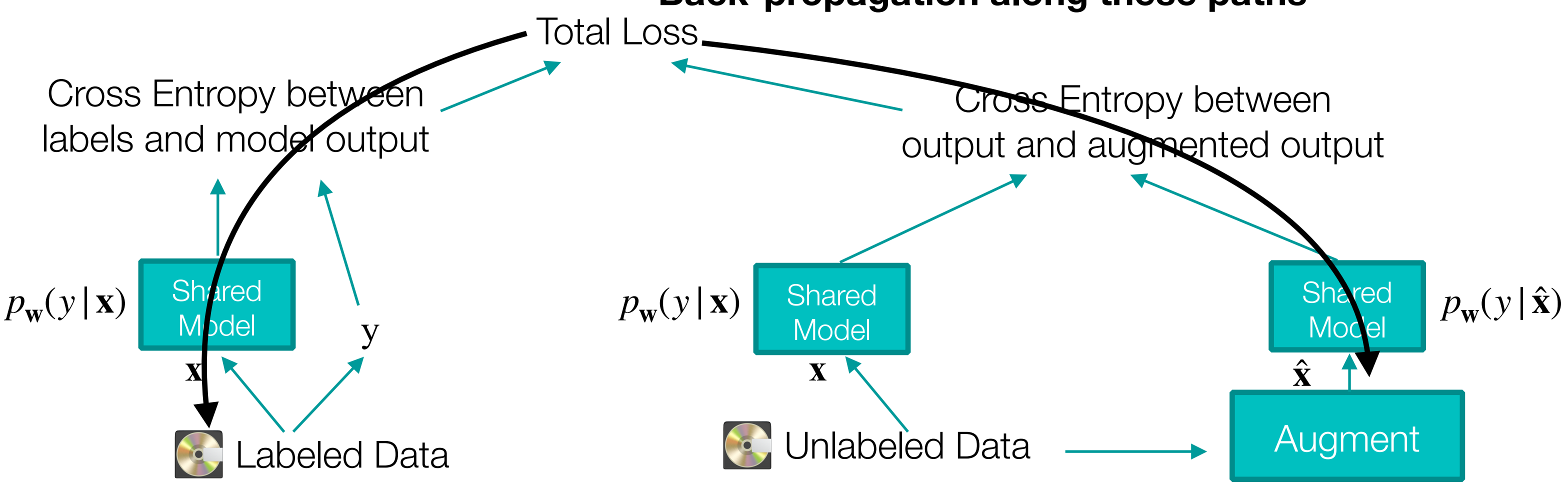
Minimize cross entropy of two models

Get accustomed to this notation

Update Model with
Back-propagation along these paths



Unsupervised Data Augmentation (UDA) for Consistency Training, Xie et al., NeurIps 2019

$$\min_{\mathbf{w}} \overbrace{\mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}}(y\,|\,\mathbf{x})]}^{\text{cross entropy}} + \lambda \underbrace{\mathcal{D}_{KL}\left(p_{\mathbf{w}}(y\,|\,\mathbf{x})\,||\,p_{\mathbf{w}}(y\,|\,\hat{\mathbf{x}})\right)}^{\text{consistency in augmentation}}$$

$$E[g] = \sum p(g)\cdot g$$ definition of expected value

$$E[-\log p_{\mathbf{w}}(y\,|\,\mathbf{x})] = -\sum p(y)\cdot \log p_{\mathbf{w}}(y\,|\,\mathbf{x})$$ insert -log probability, log likelihood

$$NLL(y, p_{\mathbf{w}}(y\,|\,\mathbf{x})) = -\sum_{c} p(y=c)\cdot \log p_{\mathbf{w}}(y=c\,|\,\mathbf{x})$$ negative log likelihood

$$CE(f,g) = -\sum f(x)\cdot \log g(x)$$ cross entropy of two functions

$$CE(y, p_{\mathbf{w}}(y\,|\,\mathbf{x})) = -\sum_{c} (y=c)\cdot \log p_{\mathbf{w}}(y=c\,|\,\mathbf{x})$$ if y=c is a probability, these are same equation

```
cce = tf.keras.losses.CategoricalCrossentropy()
cce(y_true, y_pred)
```

$$\min_{\mathbf{w}} \overbrace{\mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}}(y\,|\,\mathbf{x})]}^{\text{cross entropy}} + \lambda \overbrace{\mathscr{D}_{KL}\left(p_{\mathbf{w}}(y\,|\,\mathbf{x})\,||\,p_{\mathbf{w}}(y\,|\,\hat{\mathbf{x}})\right)}^{\text{consistency in augmentation}}$$

$$\mathscr{D}_{KL}(f\,||\,g) = -\sum f(x)\cdot\log\frac{g(x)}{f(x)}$$ definition of Kullback-Leibler (KL) Divergence

$$\mathscr{D}_{KL}(p_{\mathbf{w}}(y\,|\,\mathbf{x})\,||\,p_{\mathbf{w}}(y\,|\,\hat{\mathbf{x}}))$$

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$$= -\sum p(y\,|\,\mathbf{x})\cdot\log p(y\,|\,\hat{\mathbf{x}}) + \sum p(y\,|\,\mathbf{x})\cdot\log p(y\,|\,\mathbf{x})$$

$$p(y\,|\,\mathbf{x}) \approx p(y)$$ if **x** is a very large subset of the entire domain and $p_{\mathbf{w}}$ is a good *variational* approximation

So this is lower bound!

$$= \mathbf{E}_{\mathbf{x}\in U,\hat{\mathbf{x}}\leftarrow q(\hat{\mathbf{x}}|\mathbf{x})}\left[-\log p(y\,|\,\hat{\mathbf{x}})\right] + \mathbf{E}_{\mathbf{x}\in U}\cancel{\left[\log p(y\,|\,\mathbf{x})\right]}$$ ignore

cross entropy of unsupervised labels after augmentation

entropy of unsupervised labels
cannot calculate, always > 0

```
cce = tf.keras.losses.CategoricalCrossentropy()
cce(y_pred, y_pred_augmented)
```

Aside:

- We have just seen two motivations:

Neural Network approximates $p(y|x)$ by $\mathbf{w}$
Use labeled data to minimize network

Sample new $\mathbf{x}$ from unlabeled pool with functi
function q is augmentation procedure
Minimize cross entropy of two models

$$\mathcal{D}_{KL}(p_w(y|\mathbf{x})\,||\,p_w(y|\hat{\mathbf{x}}))$$

$$\mathcal{D}_{KL}(p(y|\mathbf{x})\,||\,p(y|\hat{\mathbf{x}})) = -\sum p(y|\mathbf{x})\cdot\log\frac{p(y|\hat{\mathbf{x}})}{p(y|\mathbf{x})} = -\sum p(y|\mathbf{x})\cdot(\log p(y|\hat{\mathbf{x}}) - \log p(y|\mathbf{x}))$$

$$= -\sum p(y|\mathbf{x})\cdot\log p(y|\hat{\mathbf{x}}) + \sum p(y|\mathbf{x})\cdot\log p(y|\mathbf{x})$$

$$p(y|\mathbf{x}) \approx p(y)$$ if x is a very large subset of the entire domain and p_w is a good variational approximation

So this is lower bound!

$$= \mathbf{E}_{\mathbf{x}\in U,\hat{\mathbf{x}}\leftarrow q(\hat{\mathbf{x}}|\mathbf{x})}\left[-\log p(y|\hat{\mathbf{x}})\right] + \cancel{\mathbf{E}_{\mathbf{x}\in U}\left[\log p(y|\mathbf{x})\right]}_{\text{ignore}}$$

cross entropy of unsupervised labels after augmentation

entropy of unsupervised labels **cannot calculate, always > 0**

intuition of final product

keep labels consistent, any measure would be okay

mathematics with heavy approximation

cross entropy is lower bound
for KL divergence, which is a nice measure

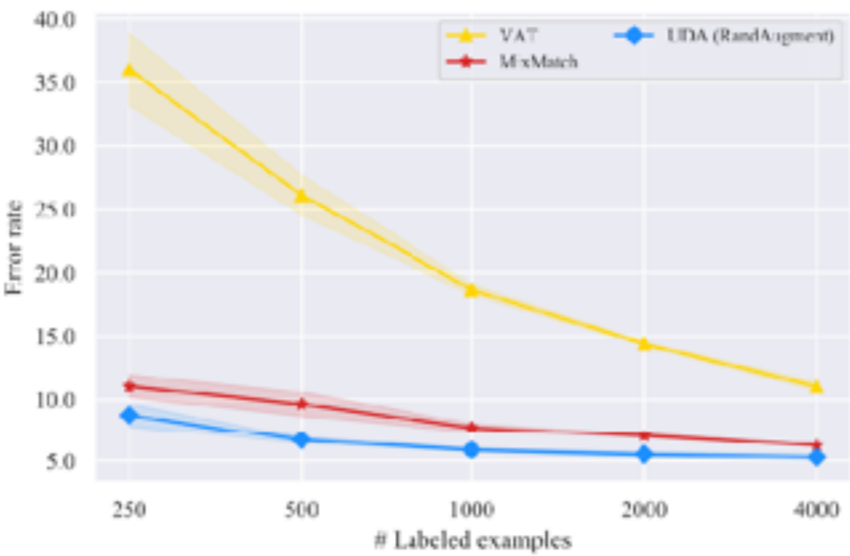
Unsupervised Consistency Loss

Augmentation (# Sup examples)	Sup (50k)	Semi-Sup (4k)
Crop & flip	5.36	16.17
Cutout	4.42	6.42
RandAugment	**4.23**	**5.29**

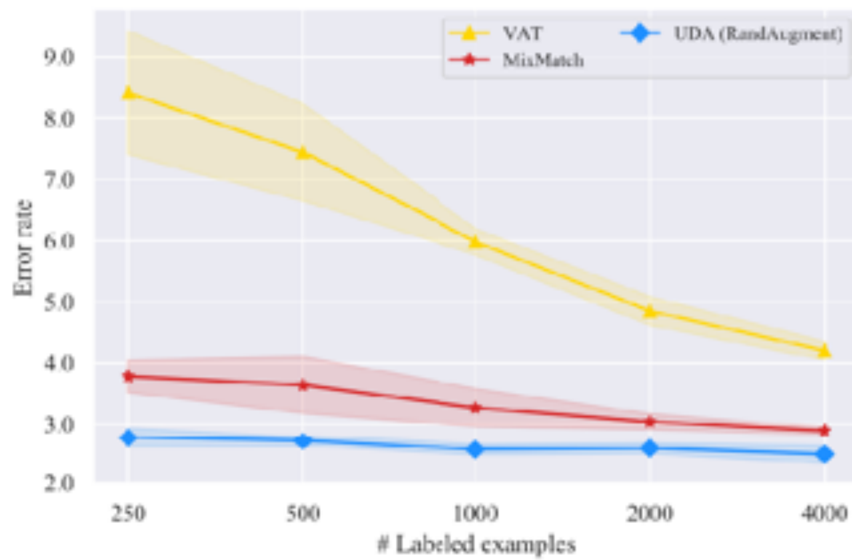
Table 1: Error rates on CIFAR-10.

Augmentation (# Sup examples)	Sup (650k)	Semi-sup (2.5k)
✗	38.36	50.80
Switchout	37.24	43.38
Back-translation	**36.71**	**41.35**

Table 2: Error rate on Yelp-5.



(a) CIFAR-10



(b) SVHN

Unsupervised Data Augmentation (UDA) for Consistency Training, Xie et al., NeurIps 2019

Unsupervised Consistency Loss

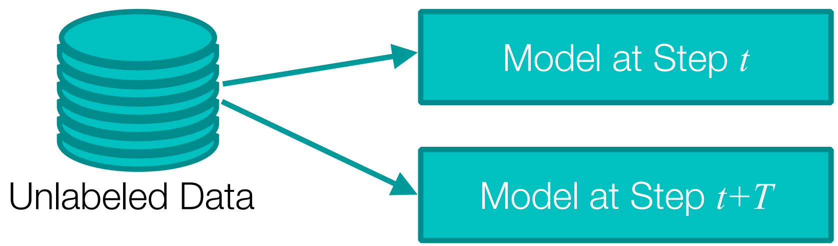
Method	Model	# Param	CIFAR-10 (4k)	SVHN (1k)
Π-Model (Laine & Aila, 2016)	Conv-Large	3.1M	12.36 ± 0.31	4.82 ± 0.17
Mean Teacher (Tarvainen & Valpola, 2017)	Conv-Large	3.1M	12.31 ± 0.28	3.95 ± 0.19
VAT + EntMin (Miyato et al., 2018)	Conv-Large	3.1M	10.55 ± 0.05	3.86 ± 0.11
SNTG (Luo et al., 2018)	Conv-Large	3.1M	10.93 ± 0.14	3.86 ± 0.27
VAdD (Park et al., 2018)	Conv-Large	3.1M	11.32 ± 0.11	4.16 ± 0.08
Fast-SWA (Athiwaratkun et al., 2018)	Conv-Large	3.1M	9.05	-
ICT (Verma et al., 2019)	Conv-Large	3.1M	7.29 ± 0.02	3.89 ± 0.04
Pseudo-Label (Lee, 2013)	WRN-28-2	1.5M	16.21 ± 0.11	7.62 ± 0.29
LGA + VAT (Jackson & Schulman, 2019)	WRN-28-2	1.5M	12.06 ± 0.19	6.58 ± 0.36
mixmixup (Hataya & Nakayama, 2019)	WRN-28-2	1.5M	10	-
ICT (Verma et al., 2019)	WRN-28-2	1.5M	7.66 ± 0.17	3.53 ± 0.07
MixMatch (Berthelot et al., 2019)	WRN-28-2	1.5M	6.24 ± 0.06	2.89 ± 0.06

Methods	SSL	10%	100%
ResNet-50 w. RandAugment	✗	55.09 / 77.26 58.84 / 80.56	77.28 / 93.73 78.43 / 94.37
UDA (RandAugment)	✓	**68.78 / 88.80**	**79.05 / 94.49**

Table 5: Top-1 / top-5 accuracy on ImageNet with 10% and 100% of the labeled set. We use image size 224 and 331 for the 10% and 100% experiments respectively.

Other Measures of Consistency: TOD

- Main idea: use unsupervised labels to prevent overfitting
- Temporal Output Discrepancy (TOD) (Huang et al., ICCV21)



$p_{\mathbf{w}_t}(y \mid \hat{\mathbf{x}})$

$p_{\mathbf{w}_{t+T}}(y \mid \hat{\mathbf{x}})$

Do not change too much between updates!

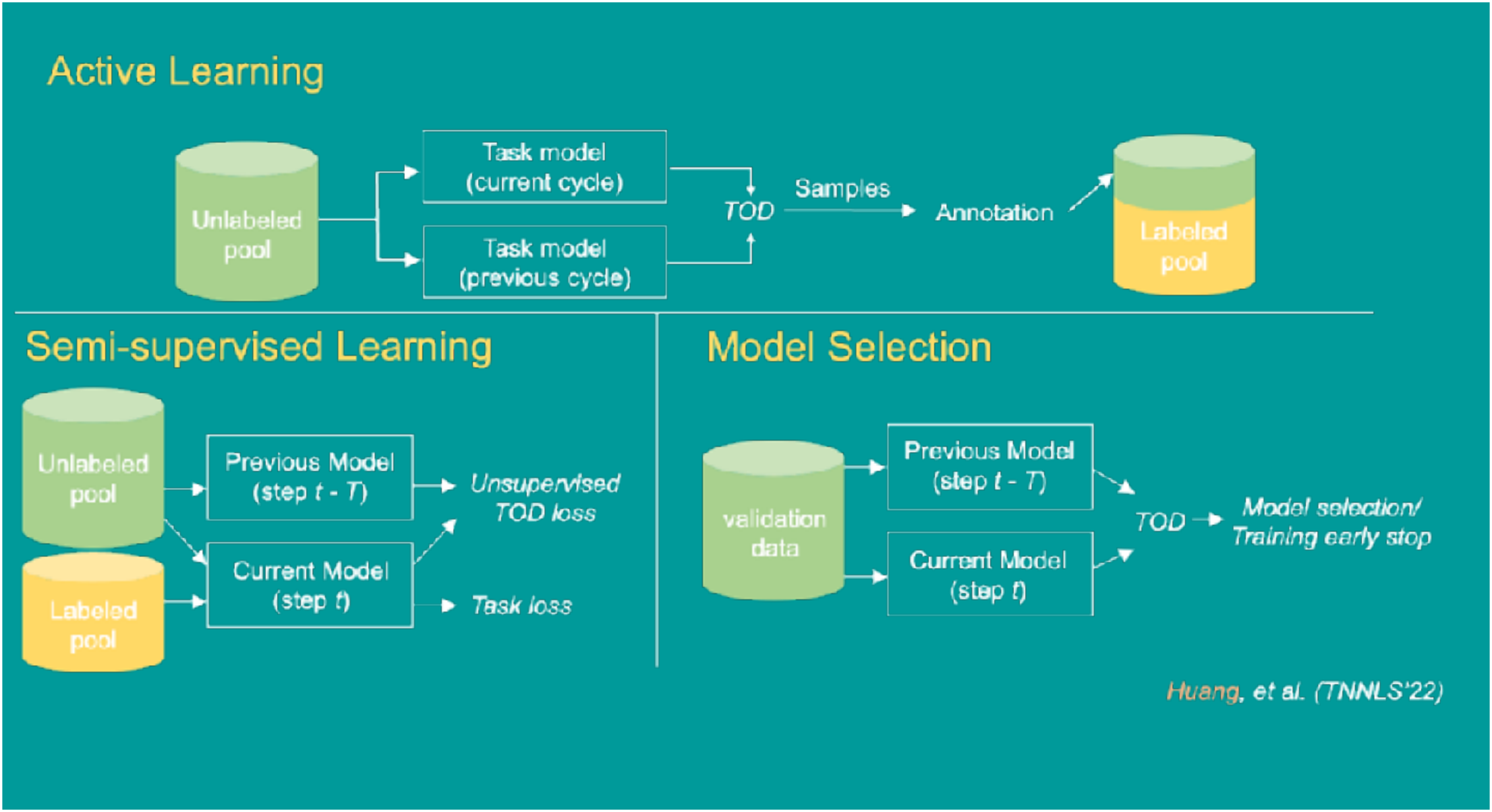
- Discrepancy

$$\left\| p_{\mathbf{w}_{t+T}}(y \mid \hat{\mathbf{x}}) - p_{\mathbf{w}_t}(y \mid \hat{\mathbf{x}}) \right\|$$

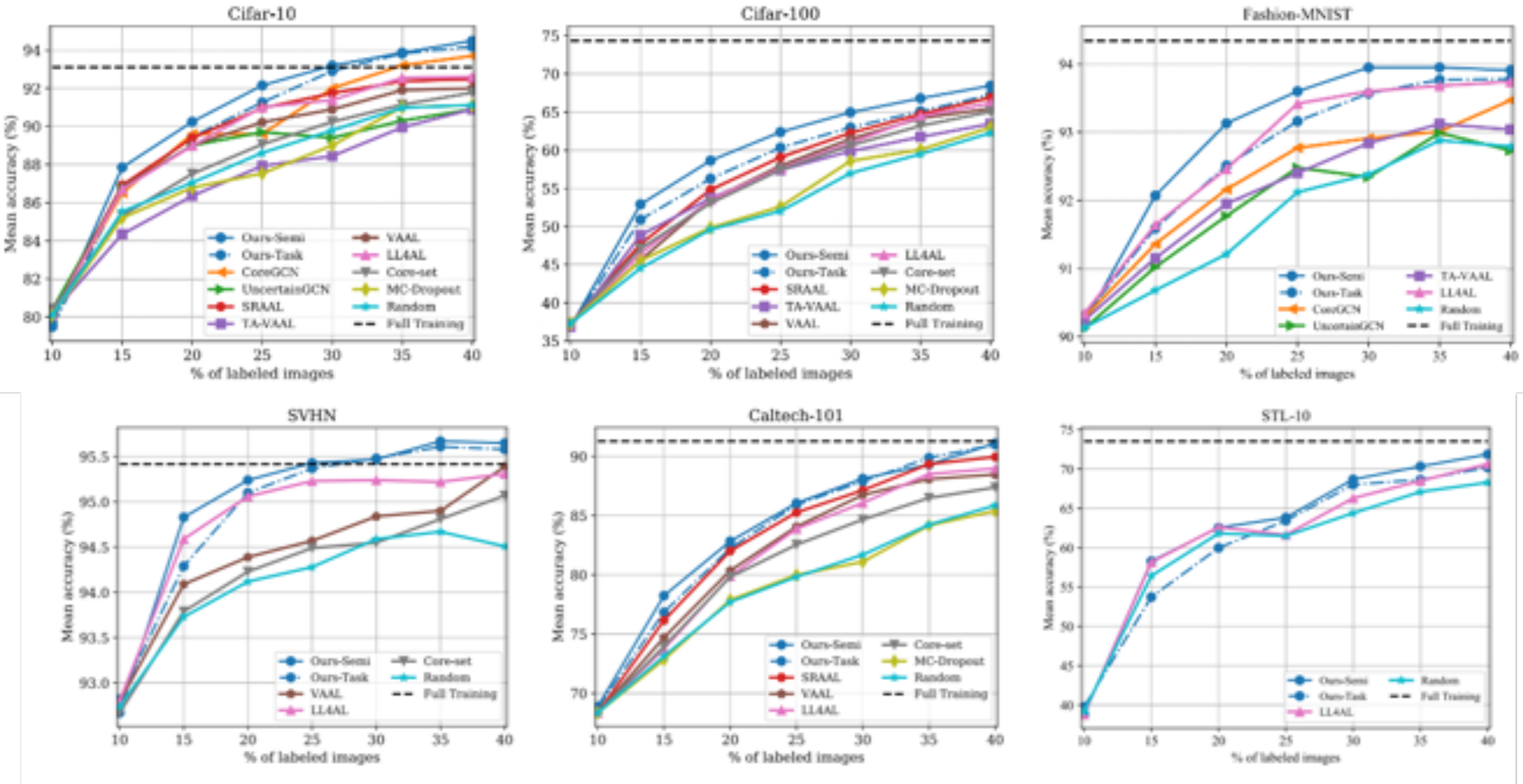
under certain conditions, this is a valid Wasserstein distance

$$\min_{\mathbf{w}} \underbrace{\mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}_{t+T}}(y \mid \mathbf{x})]}_{\text{cross entropy}} + \underbrace{\lambda \cdot \mathbf{E}_{\hat{\mathbf{x}}\in U}\left[\left\| p_{\mathbf{w}_{t+T}}(y \mid \hat{\mathbf{x}}) - p_{\mathbf{w}_t}(y \mid \hat{\mathbf{x}}) \right\| \right]}_{\text{discrepancy}}$$

Using Temporal Discrepancy



Active Learning with TOD



Paper Presentation: GPT-3

Language Models are Few-Shot Learners

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