Consistency Loss

I'm from Canada, but live in the States now.

It took me a while to get used to writing boolean variables with an "Is" prefix, instead of the "Eh" suffix that Canadians use when programming.

For example:

```
MyObj.IsVisible

MyObj.VisibleEh
```

Unsupervised Consistency Loss

$$\min_{\mathbf{w}} \mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}}(y\,|\,\mathbf{x})] + \lambda \quad \mathcal{D}_{KL}\left(p_{\mathbf{w}}(y\,|\,\mathbf{x})\,||\,p_{\mathbf{w}}(y\,|\,\hat{\mathbf{x}})\right)$$

no back prop **yes** back prop

Neural Network approximates $p(y|\mathbf{x})$ by $\mathbf{w}$

Sometimes shown as $p(y\,|\,\mathbf{x};\,\mathbf{W})$

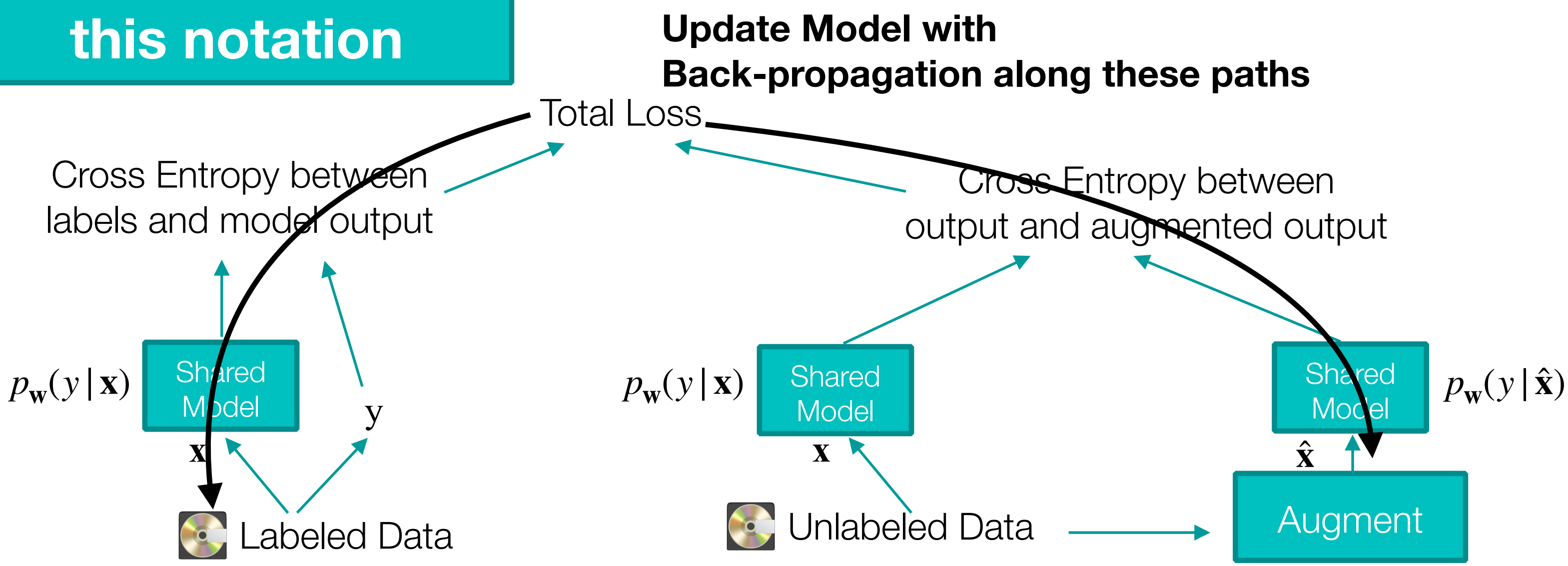
Use labeled data to minimize network

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

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

$$E[g] = \sum p(g) \cdot g$$ 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, discrete classes

$$CE(f,g) = -\sum f(x) \cdot \log g(x)$$ 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

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

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

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

constant

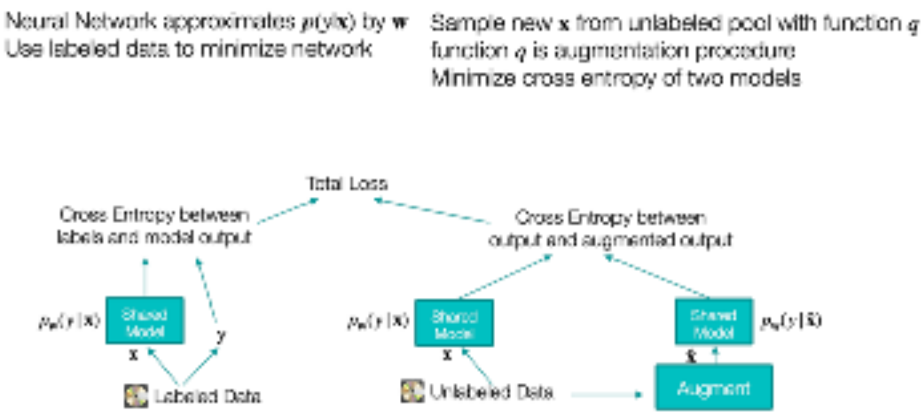
cross entropy of
augmented and not augmented
model

global entropy of model
constant as $p(y\,|\,\mathbf{x})$ has no uncertainty

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

Aside:

- We have just seen two motivations:



intuition of final product

keep labels consistent, any measure would be okay

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

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

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

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

constant

cross entropy of augmented and not augmented model

global entropy of model output constant as $p(y|\mathbf{x})$ has no uncertainty

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

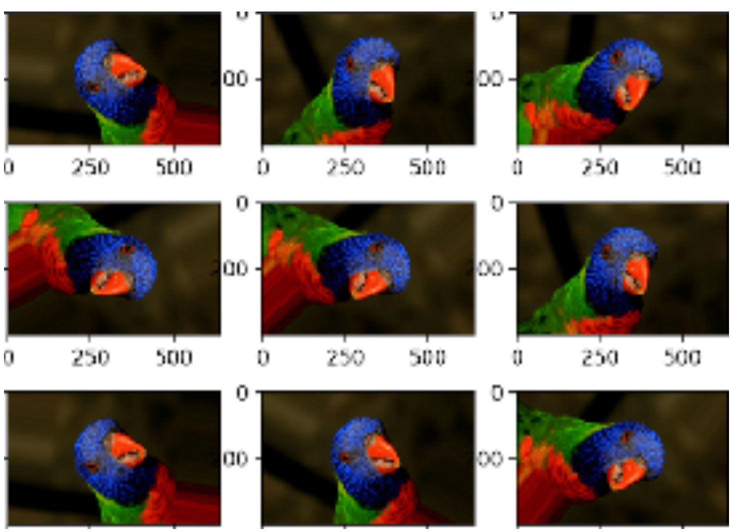
mathematics with strict assumptions

not necessarily intuitive, but provides guarantees

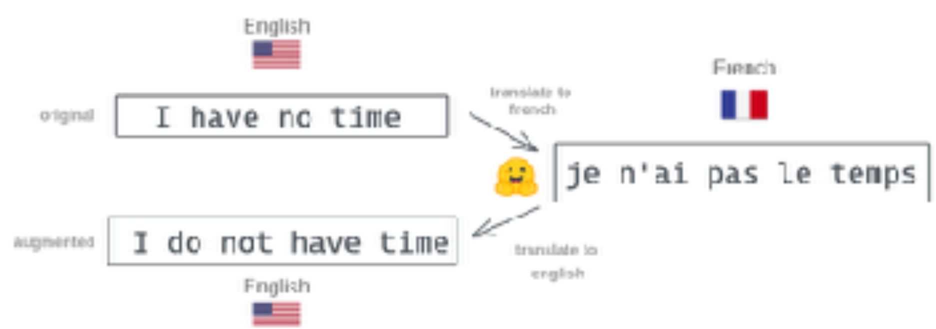
$$\min_{\mathbf{w}} \overbrace{\mathbf{E}_{\mathbf{x},y\in L}[-\log p_{\mathbf{w}}(y|\mathbf{x})]}^{\text{cross entropy}} + \lambda \overbrace{\mathscr{D}_{KL}\left(p_{\mathbf{w}}(y|\mathbf{x})||p_{\mathbf{w}}(y|\hat{\mathbf{x}})\right)}^{\text{consistency in augmentation}}$$

Augmentation with Consistency Loss

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



Synonym Replacement



Back Translation

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

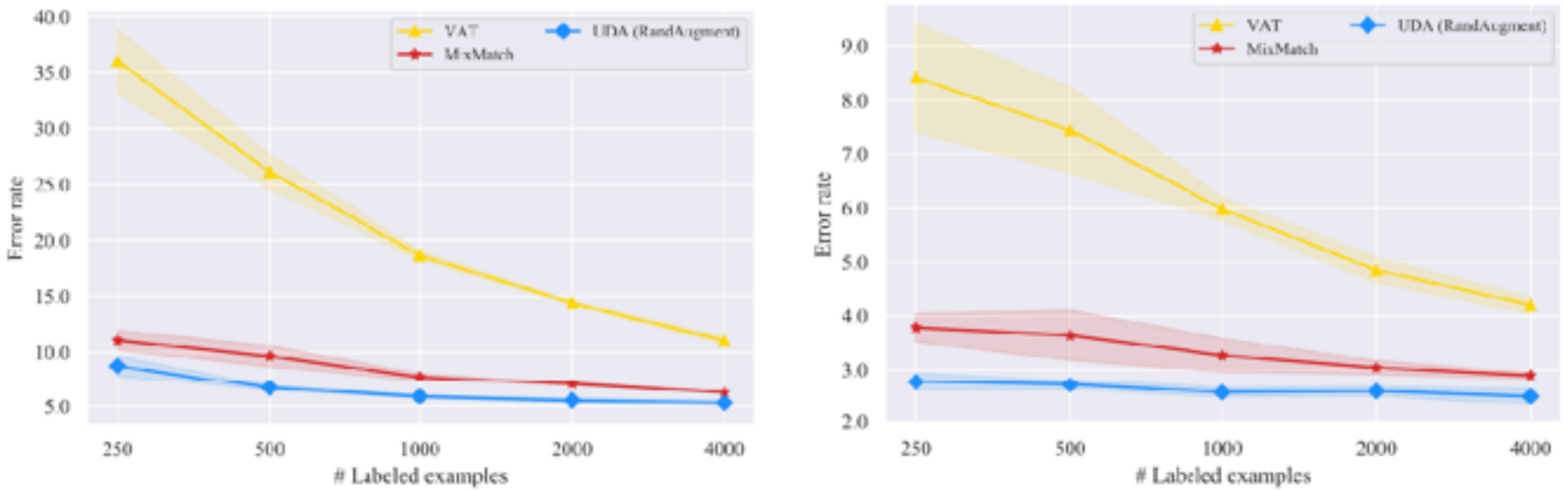
Unsupervised Consistency Loss

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	✗	55.09 / 77.26	77.28 / 93.73
w. RandAugment	✗	58.84 / 80.56	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.

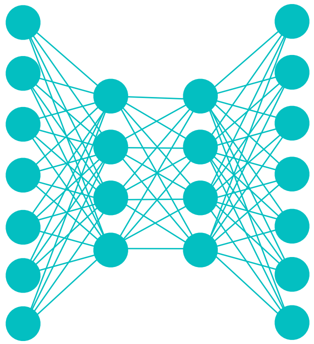
Lecture Notes for

Neural Networks and Machine Learning

SSL

Next Time:
MML and MTL

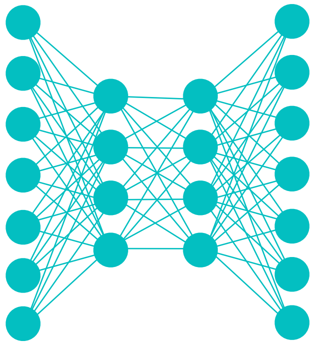
Reading: None



Lecture Notes for

Neural Networks and Machine Learning

Multi-task and Multi-Modal Learning



Logistics and Agenda

- Logistics
    - Grading Update
- Agenda
    - Student Paper Presentation
    - Multi-modal and Multi-task
- Next Time
    - Multi-task demo and Town Hall
    - Finish Demos

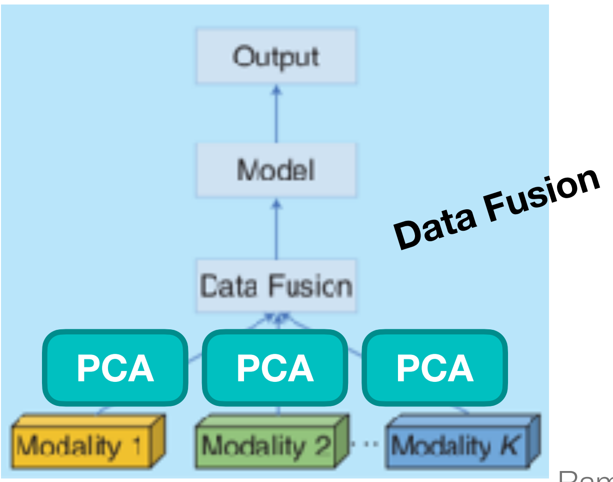
Multi-modal Review

Multi-modal == Multiple Data Sources

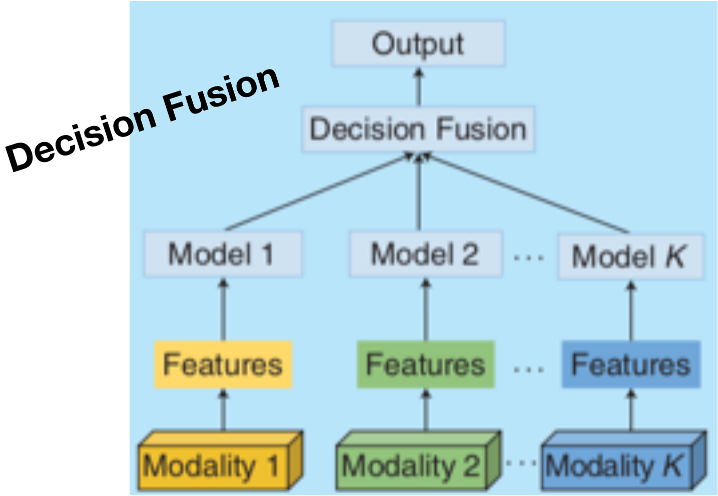
- **Modal** comes from the “sensor fusion” definition from Lahat, Adali, and Jutten (2015) for deep learning
- Using the Keras functional API, this is extremely easy to implement
  - … and we have used it since CS7324!
- But now let’s take a deeper dive and ask:
  - What are the different types of modalities that we might try?
  - Is there a more optimal way to merge information?
  - When? Early, Intermediate, and late fusion

Early and Late Stage Fusion

- **Early Fusion:** Merge sensor layers early in the process
- **Assumption**: there is some data redundancy, but modes are conditionally dependent
- **Problem**: architecture parameter explosion
  - Typically need dimensionality reduction



- **Late Fusion**: Merge sensor layers right before flattening
- Use Decision Fusion on outputs
- **Assumption**: little redundancy or conditional independence—just an ensemble architecture
- **Problem**: just separate classifiers, limited interplay

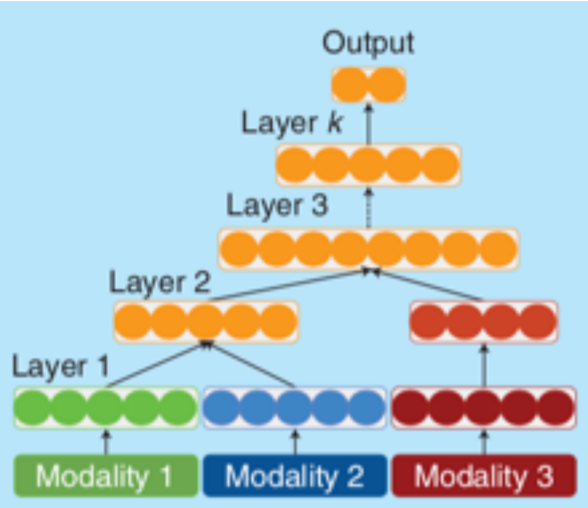


Ramamchandran and Taylor, 2017

Intermediate Fusion

- Merge sensor layers in soft way
- **Assumption**: some features interplay and others do not
- **Problem**: how to optimally tie layers together?

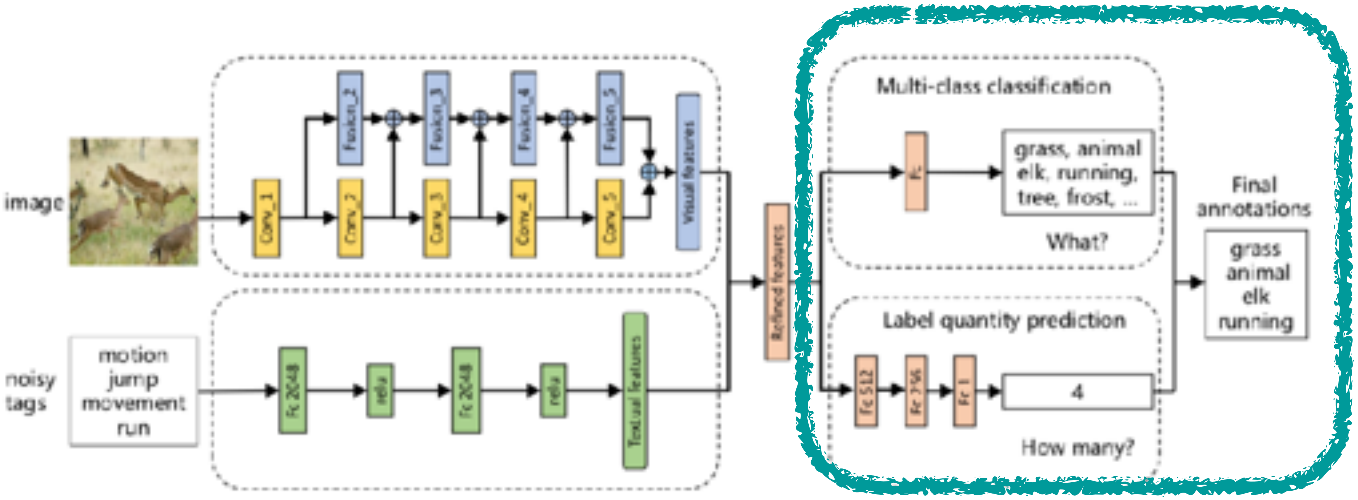
1. Stacked Auto-Encoders [Ding and Tao, 2015]
2. Early fuse layers that are correlated [Neverova *et al.* 2016]
3. Fully train each modality merge based on criterion of similarity in activations [Lu and Xu 2018]
4. Granger Cluster data in each modality and combine [Sylvester *et al.* 2023]



Ramamchandran and Taylor, 2017

Multi-modal Merging

- **Still an open research problem**
- How to develop merging techniques that
  - Can handle exponentially many pairs of modalities
  - Automatically merge meaningful modes
  - Discard poor pairings
  - Selectively merge early or late (or dynamically)

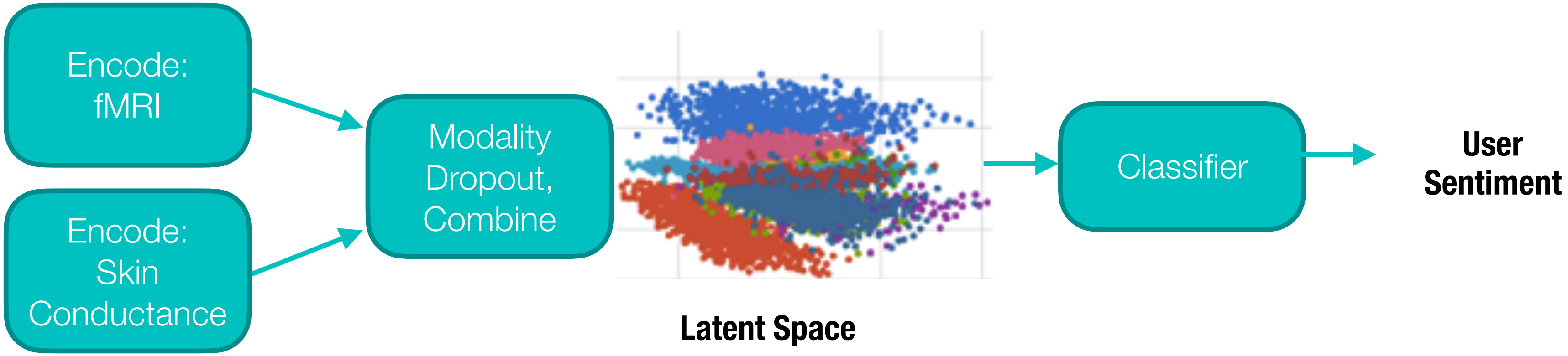


https://arxiv.org/pdf/1709.01220.pdf

Most current methods are still ad-hoc

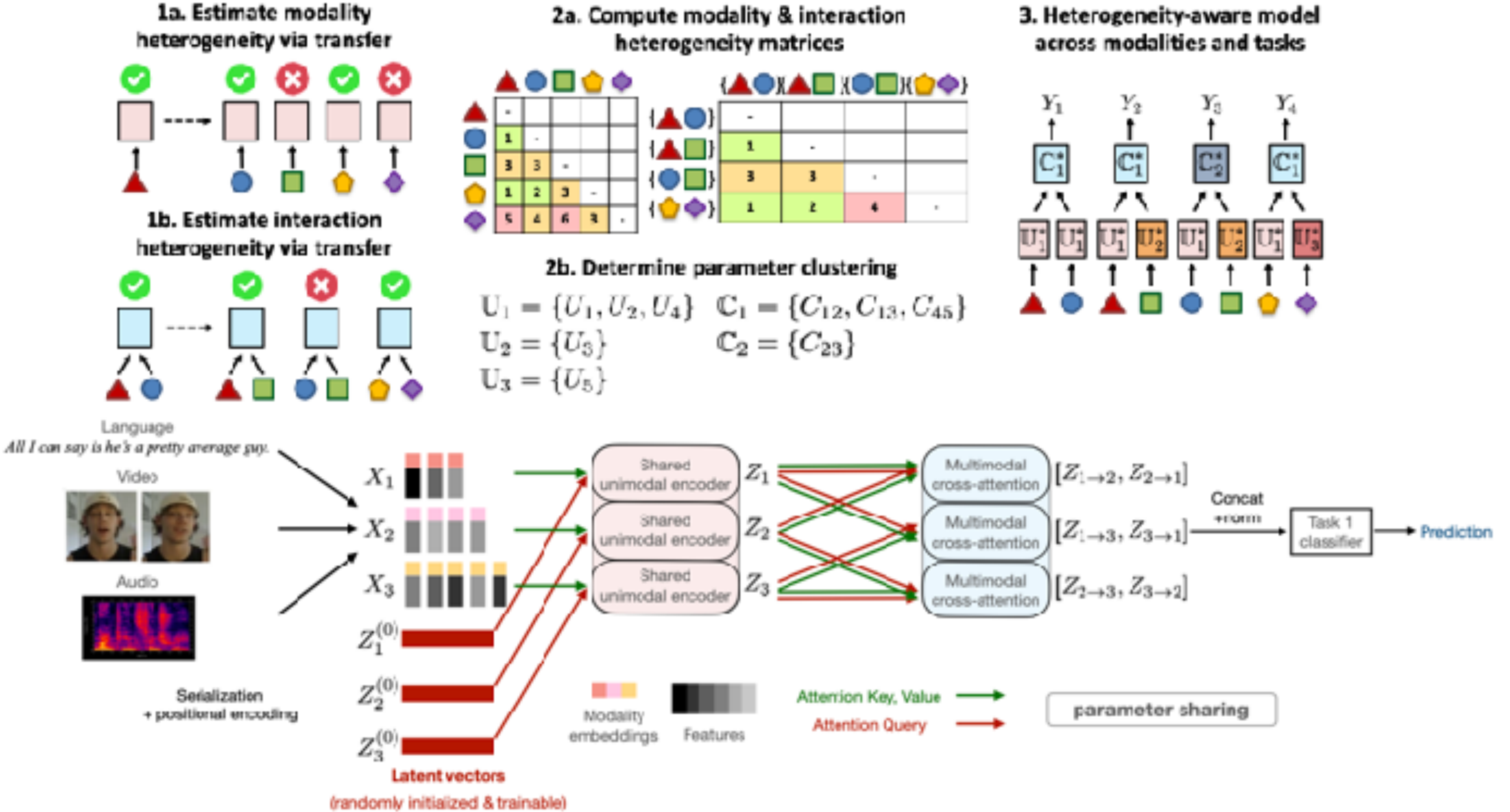
Approaches with Deep Learning

- Latent Space Transfer (universality)
    - From another domain, map to a similar latent space for the same task
    - Useful for unifying data based upon a new input mode when old mode is well understood
        - for example, biometric data
        - **2019-2023, I have never seen a research paper on this…**



High-Modality Multimodal Transformer: Quantifying Modality & Interaction Heterogeneity for High-Modality Representation Learning

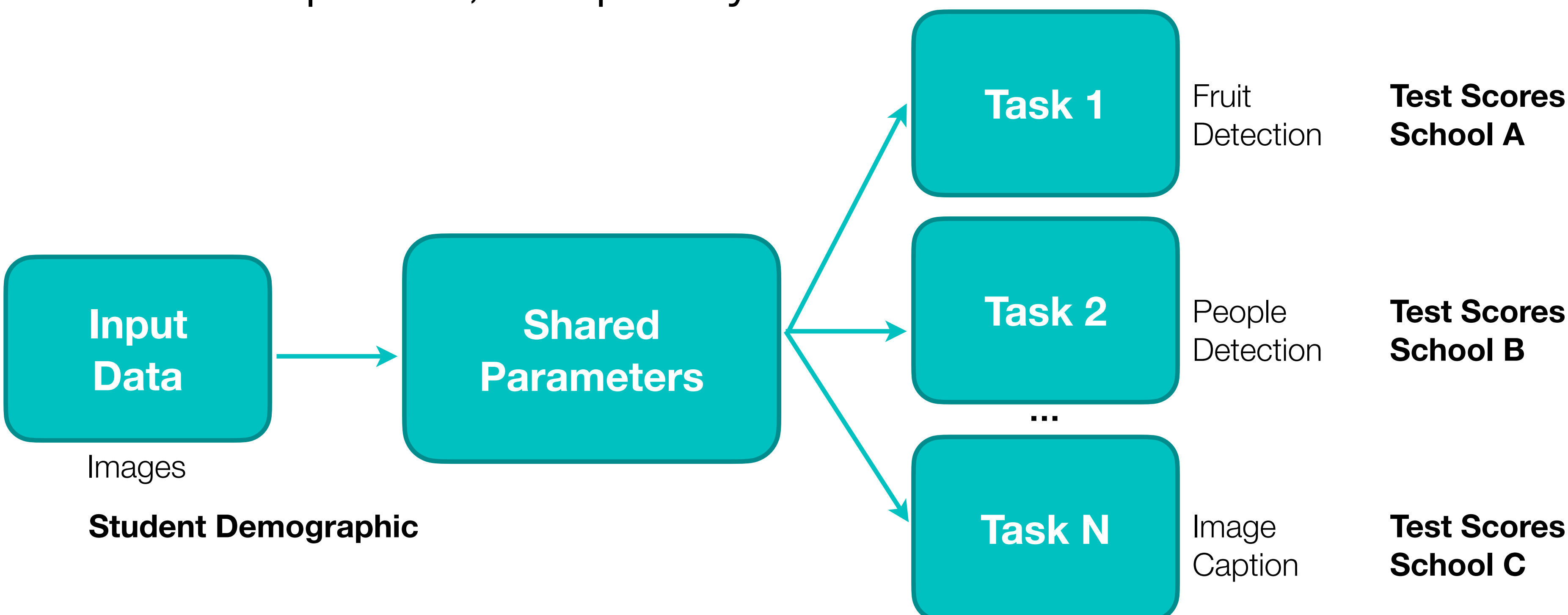
Paul Pu Liang[1], Yiwei Lyu[2], Xiang Fan[1], Jeffrey Tsaw[1], Yudong Liu[1], Shentong Mo[1], Dani Yogatama[3], Louis-Philippe Morency[1], Ruslan Salakhutdinov[1]
[1]Carnegie Mellon University, [2]University of Michigan, [3]DeepMind



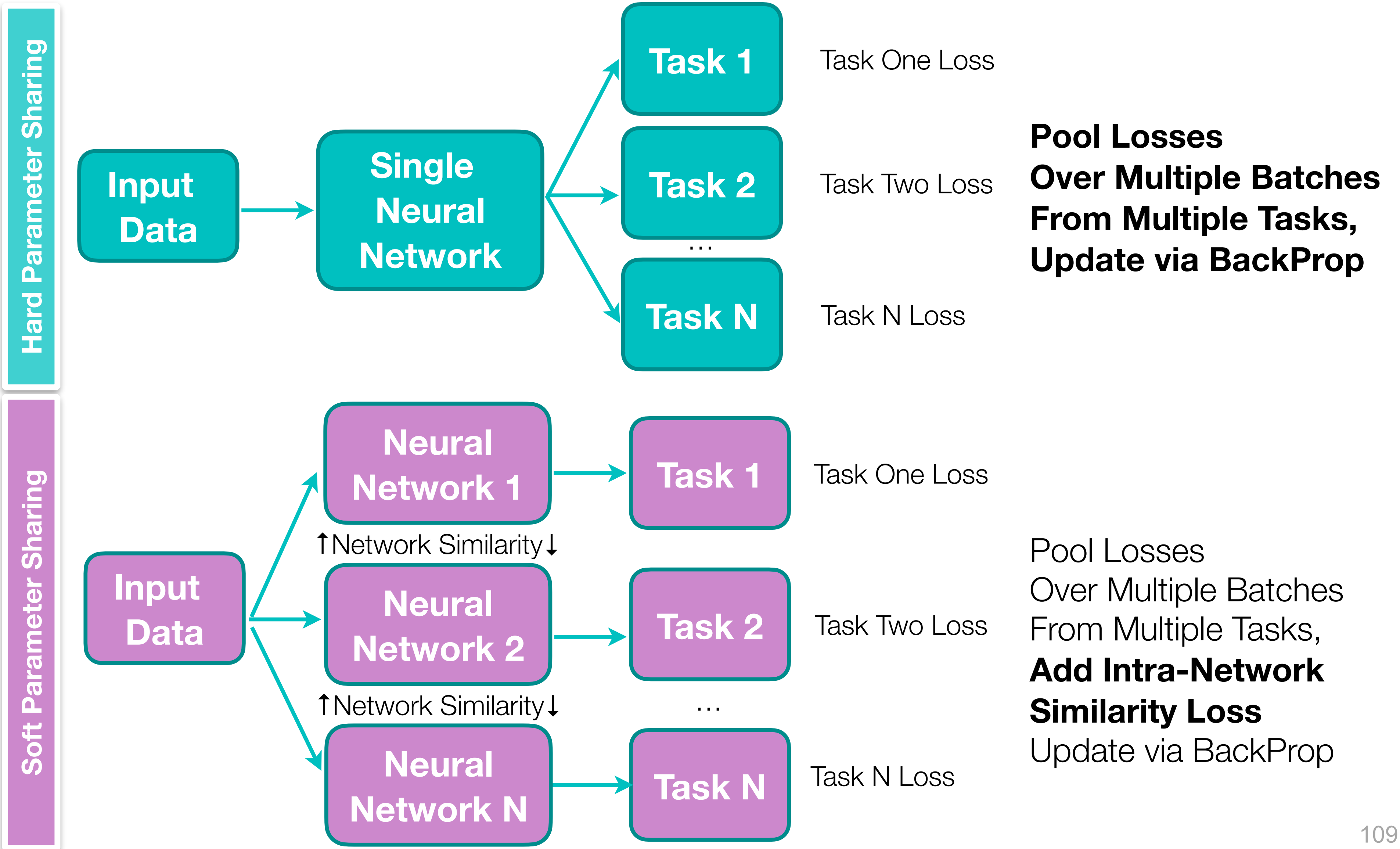
Multi-Task Models

Multi-task learning overview

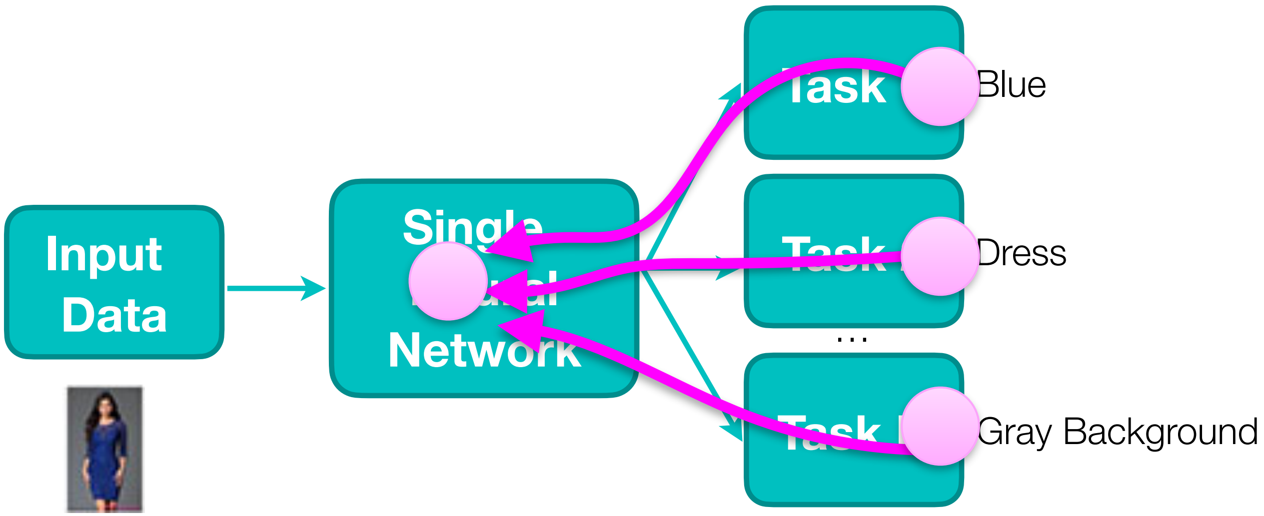
- For deep networks, simple idea: share parameters in early layers
- Used shared parameters as feature extractors
- Train separate, unique layers for each task



Multi-task Learning Parameter Sharing



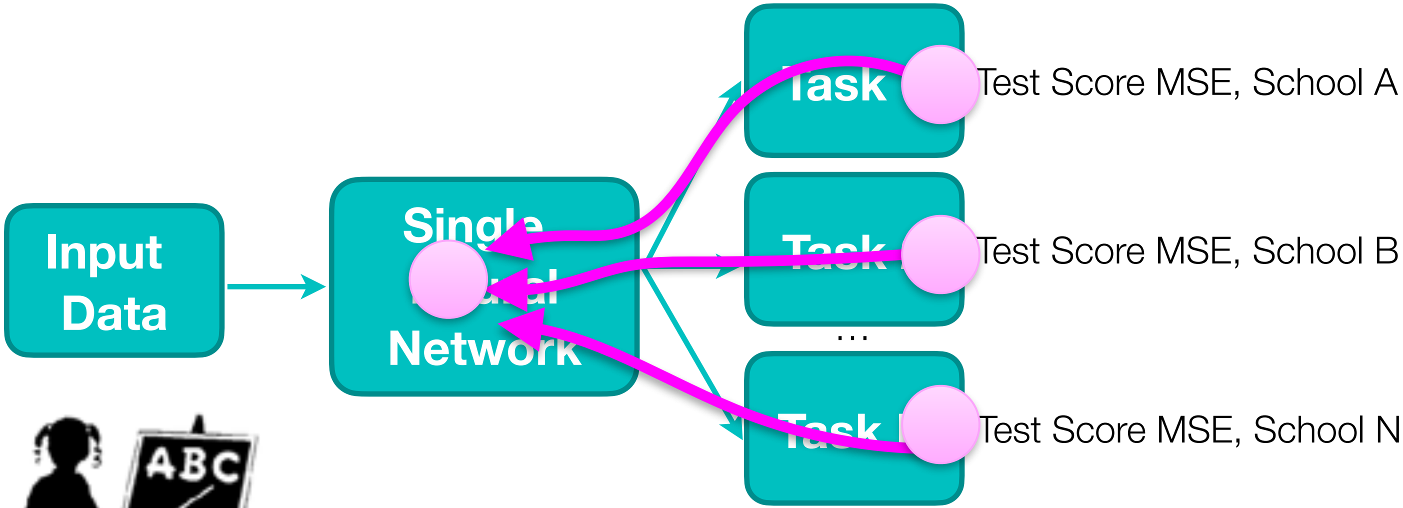
Multi-Label per Input



Measure Loss **for each label simultaneously**
Back propagate **everything at one time** for a given batch

Multi-task Optimization

Single Task Label per Input



Method One: Batch updates across multiple tasks
need to perform customized gradient calculations

Method Two: Update small batches using a random task
easier, but can cause instability in training

Multi-Task Learning in Keras with **Multi-Label Data**

Fashion week, colors and dresses

Optional Demo

Follow Along: https://www.pyimagesearch.com/2018/06/04/keras-multiple-outputs-and-multiple-losses/

Multi-Task Learning

School Data, Computer Surveys

Sponsor Follow

LukeWood Luke Wood

KerasCV Author, Full Time Keras team member & Machine Learning researcher @ Google, Part Time UCSD Ph.D student

PRO

Traian-Pop Traian Pop

Method One: Batch updates across multiple tasks
need to perform customized gradient calculations

Method Two: Update small batches using a random task
easier, but can cause instability in training

Follow Along: LectureNotesMaster/03 LectureMultiTask.ipynb

Lecture Notes for

Neural Networks and Machine Learning

Multi-Modal and Multi-Task

Next Time:
Circuits

Reading: Chollet 8.1-8.5