



復旦大學



Learning Sparse Sharing Architectures for Multiple Tasks

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Beijing, 2019/12/22

Outline



Multi-Task Learning: Sharing Mechanisms

Sparse Sharing Mechanism

Approach: Learning Sparse Sharing Architectures

Experiments

Analysis and Discussions

Conclusion

Outline



Multi-Task Learning: Sharing Mechanisms

Sparse Sharing Mechanism

Approach: Learning Sparse Sharing Architectures

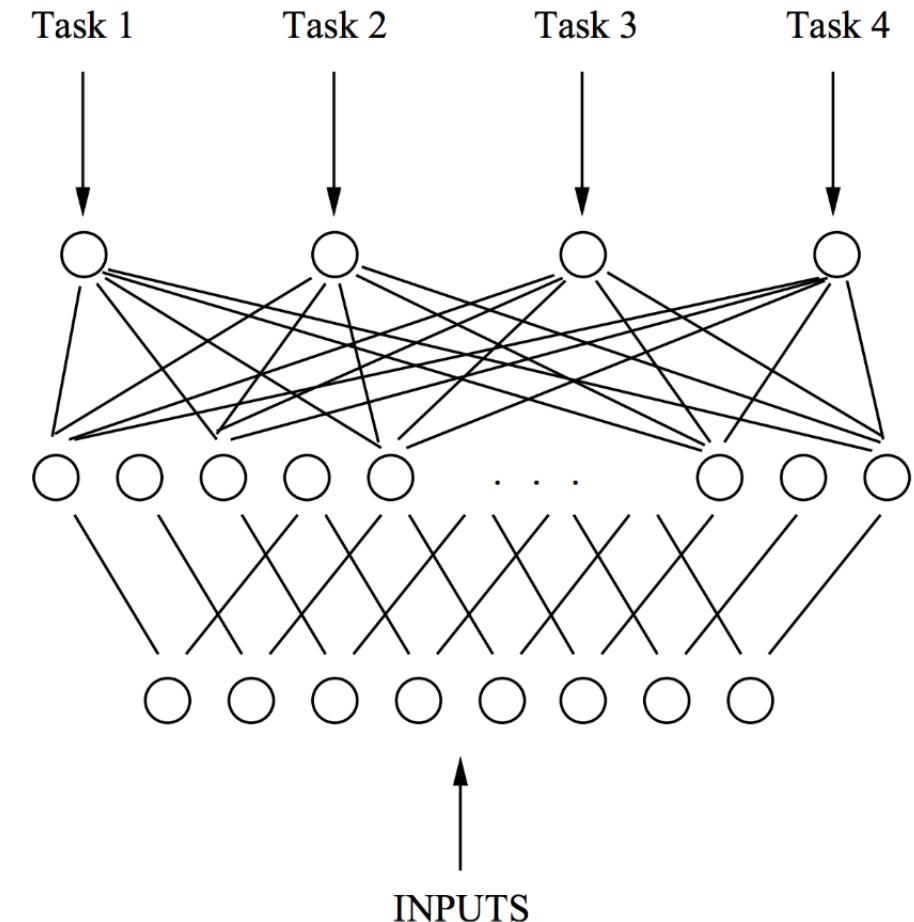
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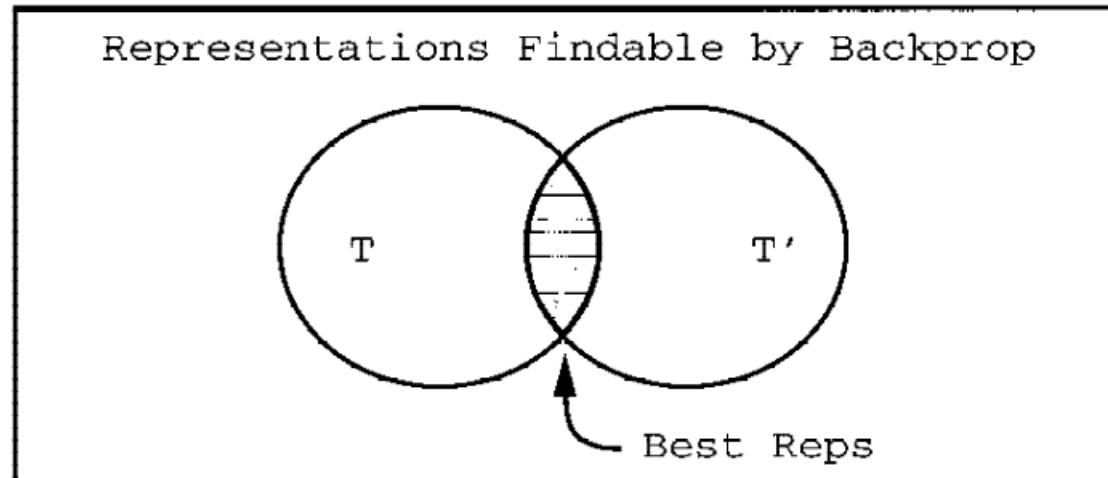
What is Multi-Task Learning(MTL)?

“Multi-task Learning is an approach to inductive transfer that improves **generalization** by using the domain information contained in the training signals of **related tasks** as an **inductive bias**.”



How does MTL work?

- Representation Bias (Inductive Bias)



Formulation

- T tasks: $\mathcal{D}_t = \{x_n^t, y_n^t\}_{n=1}^{N_t}$
- Shared layers \mathcal{E} parameterized by $\theta_{\mathcal{E}} = \{\theta_{\mathcal{E},1}, \dots, \theta_{\mathcal{E},L}\}$
- Task-specific layers \mathcal{F}^t parameterized by $\theta_{\mathcal{F}}^t$
- Parameters: $\theta = (\theta_{\mathcal{E}}, \theta_{\mathcal{F}}^1, \dots, \theta_{\mathcal{F}}^T)$
- Objective: $\mathcal{L}(\theta) = \sum_{t=1}^T \lambda_t \sum_{n=1}^{N_t} \mathcal{L}_t(\hat{y}_n^t, y_n^t)$

Multi-Task Sharing Mechanisms



MTL is typically done with *parameter sharing*:

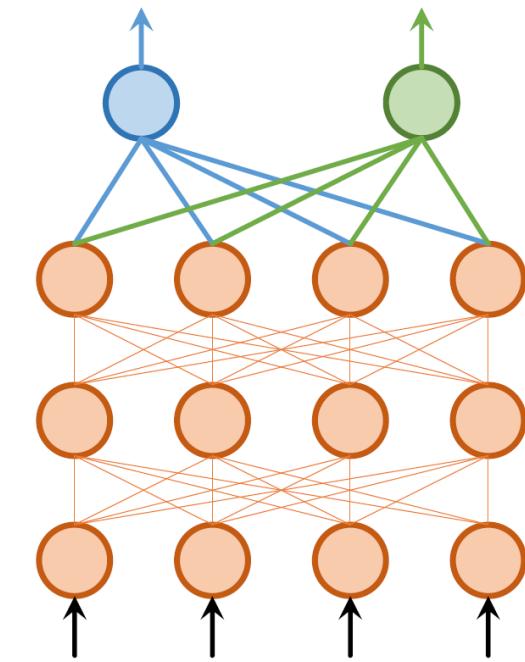
- Hard Sharing ([Collobert and Weston 2008](#); [Subramanian et al. 2018](#); [Liu et al. 2019](#))
- Soft Sharing ([Misra et al. 2016](#); [Ruder et al. 2019](#))
- Hierarchical Sharing ([Søgaard and Goldberg 2016](#); [Hashimoto et al. 2017](#))
- ...

Hard Sharing



- Stack the task-specific layers on the top of the shared layers
- Inference: $\hat{y}_n^t = \mathcal{F}^t(\mathcal{E}(x_n^t; \theta_{\mathcal{E}}); \theta_{\mathcal{F}}^t)$
- Advantages:
 1. simple to implement
 2. parameter efficient
- Disadvantages:

Struggle with loosely related/unrelated tasks
(Negative Transfer)



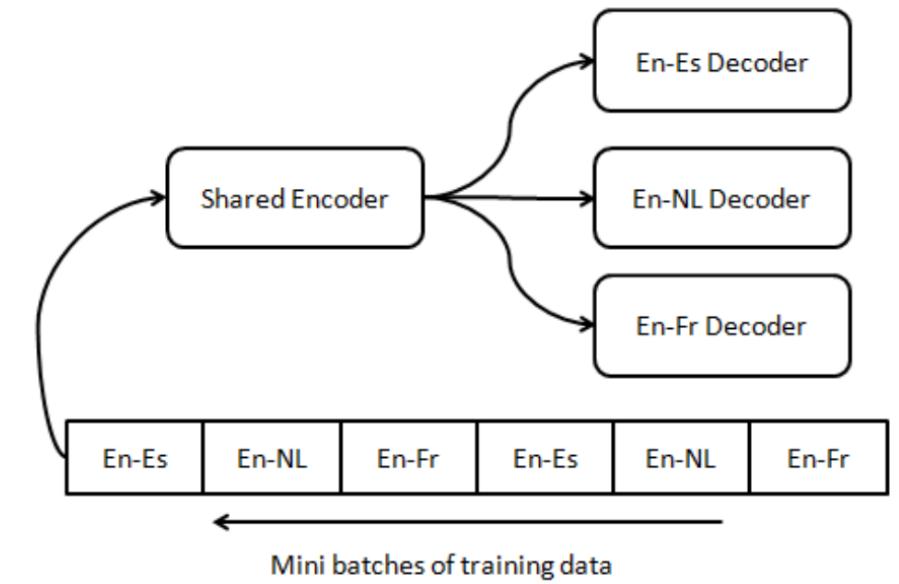
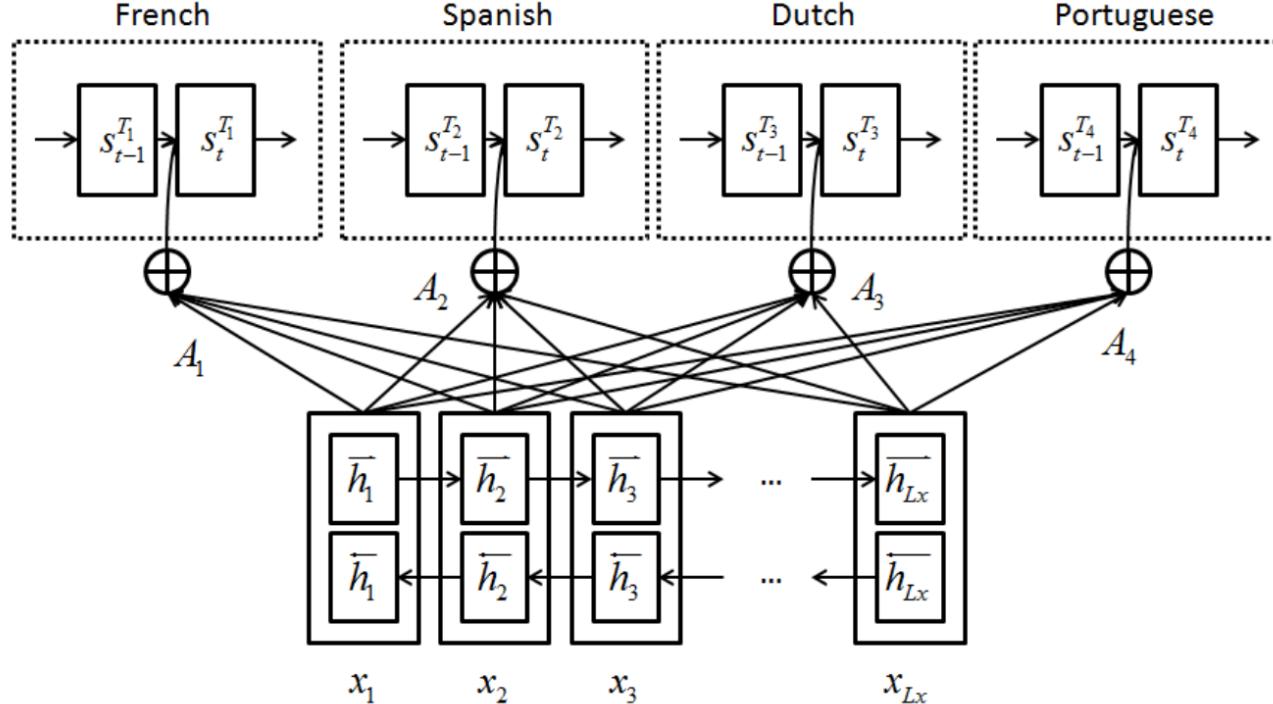
Multi-Task Learning for Multiple Language Translation

ACL 2015

Daxiang Dong, Hua Wu, Wei He, Dianhai Yu and Haifeng Wang

Baidu Inc, Beijing, China

{dongdaxiang, wu_hua, hewei06, yudianhai, wanghaifeng}@baidu.com



Recurrent Neural Network for Text Classification with Multi-Task Learning

IJCAI 2016

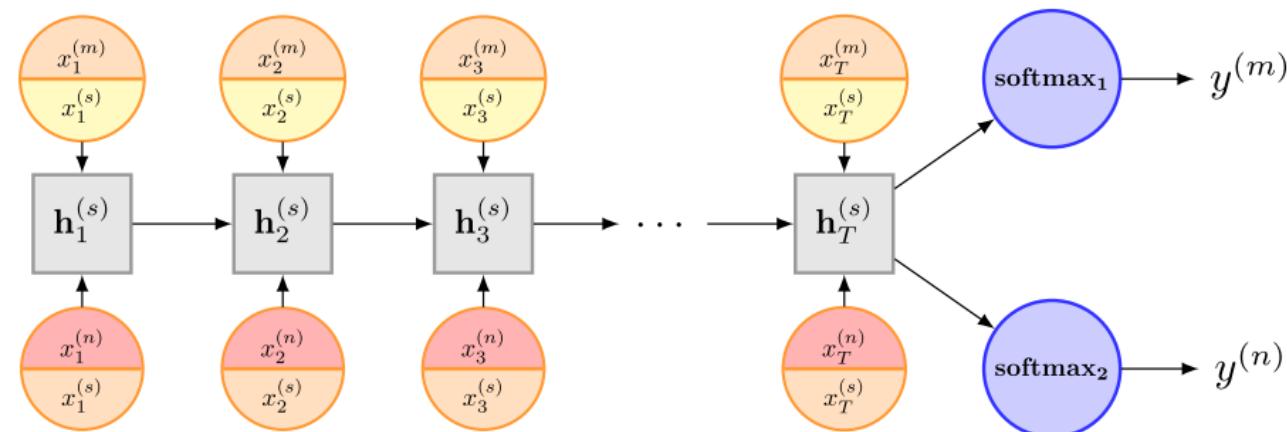
Pengfei Liu Xipeng Qiu* Xuanjing Huang

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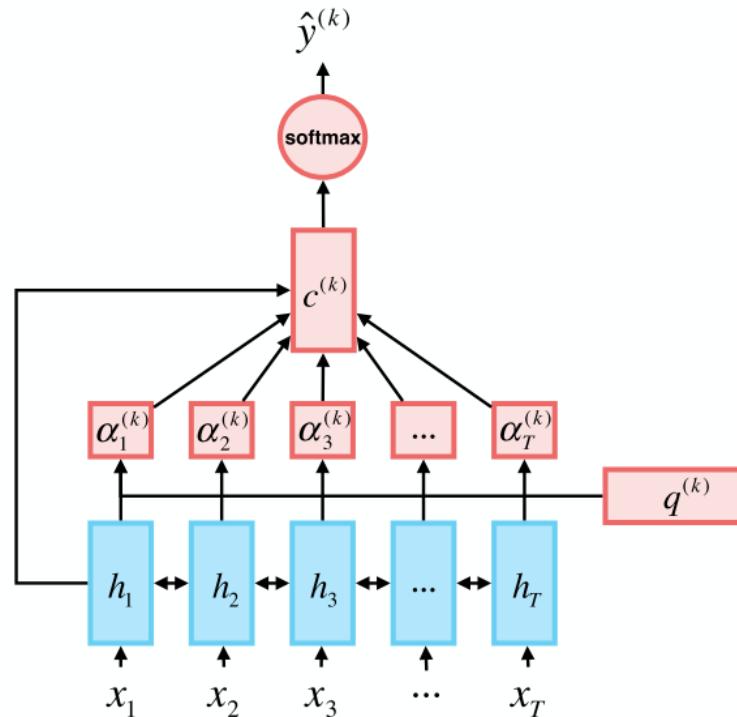


Same Representation, Different Attentions: Shareable Sentence Representation Learning from Multiple Tasks

IJCAI 2018

Renjie Zheng, Junkun Chen, Xipeng Qiu*

Shanghai Key Laboratory of Intelligent Information Processing, Fudan University
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825 Zhangheng Road, Shanghai, China

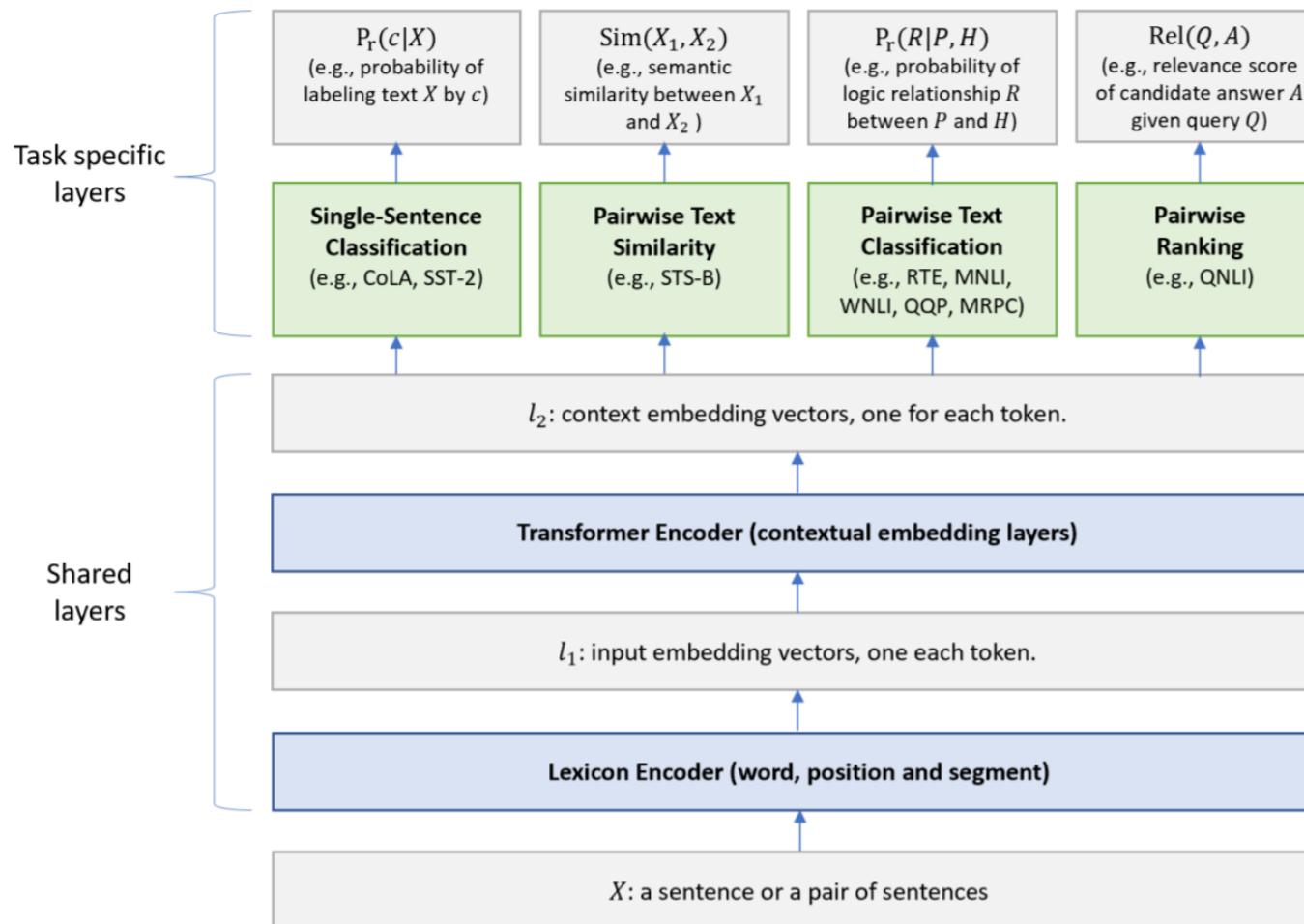


Xiaodong Liu^{*1}, Pengcheng He^{*2}, Weizhu Chen², Jianfeng Gao¹

¹ Microsoft Research

² Microsoft Dynamics 365 AI

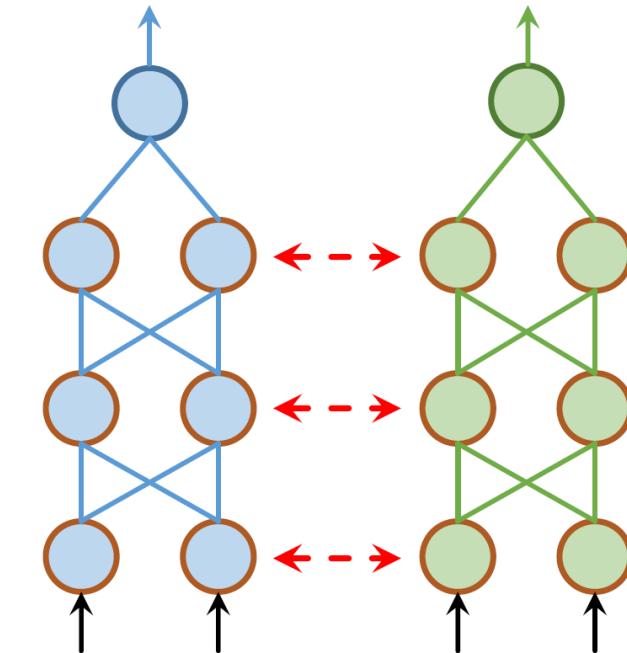
{xiaodl, penhe, wzchen, jfgao}@microsoft.com



Soft Sharing



- Each task has separate model and parameters, but each model can access the information inside other models
- Advantages:
Makes no assumptions about task relatedness
- Disadvantages:
Not parameter-efficient



Recurrent Neural Network for Text Classification with Multi-Task Learning

IJCAI 2016

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➤ Single-Task LSTM

$$\mathbf{i}_t = \sigma(\mathbf{W}_i \mathbf{x}_t + \mathbf{U}_i \mathbf{h}_{t-1} + \mathbf{V}_i \mathbf{c}_{t-1}),$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_f \mathbf{x}_t + \mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{V}_f \mathbf{c}_{t-1}),$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_o \mathbf{x}_t + \mathbf{U}_o \mathbf{h}_{t-1} + \mathbf{V}_o \mathbf{c}_t),$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \mathbf{x}_t + \mathbf{U}_c \mathbf{h}_{t-1}),$$

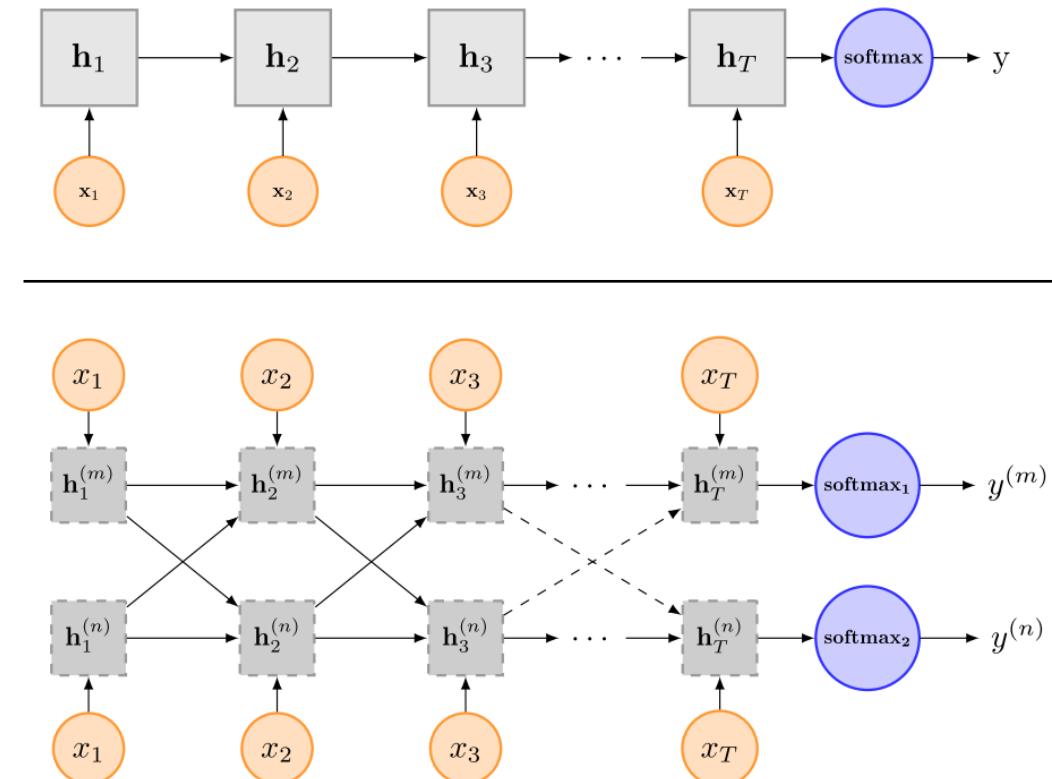
$$\mathbf{c}_t = \mathbf{f}_t^i \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t,$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t),$$

➤ Add signal flow across tasks

$$\tilde{\mathbf{c}}_t^{(m)} = \tanh \left(\mathbf{W}_c^{(m)} \mathbf{x}_t + \sum_{i \in \{m, n\}} \mathbf{g}^{(i \rightarrow m)} U_c^{(i \rightarrow m)} \mathbf{h}_{t-1}^{(i)} \right)$$

$$\mathbf{g}^{(i \rightarrow m)} = \sigma(\mathbf{W}_g^{(m)} \mathbf{x}_t + \mathbf{U}_g^{(i)} \mathbf{h}_{t-1}^{(i)})$$



Cross-stitch Networks for Multi-task Learning

CVPR 2016

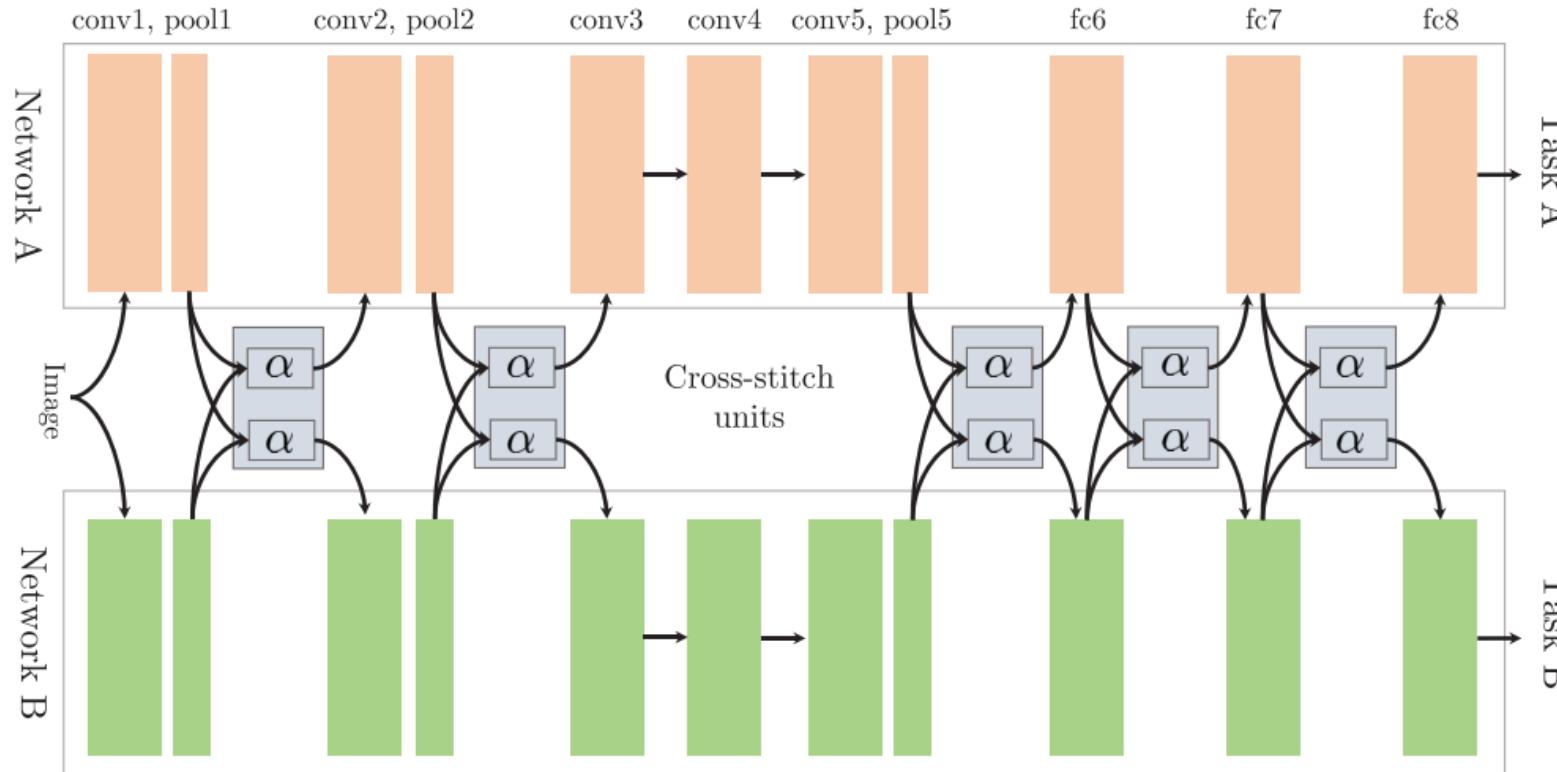
Ishan Misra*

Abhinav Shrivastava*

Abhinav Gupta

Martial Hebert

The Robotics Institute, Carnegie Mellon University



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

Latent Multi-task Architecture Learning

AAAI 2019

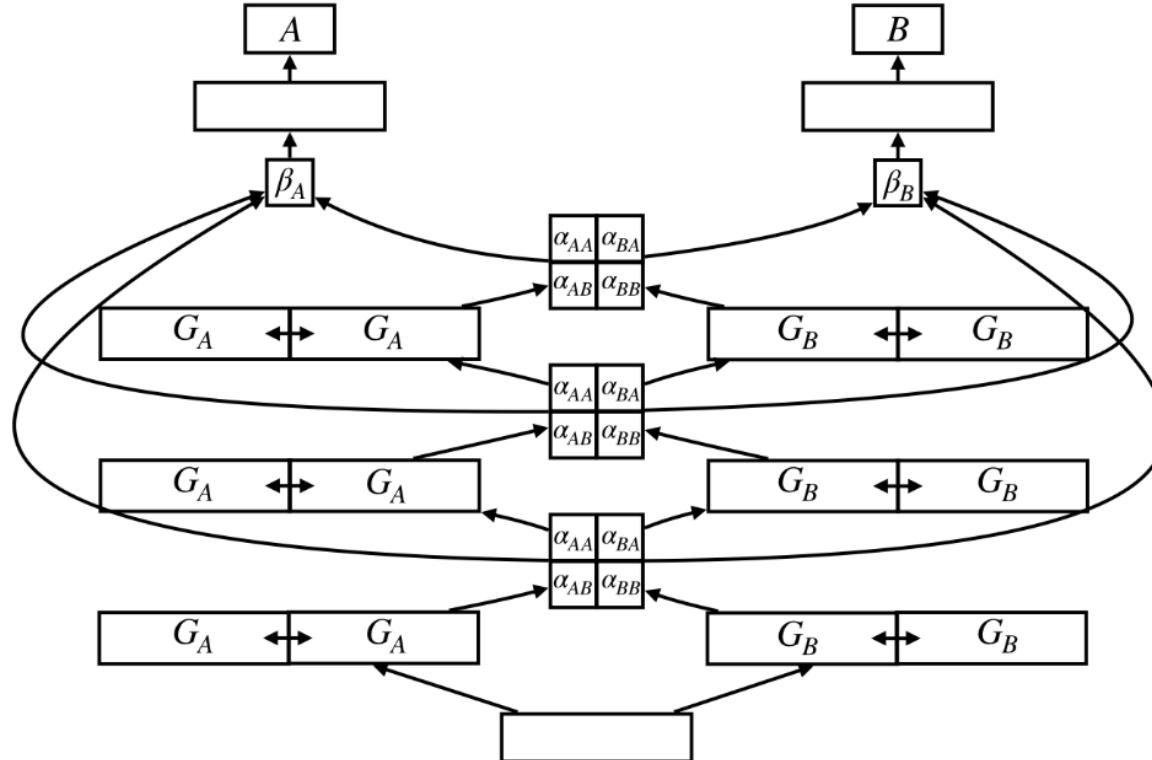
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$$\begin{bmatrix} \tilde{h}_{A_1,k} \\ \vdots \\ \tilde{h}_{B_2,k} \end{bmatrix} = \begin{bmatrix} \alpha_{A_1A_1} & \dots & \alpha_{B_2A_1} \\ \vdots & \ddots & \vdots \\ \alpha_{A_1B_2} & \dots & \alpha_{B_2B_2} \end{bmatrix} [h_{A_1,k}^\top, \dots, h_{B_2,k}^\top]$$

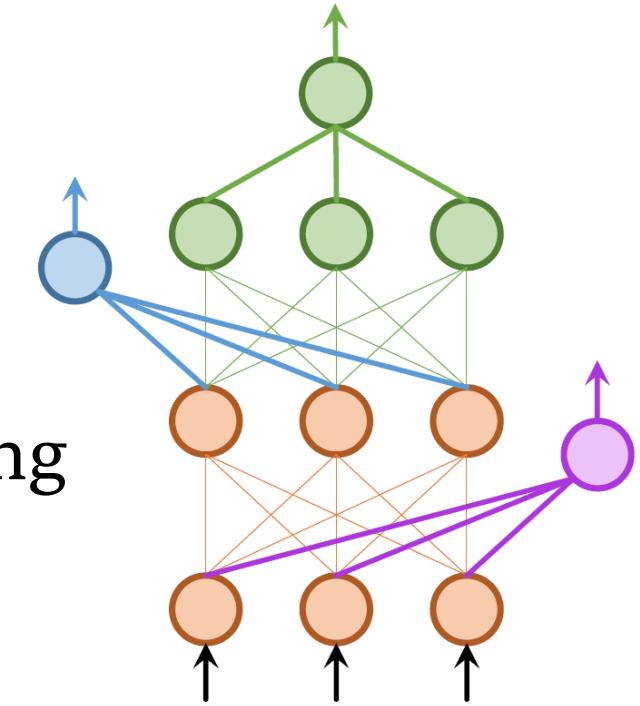
$$\tilde{h}_A^\top = \begin{bmatrix} \beta_{A,1} \\ \vdots \\ \beta_{A,k} \end{bmatrix}^\top [h_{A,1}^\top, \dots, h_{A,k}^\top]$$

Hierarchical Sharing



- Put different task supervisions at different layers
- Inference: $\hat{y}_n^t = \mathcal{F}^t(\mathcal{E}(x_n^t; \theta_{\mathcal{E}(1:l)}); \theta_{\mathcal{F}}^t)$
- Advantages:
 1. more flexible than hard sharing
 2. more parameter-efficient than soft sharing
- Disadvantages:

Hard to design an effective hierarchy



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$$\begin{aligned} pos_tag(w_{1:n}, i) &= f_{pos}(v_i^{\ell(pos)}) \\ chunk_tag(w_{1:n}, i) &= f_{chunk}(v_i^{\ell(chunk)}) \\ ccg_tag(w_{1:n}, i) &= f_{ccg}(v_i^{\ell(ccg)}) \\ v_i^\ell &= BIRNN^\ell(x_{1:n}, i) \\ x_{1:n} &= E(w_1), E(w_2), \dots, E(w_n) \end{aligned}$$

A Joint Many-Task Model: Growing a Neural Network for Multiple NLP Tasks

EMNLP 2017

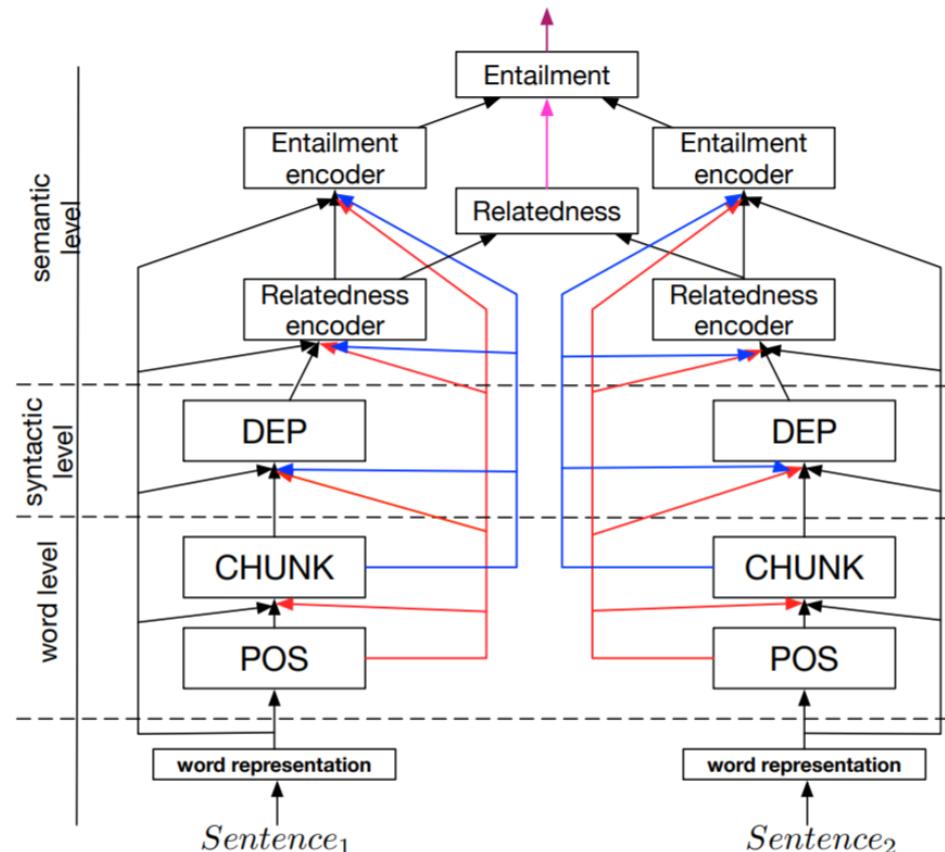
Kazuma Hashimoto*, Caiming Xiong[†], Yoshimasa Tsuruoka, and Richard Socher

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A Hierarchical Multi-task Approach for Learning Embeddings from Semantic Tasks

AAAI 2019

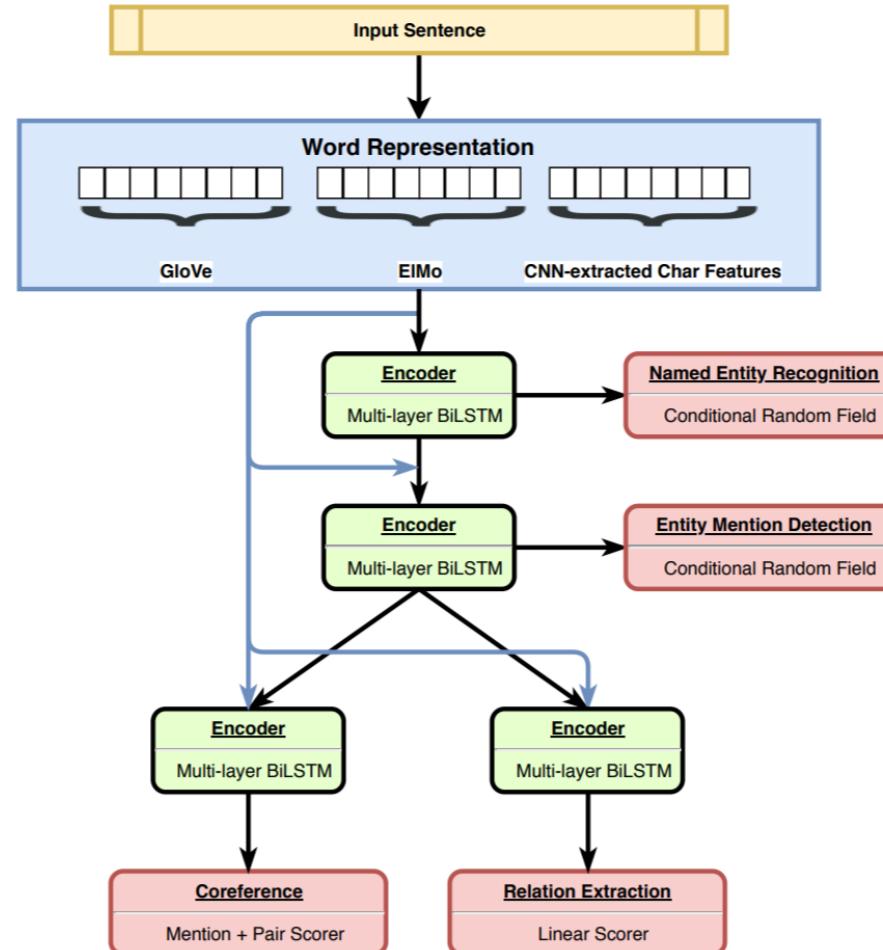
Victor Sanh¹, Thomas Wolf¹, Sebastian Ruder^{2,3}

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Limitations of Existing Sharing Mechanisms



- **Hard sharing:** Struggle with loosely related tasks
- **Hierarchical sharing:** Dependent on manually design
- **Soft sharing:** Parameter-inefficient



Does there exist a multi-task sharing mechanism:

1. It is compatible with a wide range of tasks, regardless of whether the tasks are related or not.
2. It does not depend on manually designing the sharing structure based on characteristic of tasks.
3. It is parameter efficient.

Outline



Multi-Task Learning: Sharing Mechanisms

Sparse Sharing Mechanism

Approach: Learning Sparse Sharing Architectures

Experiments

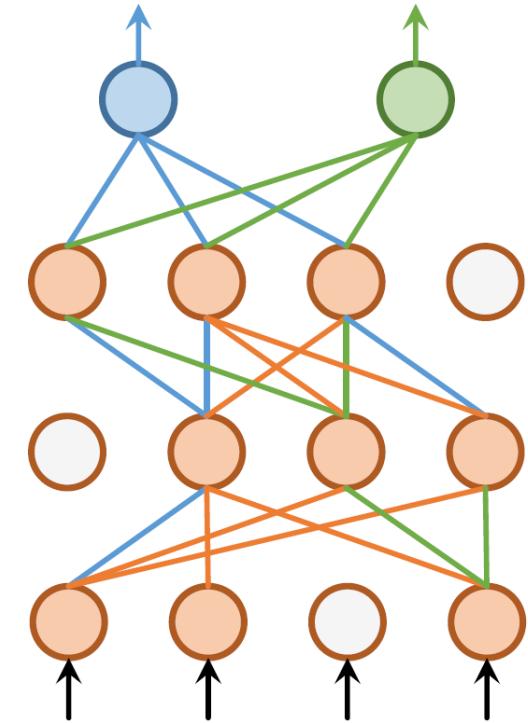
Analysis and Discussions

Conclusion

Sparse Sharing Mechanism



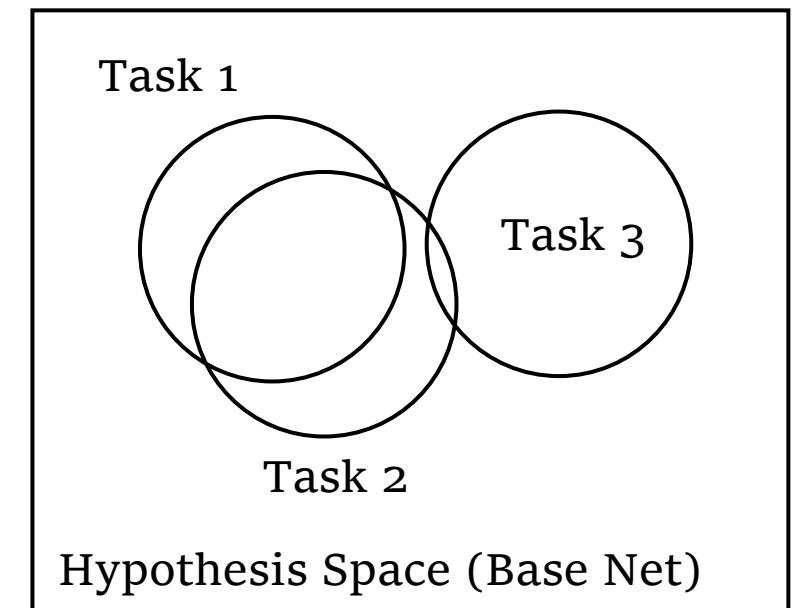
- Assign each task a subnet
- Base Network: \mathcal{E}
- Subnet: $\mathcal{E}^t(x) = \mathcal{E}(x; M_t \odot \theta_{\mathcal{E}})$
- Hard sharing $\rightarrow M_t = \mathbf{1}$
- Hierarchical sharing \rightarrow
 $\theta_{\mathcal{E}} = \{\theta_{\mathcal{E},1}, \theta_{\mathcal{E},2}\}$ $M_1 = \{1, 0\}$ $M_2 = \{1, 1\}$



Views of Sparse Sharing



- Over-parameterized base net → Large hypothesis space
- Subnet → Hypothesis subspace
- Inductive bias → Subnet structure
- Parameter overlap → Task relatedness
- Biologically intuitive:
 1. Sparse topology ([Pessoa 2014](#))
 2. Different subnets for different tasks ([MacLeod 1991](#))



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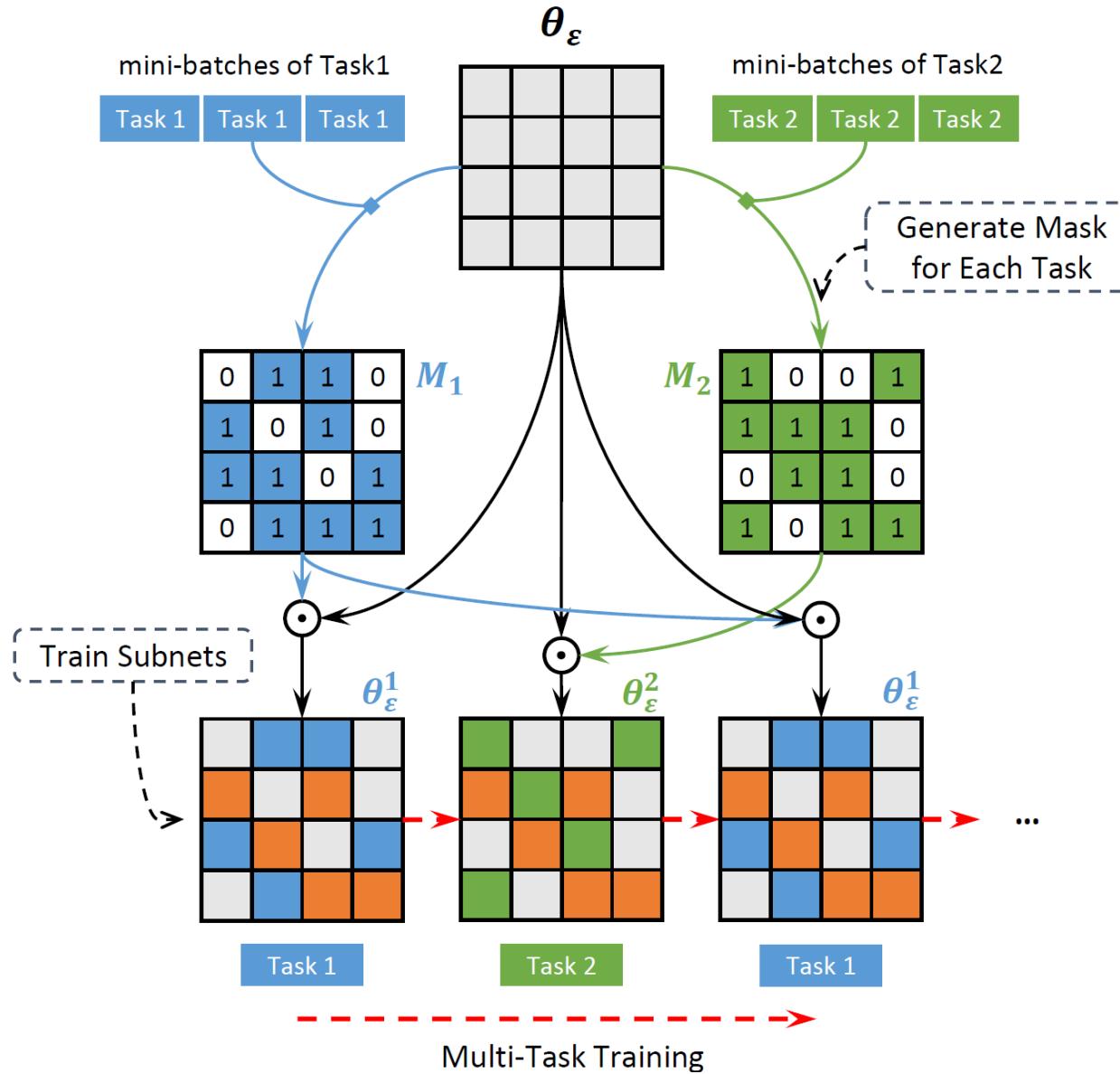
Approach: Learning Sparse Sharing Architectures

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Overview of Our Approach





Generating Subnets for Each Task

➤ Iterative Magnitude Pruning (IMP)

proposed in ([Frankle and Carbin 2019](#)) (ICLR'2019 best paper)

1. Randomly initialize a neural network $f(x; \theta_0)$ (where $\theta_0 \sim \mathcal{D}_\theta$).
2. Train the network for j iterations, arriving at parameters θ_j .
3. Prune $p\%$ of the parameters in θ_j , creating a mask m .
4. Reset the remaining parameters to their values in θ_0 , creating the winning ticket $f(x; m \odot \theta_0)$.

Generating Subnets for Each Task

➤ Iterative Magnitude Pruning (IMP)

Algorithm 1 Sparse Sharing Architecture Learning

Require: Base Network \mathcal{E} ; Pruning rate α ; Minimal sparsity S ; Datasets for T tasks $\mathcal{D}_1, \dots, \mathcal{D}_T$, where $\mathcal{D}_t = \{x_n^t, y_n^t\}_{n=1}^{N_t}$.

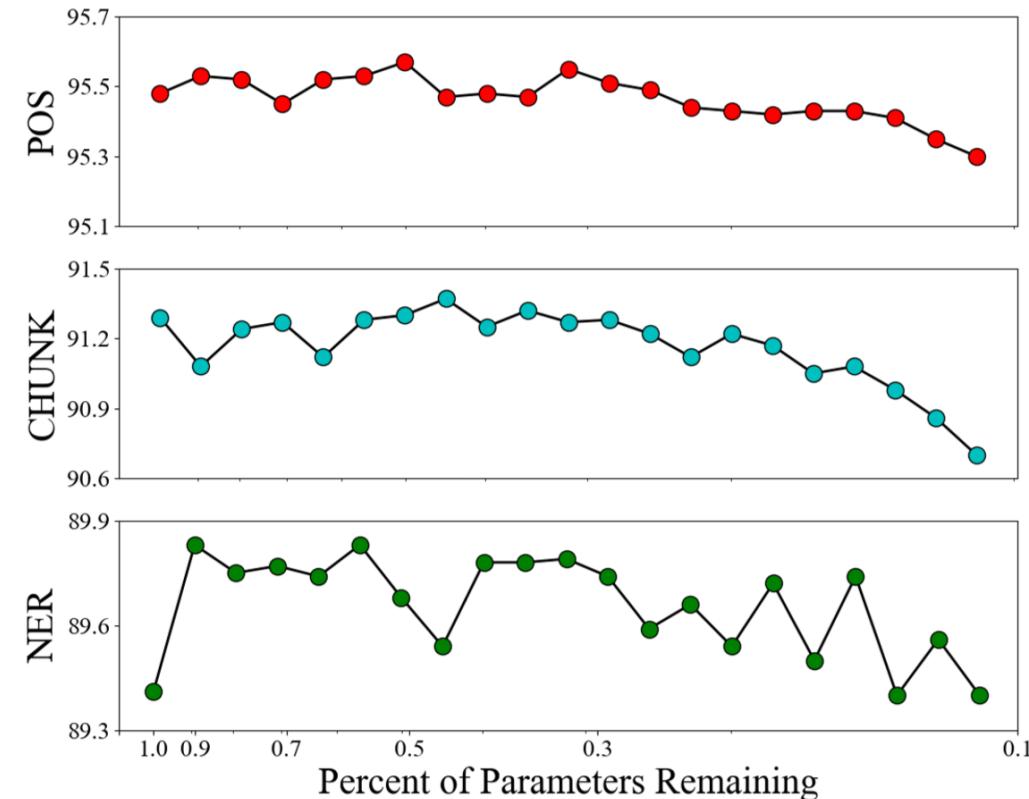
- 1: Randomly initialize $\theta_{\mathcal{E}}$ to $\theta_{\mathcal{E}}^{(0)}$.
 - 2: **for** $t = 1 \dots T$ **do**
 - 3: Initialize mask $M_t^z = \mathbf{1}^{|\theta_{\mathcal{E}}|}$, where $z = 1$.
 - 4: Train $\mathcal{E}(x; M_t^z \odot \theta_{\mathcal{E}})$ for k steps with data sampled from \mathcal{D}_t , producing network $\mathcal{E}(x; M_t^z \odot \theta_{\mathcal{E}}^{(k)})$. Let $z \leftarrow z + 1$.
 - 5: Prune α percent of the remaining parameters with the lowest magnitudes from $\theta_{\mathcal{E}}^{(k)}$. That is, let $M_t^z[j] = 0$ if $\theta_{\mathcal{E}}^{(k)}[j]$ is pruned.
 - 6: If $\frac{\|M_t^z\|_0}{|\theta_{\mathcal{E}}|} \leq S$, the masks for task t are $\{M_t^i\}_{i=1}^z$.
 - 7: Otherwise, reset $\theta_{\mathcal{E}}$ to $\theta_{\mathcal{E}}^{(0)}$ and repeat steps 4-6 iteratively to learn more sparse subnetwork.
 - 8: **end for**
 - 9: **return** $\{M_1^i\}_{i=1}^z, \{M_2^i\}_{i=1}^z, \dots, \{M_T^i\}_{i=1}^z$.
-

Select Subnets



- Pick the subnet that performs best on the dev set.
- If there are multiple best-performing subnets, take the subnet with the lowest sparsity.

| POS | CHUNK | NER |
|--------|--------|--------|
| 50.12% | 44.67% | 56.23% |



Training Subnets in Parallel

1. Select the next task t .
 - Proportional sampling ([Sanh, Wolf, and Ruder 2019](#))
2. Select a random mini-batch for task t .
3. Feed this batch of data into the subnetwork corresponding to task t , i.e. $\mathcal{E}(x; M_t \odot \theta_{\mathcal{E}})$.
4. Update the subnetwork parameters for this task by taking a gradient step with respect to this mini-batch.
5. Go to 1.

$$\mathcal{L}(\theta) = \sum_{t=1}^T \lambda_t \sum_{n=1}^{N_t} \mathcal{L}_t(\hat{y}_n^t, y_n^t)$$

Multi-Task Warmup (MTW)



Algorithm 1 Sparse Sharing Architecture Learning

Require: Base Network \mathcal{E} ; Pruning rate α ; Minimal sparsity S ; Datasets for T tasks $\mathcal{D}_1, \dots, \mathcal{D}_T$, where $\mathcal{D}_t = \{x_n^t, y_n^t\}_{n=1}^{N_t}$.

- 1: Randomly initialize $\theta_{\mathcal{E}}$ to $\theta_{\mathcal{E}}^{(0)}$. MTW: $\theta_{\mathcal{E}}^{(0)} \rightarrow \theta_{\mathcal{E}}^{(w)}$
 - 2: **for** $t = 1 \dots T$ **do**
 - 3: Initialize mask $M_t^z = \mathbf{1}^{|\theta_{\mathcal{E}}|}$, where $z = 1$.
 - 4: Train $\mathcal{E}(x; M_t^z \odot \theta_{\mathcal{E}})$ for k steps with data sampled from \mathcal{D}_t , producing network $\mathcal{E}(x; M_t^z \odot \theta_{\mathcal{E}}^{(k)})$. Let $z \leftarrow z + 1$.
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-

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➤ Tasks: Part-of-Speech, NER, Chunking

➤ Datasets

Exp1: CoNLL-2003

Exp2: OntoNotes 5.0

Exp3: PTB + CoNLL-2003 + CoNLL-2000

➤ Model Settings

Base model: CNN-BiLSTM ([Ma and Hovy 2016](#))

Multi-Task baselines: hard/soft/hierarchical sharing

Exp1 & Exp2



| Systems | POS | | NER | | Chunking | | # Params |
|------------------------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|
| | Test Acc. | Δ | Test F1 | Δ | Test F1 | Δ | |
| Exp1: CoNLL-2003 | | | | | | | |
| Single task | 95.09 | - | 89.36 | - | 89.92 | - | 1602k |
| Single task (subnet) | 95.11 | +0.02 | 89.39 | +0.03 | 89.96 | +0.04 | 811k |
| Hard sharing | 95.34 | +0.25 | 88.68 | -0.68 | 90.92 | +1.00 | 534k |
| Soft sharing | 95.16 | +0.07 | 89.35 | -0.01 | 90.71 | +0.79 | 1596k |
| Hierarchical sharing | 95.09 | +0.00 | 89.30 | -0.06 | 90.89 | +0.97 | 1497k |
| Sparse sharing (ours) | 95.56 | +0.47 | 90.35 | +0.99 | 91.55 | +1.63 | 396k |
| Exp2: OntoNotes 5.0 | | | | | | | |
| Single task | 97.40 | - | 82.72 | - | 95.21 | - | 4491k |
| Single task (subnet) | 97.42 | +0.02 | 82.94 | +0.22 | 95.28 | +0.07 | 1459k |
| Hard sharing | 97.46 | +0.06 | 82.95 | +0.23 | 95.52 | +0.31 | 1497k |
| Soft sharing | 97.34 | -0.06 | 81.93 | -0.79 | 95.29 | +0.08 | 4485k |
| Hierarchical sharing | 97.22 | -0.18 | 82.81 | +0.09 | 95.53 | +0.32 | 1497k |
| Sparse sharing (ours) | 97.54 | +0.14 | 83.42 | +0.70 | 95.56 | +0.35 | 662k |

Exp1 & Exp2



| Systems | POS | | NER | | Chunking | | # Params |
|------------------------------|--------------|-------|--------------|-------|--------------|-------|-------------|
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| Hierarchical sharing | 97.22 | -0.18 | 82.81 | +0.09 | 95.53 | +0.32 | 1497k |
| Sparse sharing (ours) | 97.54 | +0.14 | 83.42 | +0.70 | 95.56 | +0.35 | 662k |

- Compared with results reported in previous work
- Equipped with CRF

| Systems | POS | NER | Chunk. |
|------------------------------|--------------|--------------|--------------|
| <i>Single Task Models:</i> | | | |
| (Collobert et al. 2011) | 97.29 | 89.59 | 94.32 |
| (Huang, Xu, and Yu 2015) | 97.25 | 89.91 | 93.67 |
| (Chen et al. 2018) | 97.30 | 90.08 | 93.71 |
| <i>Multi-Task Models:</i> | | | |
| Hard sharing† | 97.23 | 90.38 | 94.32 |
| Meta-MTL-LSTM† | 97.45 | 90.72 | 95.11 |
| Sparse sharing (ours) | 97.57 | 90.87 | 95.26 |

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About Negative Transfer



In the future studies, there are several issues to be addressed. Firstly, outlier tasks, which are unrelated to other tasks, are well known to hamper the performance of all the tasks when learning them jointly. There are some methods to alleviate negative effects outlier tasks bring. However, there lacks principled ways and theoretical analyses to study the resulting negative effects. In order to make MTL safe to be used by human, this is an important issue and needs more studies.

About Negative Transfer



- Construct a loosely related multi-task setting
 - Real: Named Entity Recognition (NER)
 - Synthetic: Position Prediction (PP)

| | NER | Δ | PP | Δ |
|----------------|-------|----------|-------|----------|
| Single task | 71.05 | - | 99.21 | - |
| Hard sharing | 61.62 | -9.43 | 99.50 | +0.29 |
| Sparse sharing | 71.46 | +0.41 | 99.45 | +0.24 |

About Task Relatedness



- Define mask overlap ratio (OR) as:

$$\text{OR}(M_1, M_2, \dots, M_T) = \frac{\|\cap_{t=1}^T M_t\|_0}{\|\cup_{t=1}^T M_t\|_0}$$

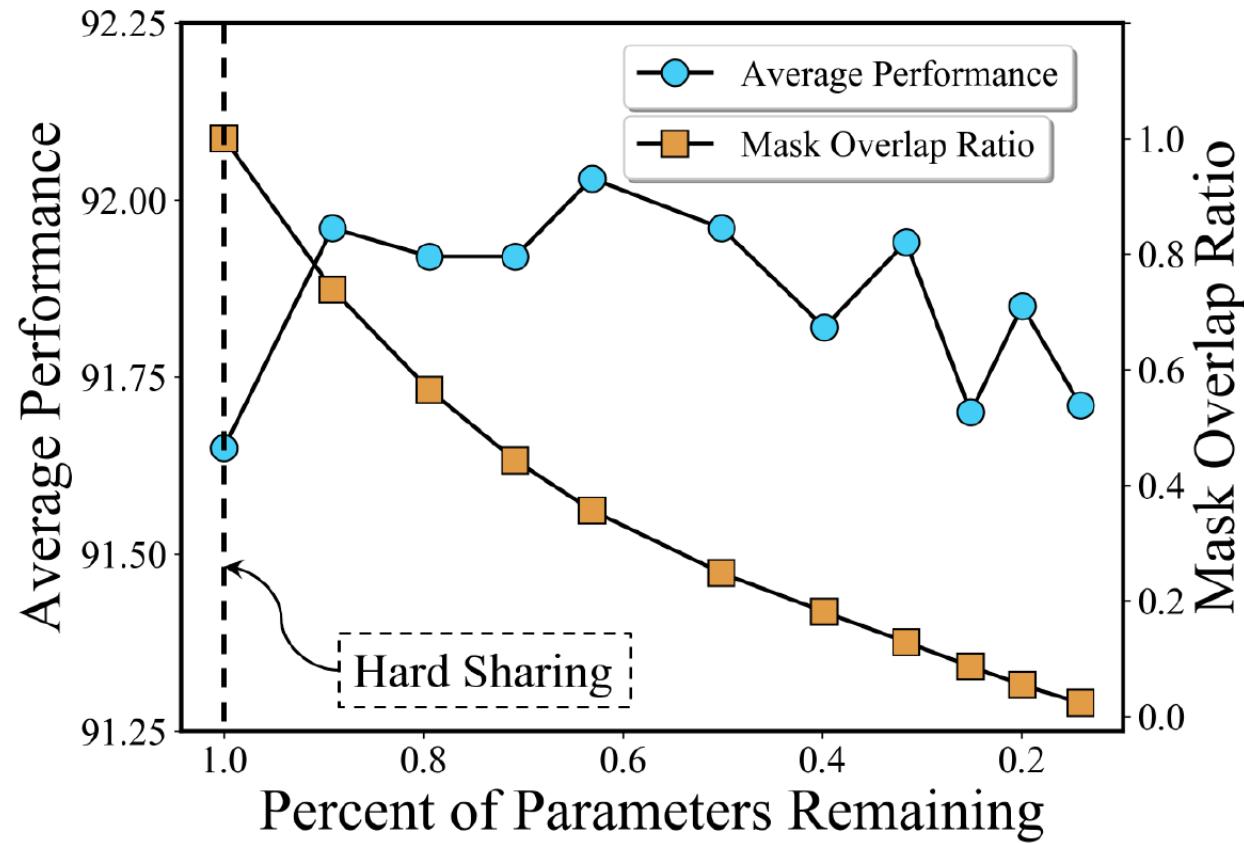
| Task Pairs | Mask OR | $\Delta(S^2 - HS)$ |
|----------------|---------|--------------------|
| POS & NER | 0.18 | 0.4 |
| NER & Chunking | 0.20 | 0.34 |
| POS & Chunking | 0.50 | 0.05 |

Table 7: Mask Overlap Ratio (OR) and the improvement for sparse sharing (S^2) compared to hard sharing (HS) of tasks on CoNLL-2003. The improvement is calculated using the average performance on the test set.

About Sparsity



- Combinations of subnets with different sparsity



About Multi-Task Warmup: An ablation study



- Stabilize subnets ([Frankle et al. 2019](#))

| | POS | NER | Chunking |
|----------------|-------|-------|----------|
| CoNLL-2003 | | | |
| Sparse sharing | 95.56 | 90.35 | 91.55 |
| – MTW | 95.36 | 89.62 | 91.04 |
| OntoNotes 5.0 | | | |
| Sparse sharing | 97.54 | 83.42 | 95.56 |
| – MTW | 97.53 | 81.15 | 95.48 |

Outline



Multi-Task Learning: Sharing Mechanisms

Sparse Sharing Mechanism

Approach: Learning Sparse Sharing Architectures

Experiments

Analysis and Discussions

Conclusion

Conclusion



- Does sparse sharing architecture meets the requirements?
 1. It is compatible with a wide range of tasks, regardless of whether the tasks are related or not.
 2. It does not depend on manually designing the sharing structure based on characteristic of tasks.
 3. It is parameter efficient.
- It seems **YES!**



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Thanks !

Q & A

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Sequence Labeling Tasks



➤ POS, NER and Chunking

| Words | Results | of | South | Korean |
|--------|---------|------|--------|--------|
| POS | NNS | IN | JJ | JJ |
| NER | O | O | B-MISC | I-MISC |
| Chunk. | B-NP | B-PP | B-NP | I-NP |



CNN-BiLSTM: A popular architecture in sequence labeling tasks

