



# Multi-Task Recurrent Modular Networks

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# Agenda

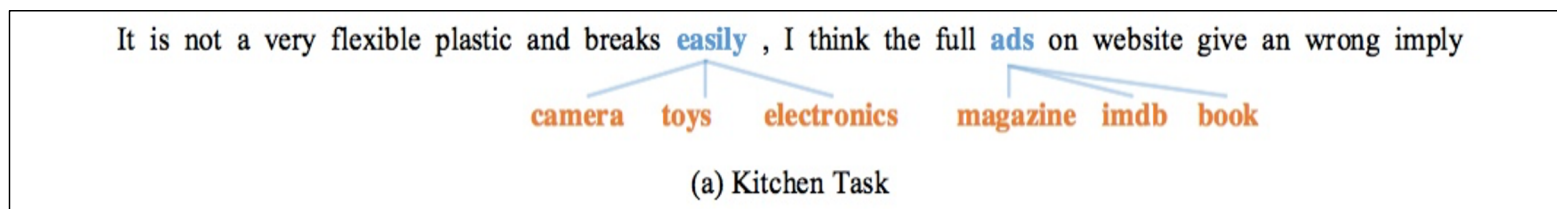
- Motivations
- Challenges
- Proposed Model: MT-RMN
- Experiments

# Motivations

- Sequence Learning
  - E.g., Sentiment classification, sequence labelling
- Multi-Task Learning
  - Advantages: Computational advantage
- However, multi-task architectures applicable to recurrent models are underexplored
- Goal: A Recurrent Module
  - Can be integrated into any multi-task learning approach for sequential data
  - To improve model capacity, flexibility, generalization

# Challenges

- Dynamics of task relationships
- Limited knowledge of the task relatedness
- Generalization ability [2]
- Example: Dynamic task relatedness in NLP [1]
  - Sentiment prediction of 16 datasets (multi-task learning)



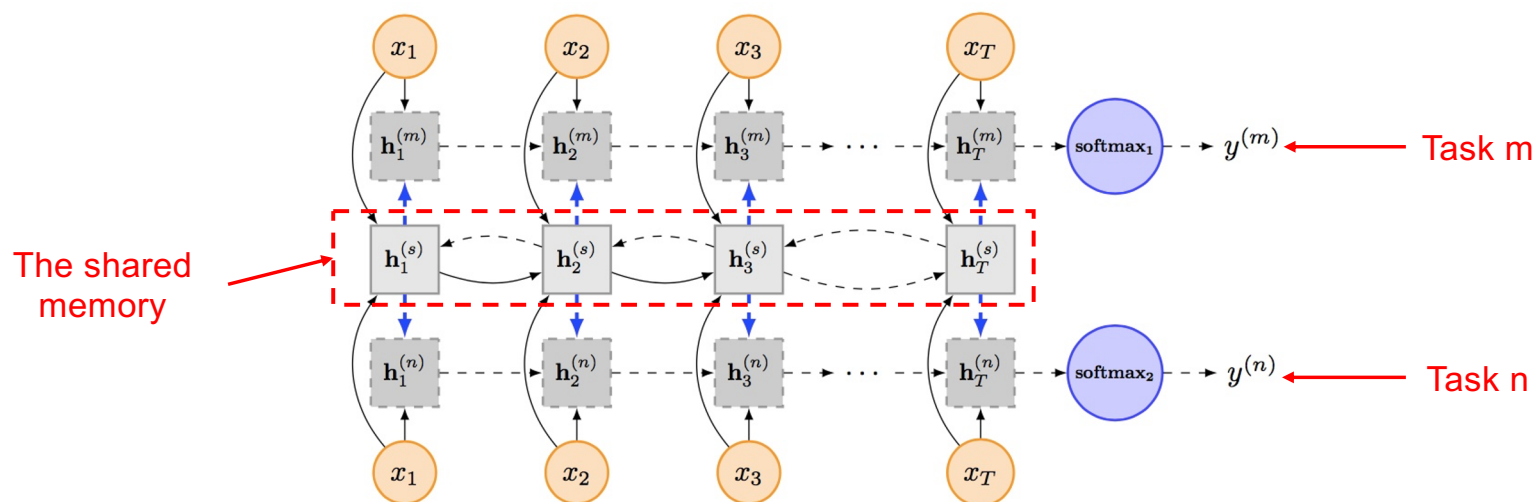
Illustrations of the three most relevant tasks for each word in the “Kitchen” task.

[1] Learning Multi-Task Communication with Message Passing for Sequence Learning, AAAI 2019.

[2] Lake, Brenden M. "Compositional generalization through meta sequence-to-sequence learning." NeurIPS 2019.

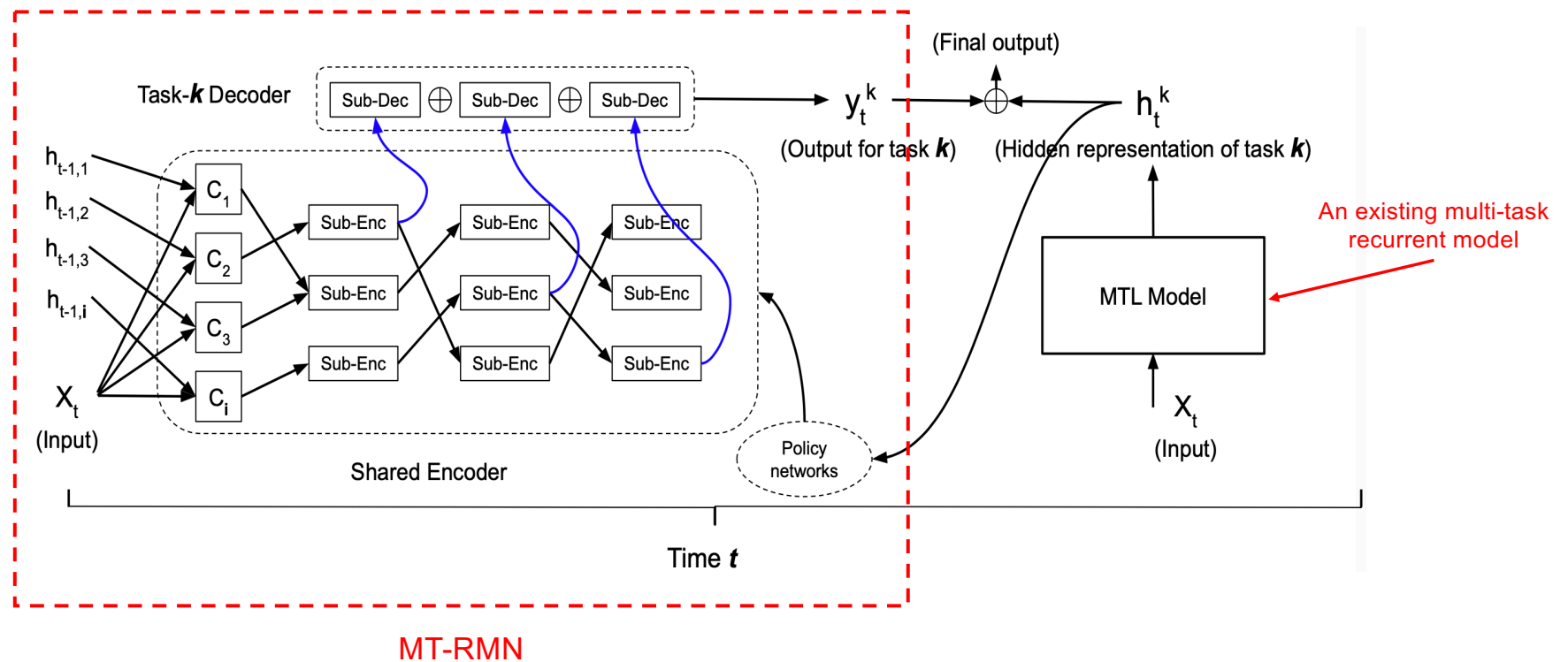
# Typical Architecture

- Existing approaches are not flexible enough to learn the dynamic relationship



PSP-MTL (IJCAI'16)

# Proposed Model: MT-RMN



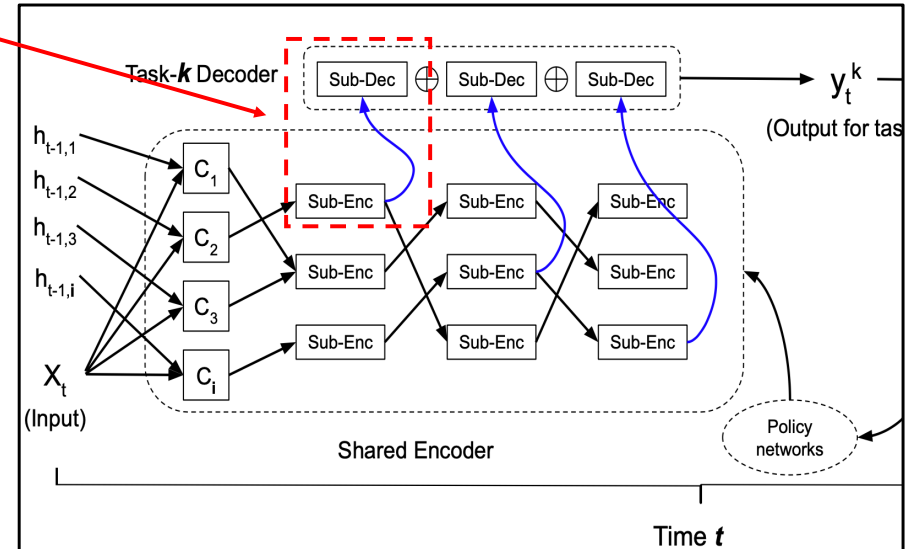
# How to Make Connection Decision

- 1) Generate decision vector
  - Using Policy Network

$$\beta_{t,j}^k = \hat{\mathcal{N}}^k(\mathbf{u}_{t,j}) = MLP(\mathbf{u}_{t,j} \oplus \mathbf{W}_k \mathbf{h}_t^k)$$

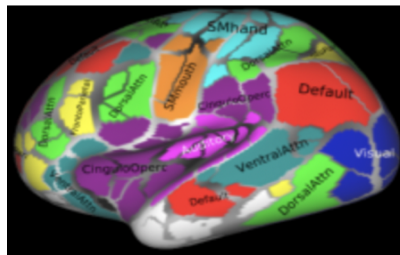
- 2) Estimate the binary decision value
  - Using Straight-Through Router

$$\zeta = \arg \max_i [\alpha_i + g_i], i \in \{0, 1\}$$

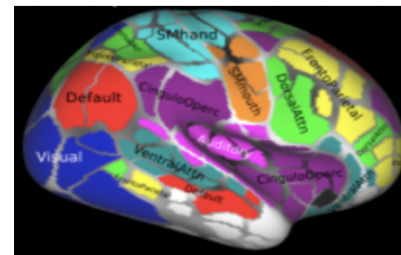


# Experiments on Task-fMRI

- Task-Evoked Functional MRI Data[1]
  - To analyze the relationship between brain connectivity and human behavior



The left side of brain



The right side of brain

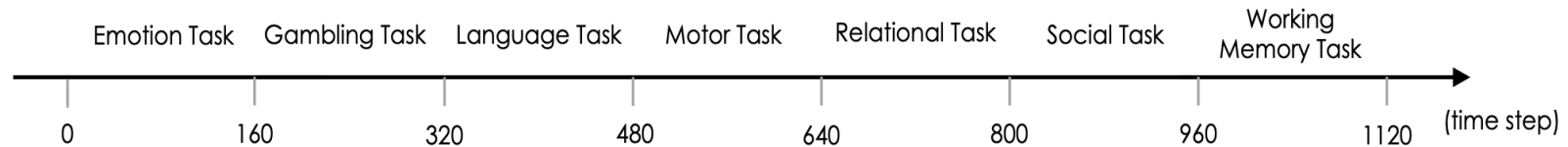


Figure 5: Seven tasks and each task lasts 160 time steps.

[1] Barch, Deanna M., et al. "Function in the human connectome: task-fMRI and individual differences in behavior." *Neuroimage* 80 (2013): 169-189.



# Experiments on Task-fMRI

- Construct four tasks

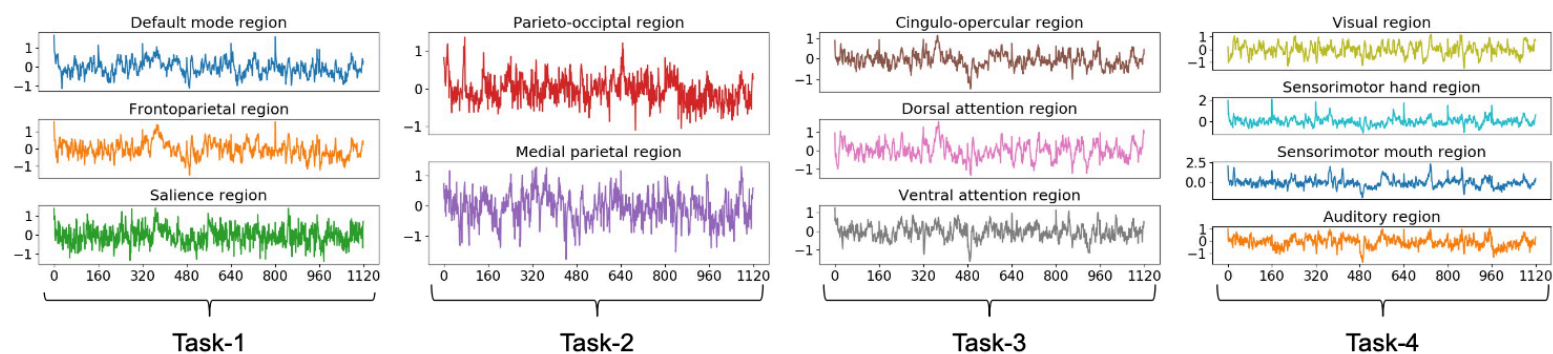


Figure 2: The task-fMRI data of twelve high-order brain regions of a participant. The regions are grouped into four groups based on their functionalities. Each group is used to construct a multi-class classification task of time series. The participant was asked to perform seven tasks successively (Barch, Burgess et al. 2013).

# Experiments on Task-fMRI

- Results on the Task-fMRI data

Table 1: Results (accuracy %) on two groups of *tfMRI* tasks.

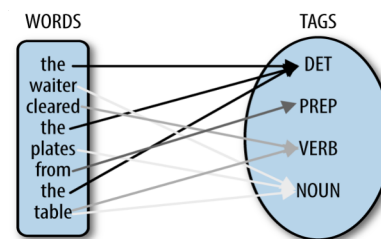
Groups	Group-1			Group-2		
	Task-1	Task-2	Task-3	Task-1	Task-3	Task-4
FS-MTL	89.7±0.6	93.5±1.1	89.1±0.3	73.2±0.5	81.2±0.6	81.3±1.4
SP-MTL	88.7±1.4	94.0±1.9	90.7±2.3	73.7±1.5	78.0±1.5	81.2±2.1
DC-MTL	89.2±0.6	95.6±1.2	90.8±1.0	74.5±0.6	80.0±0.7	80.8±1.3
IC-MTL	89.6±0.4	95.7±1.1	91.3±1.7	74.5±0.4	81.4±1.1	81.8±2.6
RRNs	88.9±3.4	95.4±2.2	90.5±2.8	75.4±2.2	83.2±3.0	82.6±3.8
<i>mtl</i> -RMN	<b>90.8±2.1</b>	<b>96.7±1.6</b>	<b>92.9±2.4</b>	<b>76.1±1.8</b>	<b>84.4±2.4</b>	<b>83.5±2.2</b>

Table 2: Four test-time scenarios to evaluate generalization ability and the results (accuracy%).

Scenario settings					Results of different methods				
Scenarios	Training tasks			Test task	LSTM	RMN <sub>un</sub>	RRNs	IC-MTL	RMN <sub>tr</sub>
A	Task-1	Task-2	Task-3	Task-4	82.6±1.0	82.9±1.2	83.0±2.7	81.2±1.7	<b>83.3±2.3</b>
B	Task-1	Task-2	Task-4	Task-3	82.3±0.6	84.5±1.5	84.8±2.5	82.7±1.3	<b>85.6±1.7</b>
C	Task-1	Task-3	Task-4	Task-2	93.7±0.6	95.3±0.8	95.6±1.7	95.5±0.7	<b>97.0±1.8</b>
D	Task-2	Task-3	Task-4	Task-1	71.7±1.4	73.1±1.7	78.4±4.0	77.3±2.1	<b>79.3±2.6</b>

# Experiments on POS Tagging

- POS (Part-of-Speech) Tagging of Code-Switched Sentences
  - POS Tagging: To mark up a word in a corpus to a corresponding speech tag
  - Code-Switched Text: Words from multiple languages



POS Tagging

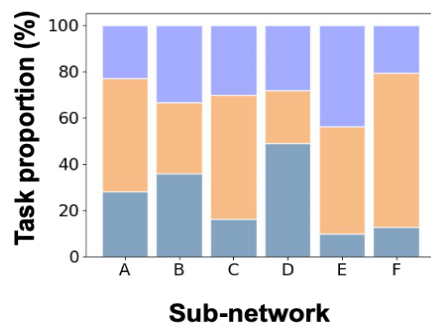
- Data sets [1]
  - Task 1: A Hindi-English code-switch data POS tagging
  - Task 2: Hindi POS tagging
  - Task 3: English POS tagging

[1] "Girnet: Interleaved multi-task recurrent state sequence models." Proceedings of AAAI. Vol. 33. 2019.

# Experiments on POS Tagging

- Results on the POS Tagging of Code-Switched Sentences

Methods	Original		DC-MTL		IC-MTL		<i>rrn</i> -RMN		MT-RMN	
	Accuracy	F <sub>1</sub>	Accuracy	F <sub>1</sub>	Accuracy	F <sub>1</sub>	Accuracy	F <sub>1</sub>	Accuracy	F <sub>1</sub>
NS-MTL	44.3±0.7	38.9±1.6	51.5±0.5	49.4±0.9	51.4±1.4	49.7±0.8	53.5±1.9	52.7±0.8	<b>55.2±1.2</b>	<b>53.4±2.4</b>
Cross-stitch.	46.0±1.9	12.7±0.8	48.5±0.9	16.1±1.3	47.7±1.7	14.3±0.7	<b>52.1±1.0</b>	19.5±0.6	51.7±1.9	<b>21.4±3.2</b>
Sluice	58.7±0.7	55.4±2.1	59.2±1.7	56.0±2.3	59.5±1.9	56.2±0.7	60.4±1.2	56.6±0.7	<b>61.5±1.7</b>	<b>57.2±1.8</b>
GIRNet	62.8±0.6	46.6±0.4	62.5±1.1	57.4±0.5	63.1±1.5	58.6±1.3	63.6±1.7	61.3±1.5	<b>64.5±2.1</b>	<b>62.6±2.4</b>



- 1) The proportion of tasks assigned to each sub-network
- 2) Different colors distinguish different tasks
- 3) A-F represent the six sub-networks

Thanks!

Q & A