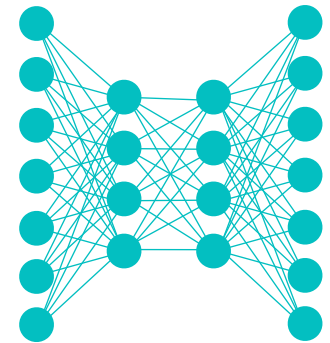


# Lecture Notes for **Neural Networks and Machine Learning**



Multi-Task and Demo



# Logistics and Agenda

- Logistics
  - Schedule Updated!
- Agenda
  - Multi-Task Examples
  - Multi-Task Demos
  - Multi-Task Town Hall
  - *if time: AlphaCode*
- Next Time
  - Circuits



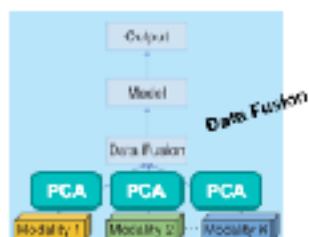
# Remaining Presentations

Student									
			Total Assigned	Responded?	Data Augmentation	Group Normalization	Perceptual Losses	Radford GANs	AlphaFold
Barajas, Cynthia	DUSSect 4	✓	0	1	x		x		
Canter, Austin	DUSSect 4	✓	1	1			1	0	
Collins, Joel	DUSSect 4	✓	1	1					1
Du, Jinyu	DUSSect 0	✓	1	1	1			0	
Ebrahimi, Jonathan	DUSSect P	✓	1	1				1	
Emami, Hestam	DUSSect 4	✓	1	1	1			0	
Gage, Nathan	DUSSect 0	✓	1	1					
Gao, Qing	DUSSect 4	✓	1	1	1			0	
Geng, Zicheng	DUSSect 0	✓	1	1	1			0	
Havard, Andrew	DUSSect P	✓	1	1				1	
Hu, Yvon	DUSSect 0	✓	1	1	0				
Klinkert, Jake	DUSSect 0	✓	1	1			1	0	
Larsen, Nicholas	DUSSect 4	✓	1	1					
Larsen, Steven	DUSSect 4	✓	1	1					
Lazaro, Irvin	DUSSect 4	✓	0	1	x		x		
Lu, Yifan	DUSSect 4	✓	1	1	0		1		
Mage, Ayesh Madushanka	DUSSect 0	✓	1	1					1
McNitt, Troy	DUSSect P	✓	1	1					
Moros, Jonas	DUSSect 0	✓	1	1					
Rajapandian, Koushik	DUSSect 4	✓	1	1				x	x
Rosenblatt, Jack	DUSSect 0	✓	1	1	0				1
Srinama, Nathan	DUSSect 0	✓	1	1	0			0	
Tsai, Amor	DUSSect 0	✓	1	1	0				
Wall, Nick	13.21 Sect 0	✓	0	0					
Wang, Kuo	DUSSect 0	✓	1	1					
Yang, Chenyu	DUSSect 4	✓	0	1	x				
Yassien, Sam	13.21 Sect 0	✓	1	1			1		
Yu, Hongjin	DUSSect 0	✓	1	1			0	0	
Zepeda, Juan	DUSSect 4	✓	0	1	x	x			
								</	



# Last Time

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



Decision Fusion and Textile 2017



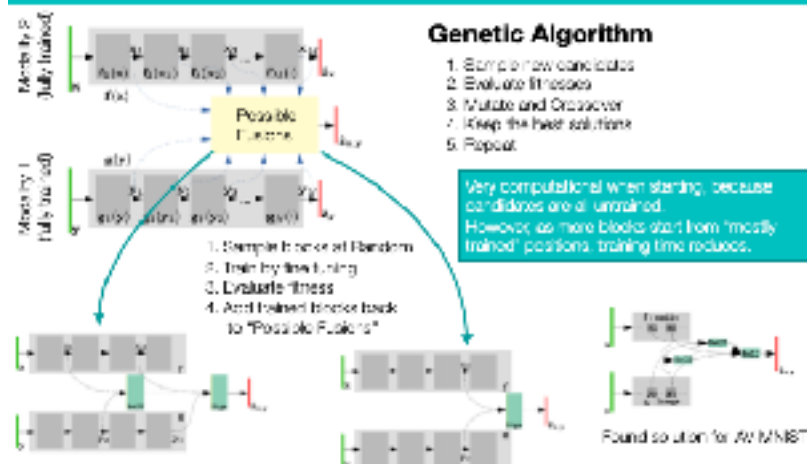
90

## Neural Architecture Search for Mode Fusion

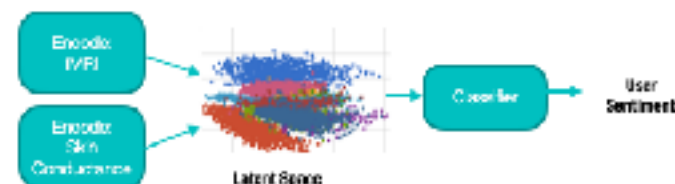
### Genetic Algorithm

1. Sample new candidates
2. Evaluate fitness
3. Mutate and Crossover
4. Keep the best solutions
5. Repeat

Very computational when starting, because candidates are all untrained. However, as more blocks start from "mostly trained" positions, training time reduces.



- 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
  - **I have never seen a research paper on this...**

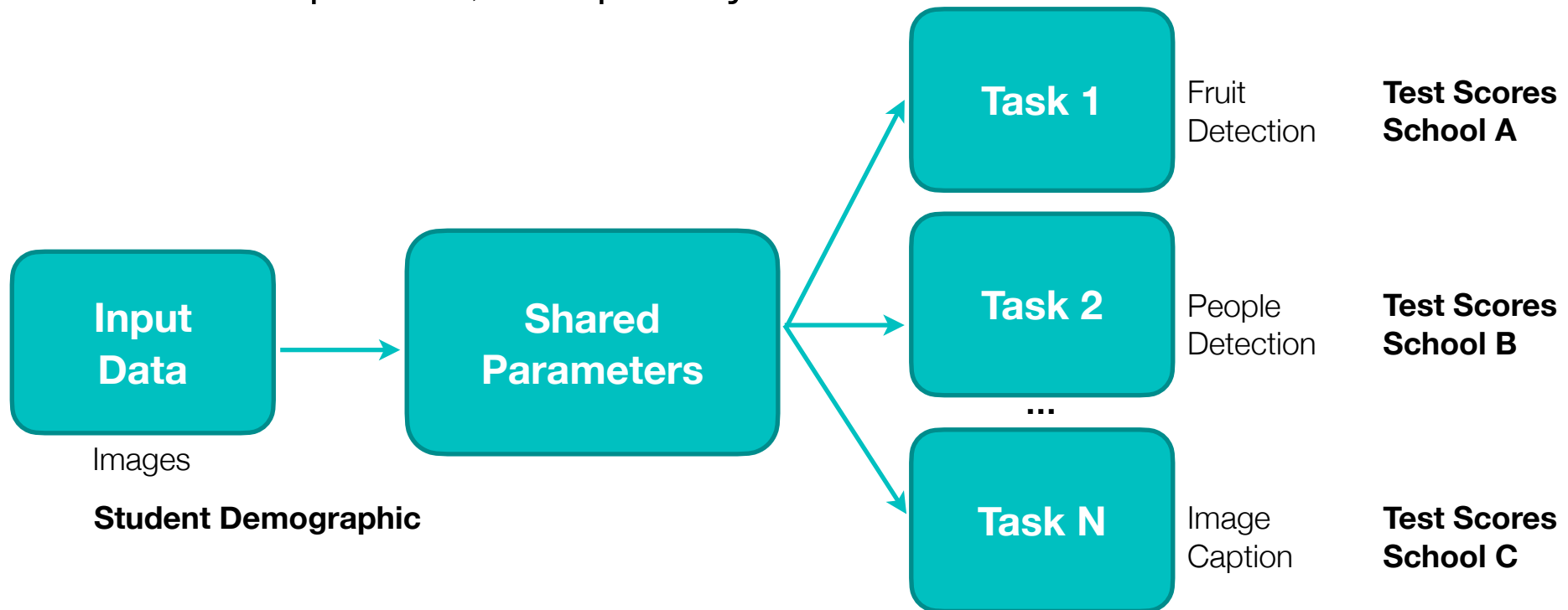


# Multi-Task Models

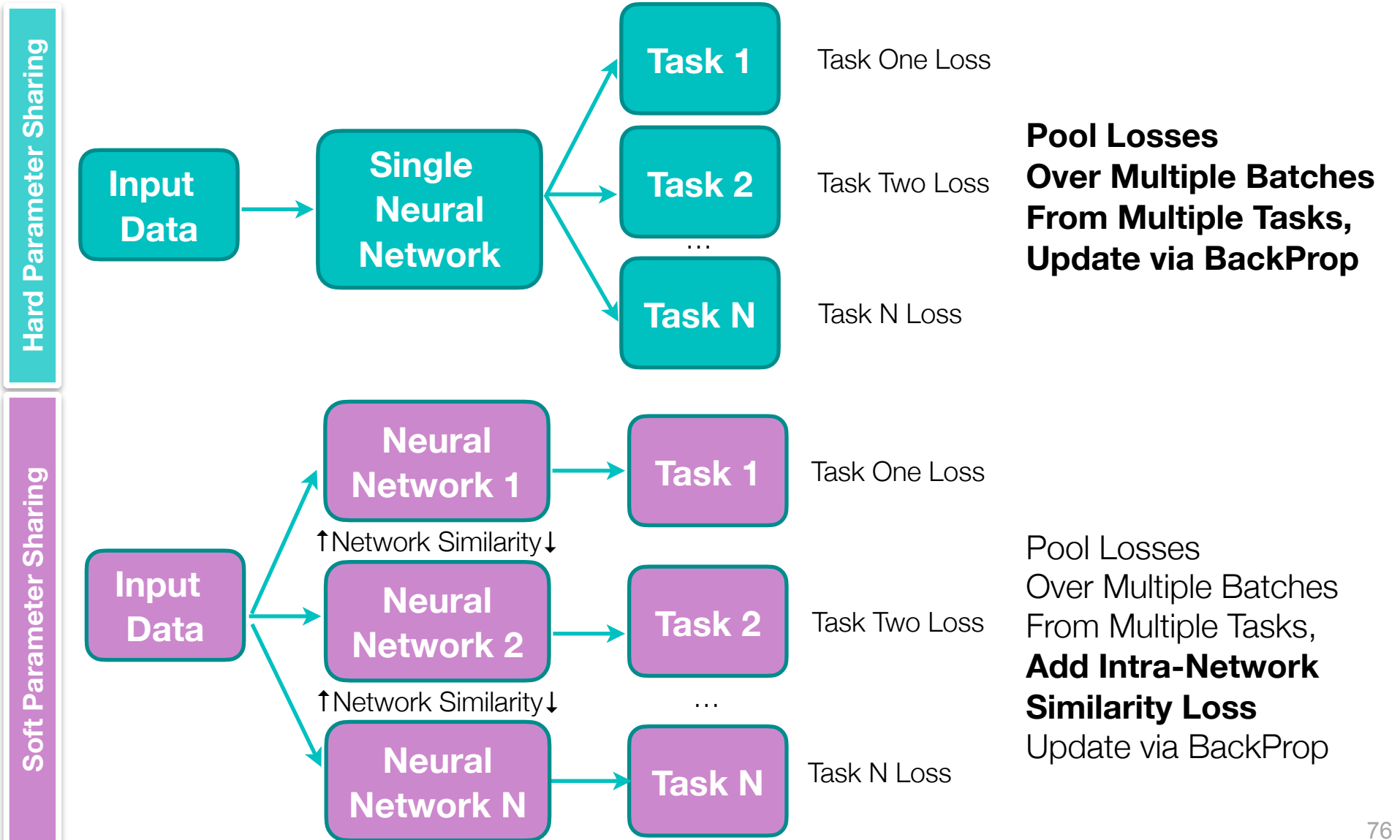


# Multi-task learning overview

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

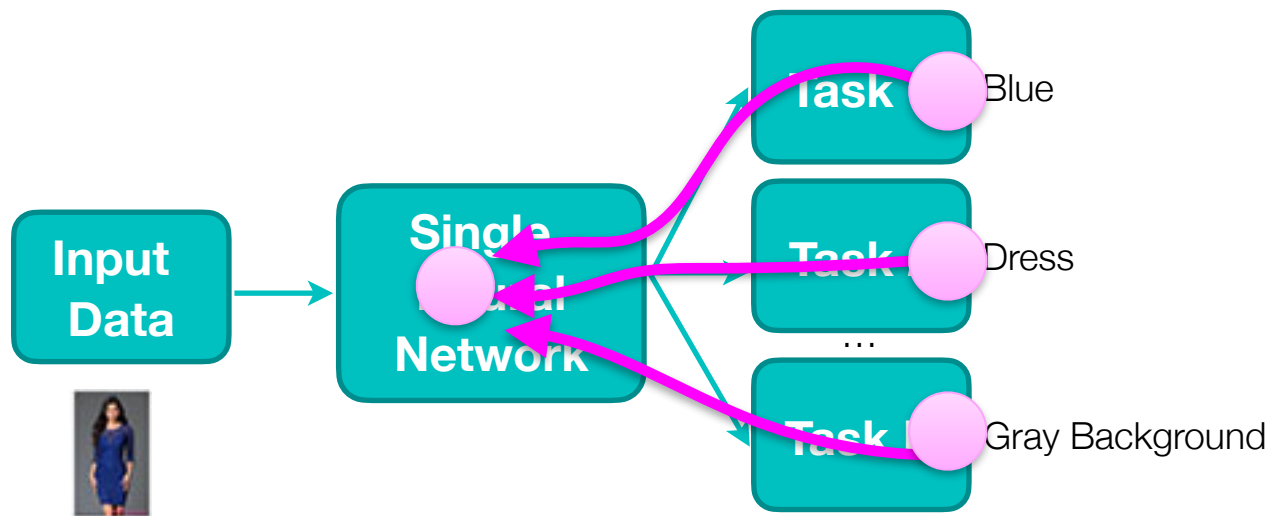


# Multi-task Learning Parameter Sharing



# Multi-task Optimization

## Multi-Label per Input



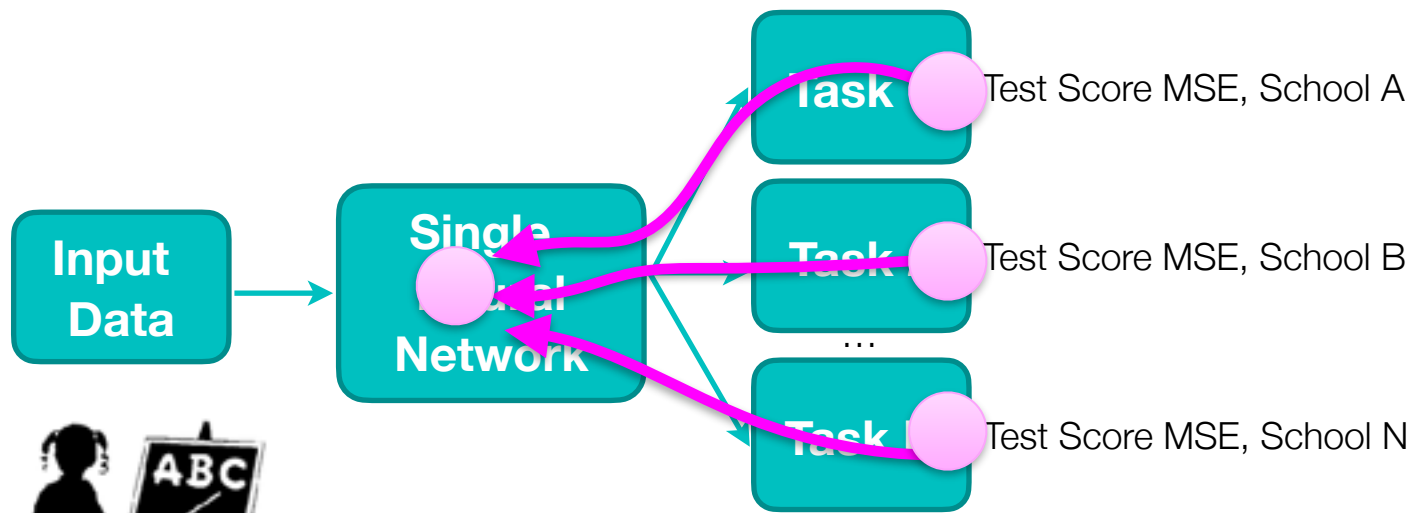
Measure Loss for each label simultaneously  
Back propagate everything at one for a given batch





# 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





Optional Demo

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

Fashion week, colors and dresses

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





# Multi-Task Learning

School Data, Computer Surveys



Traian Pop



Luke Wood

Follow Along: [LectureNotesMaster/03 LectureMultiTask.ipynb](#)



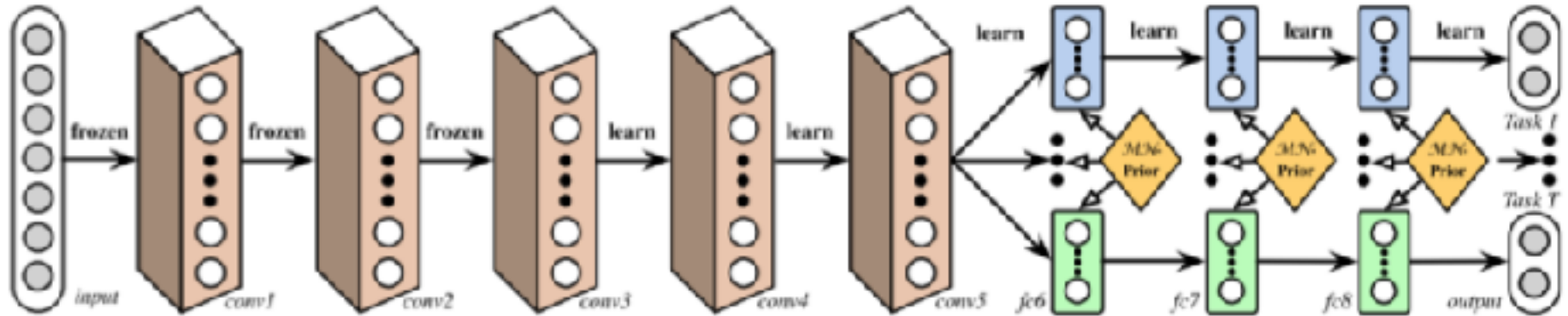
# Multi-Task Model Examples

He uses statistics like a drunken man uses a lamp post, more for support than illumination.

-- Andrew Lang



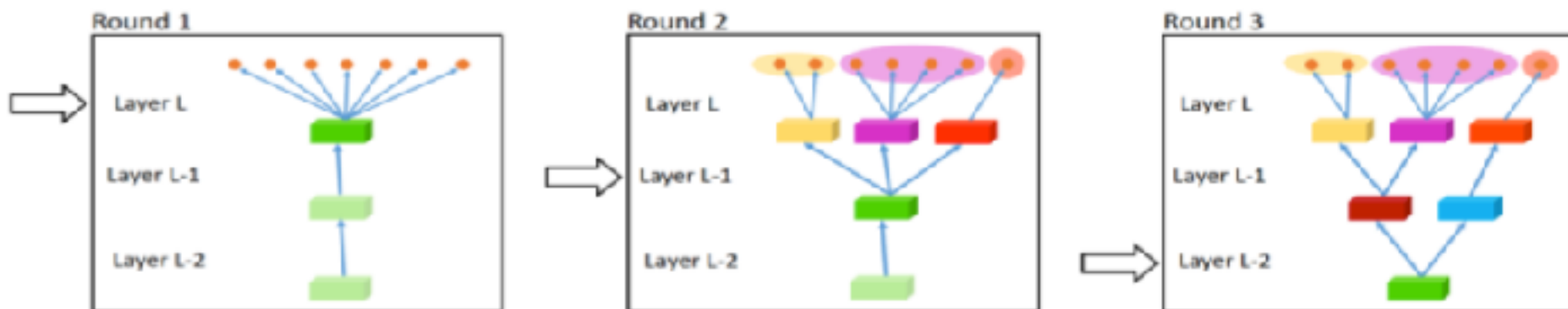
# Multi-task: Deep Relationship Networks



- Start training traditionally (CCE)
- Minimize Kroenecker Product of fully connected task specific layers (here matrices are vectorized and therefore it is an outer product)
  - intuitively: make Covariances between tasks close to a given prototype Covariance
  - encourages feature maps in each task to be **less correlated** to feature maps of another task



# Multi-task: Adaptive Feature Sharing



- Train
- Rep

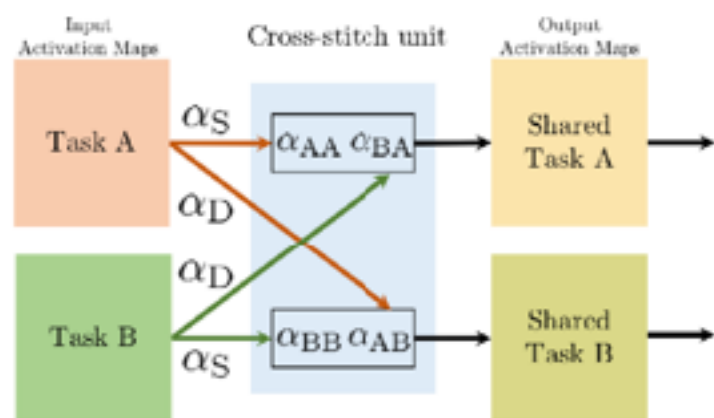
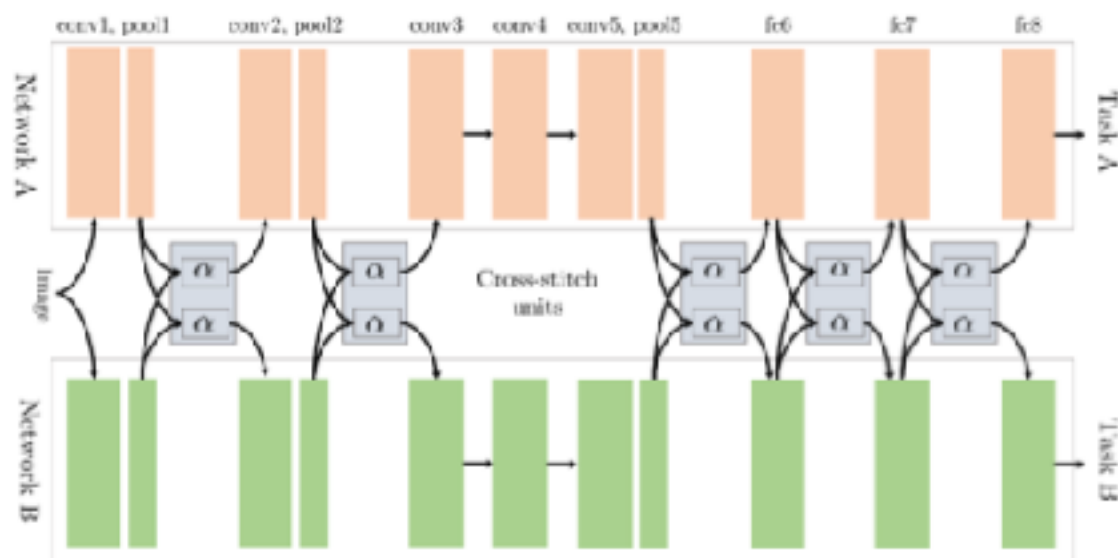
$$A^*, \omega^*(l) = \arg \min_{A \in \mathbb{R}^{d \times d'}, |\omega| = d'} ||W^{p,l} - AW_{\omega}^{p,l}||_F, \quad (2)$$

where  $W_{\omega}^{p,l}$  is a truncated weight matrix that only keeps the rows indexed by the set  $\omega$ . This problem is NP-hard, however, there exist approaches based on convex relaxation

- Cluster affinity of branch is not final layer
- Cut weights and retrain (fine tune) network
- Decrement current layer index



# Multi-task: Cross Stitch Networks



$$\begin{bmatrix} x_A^{ij} \\ x_B^{ij} \end{bmatrix} = \begin{bmatrix} \alpha_{AA} & \alpha_{AB} \\ \alpha_{BA} & \alpha_{BB} \end{bmatrix} \begin{bmatrix} x_A^{ij} \\ x_B^{ij} \end{bmatrix}$$

- Only works for simultaneous multi-label problems
  - like semantic segmentation and surface normal segmentation (clustering similarly facing objects)
- Take a learned weighted sum of the activations
- Works a little better than single task, but no worse



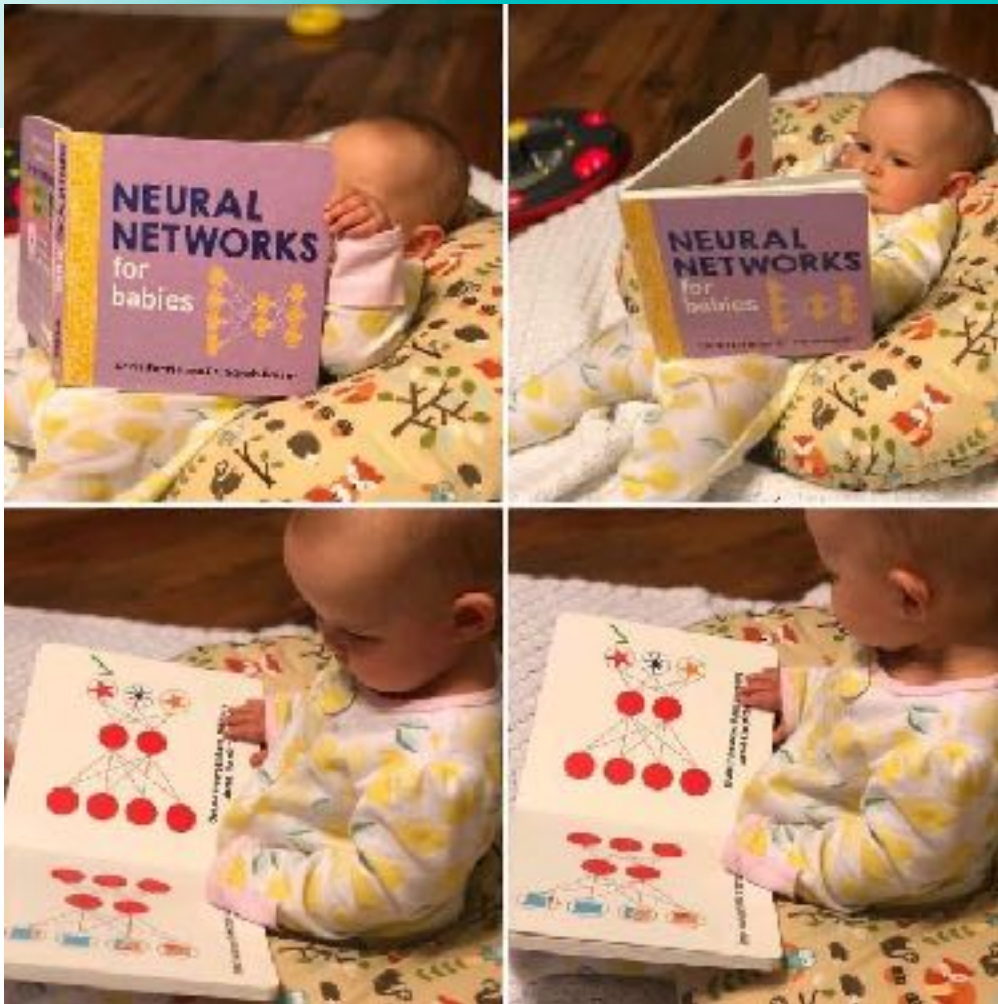
# Current Multi-task Research

- Incredibly diverse sets of solutions
- Mostly not evaluated on similar datasets
- Reasoning given is mostly ad-hoc...
- Theory is wildly under developed
  - because the problem is incredibly difficult
- Neural architecture search is an option...





# Lab One Town Hall



**Multi-Task Networks**  
**Multi-Modal Networks**



# Lecture Notes for **Neural Networks and Machine Learning**

Demo Multi-Task



**Next Time:**  
Circuits

**Reading:** Chollet 8.1-8.5

