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MeLL: Large-scale Extensible User Intent Classification for Dialogue Systems with Meta Lifelong Learning

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Introduction (1)

✓User Intent Classification: **Text-to-label Classifiers**

- Understanding users’ intents based on the input queries issued by users
- Understanding users’ responses to actions previously taken by the systems

✓Extensible User Intent Classification

- The task number is continuously growing through time

✓Challenges

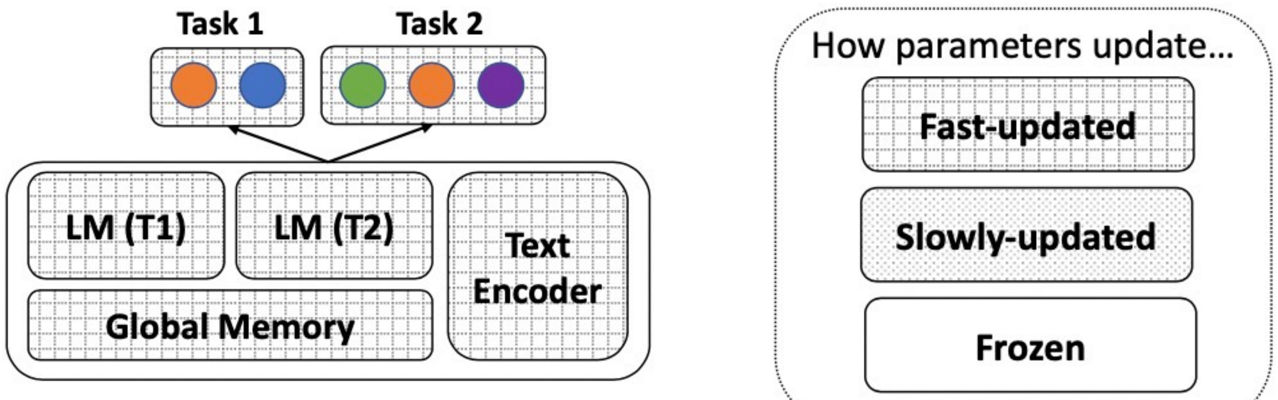
- **Parameter explosion**
- **Catastrophic forgetting**

Introduction (2)

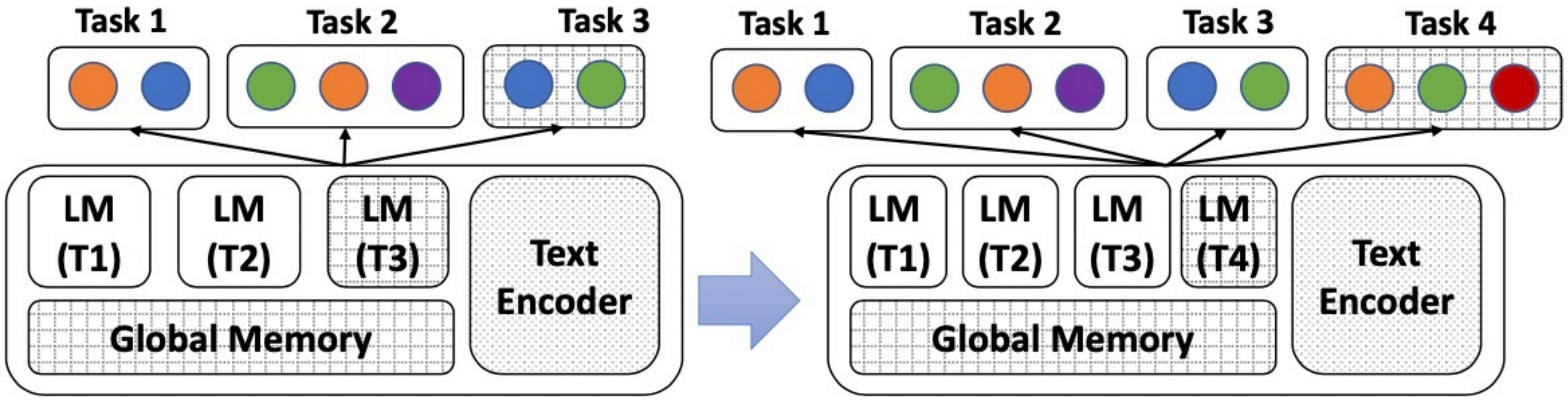
✓Solution: the **Meta Lifelong Learning** (**MeLL**) framework

✓Components

- Text Encoder
- Global Memory
- Local Memories
- Task-specific Layers



a) Initial Learning Stage

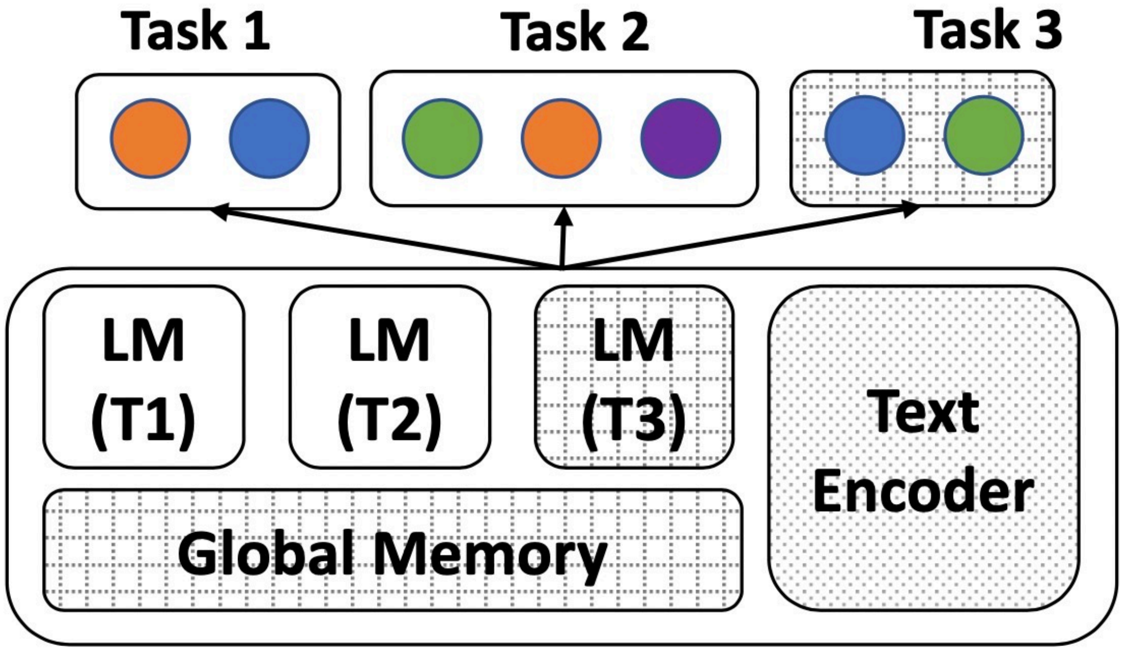


b) Lifelong Learning Stage

Introduction (3)

✓Functionalities of Different Components

- Text Encoder: learning the semantics of input texts (slowly updated)
- Global Memory: storing the class semantics across tasks (fast updated)
- Local Memories: storing the task-specific class semantics (frozen once assigned)
- Task-specific Layers: generating task-specific outputs



Related Work

MeLL: leveraging ideas of both lifelong learning and meta-learning for user intent classification based on pre-trained language models

✓User Intent Classification

✓Lifelong Learning

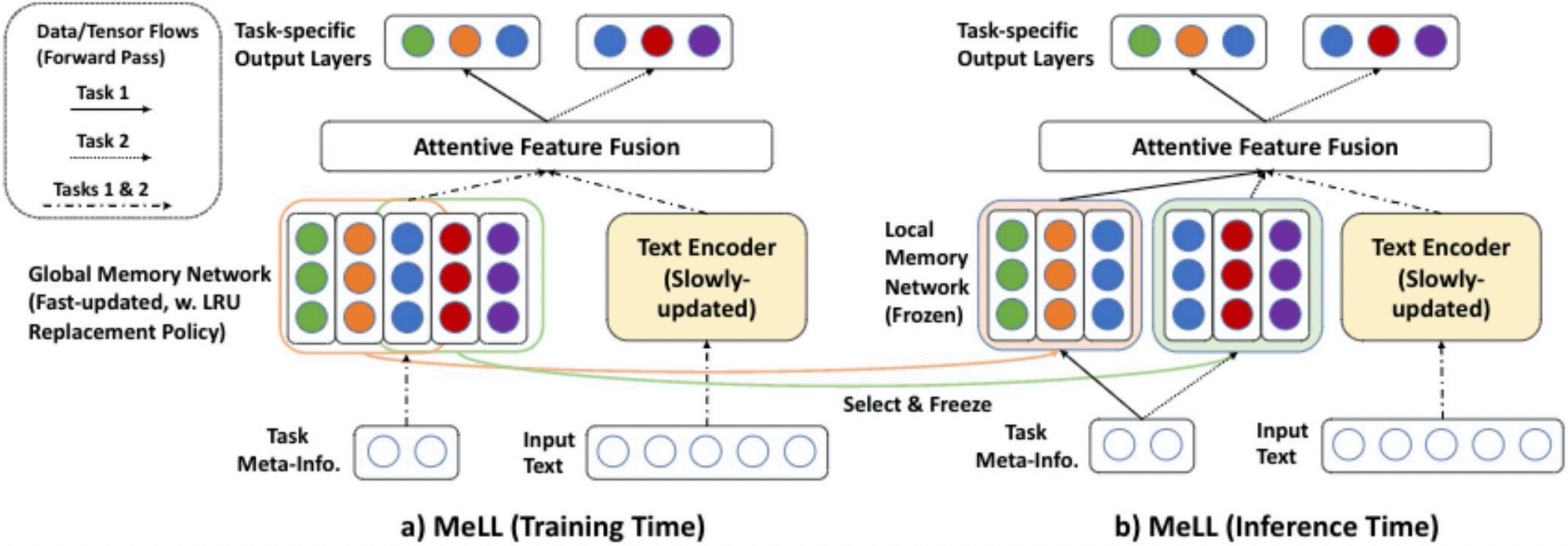
- Solving an unlimited sequence of tasks with the help of previously learned tasks

✓Meta-learning

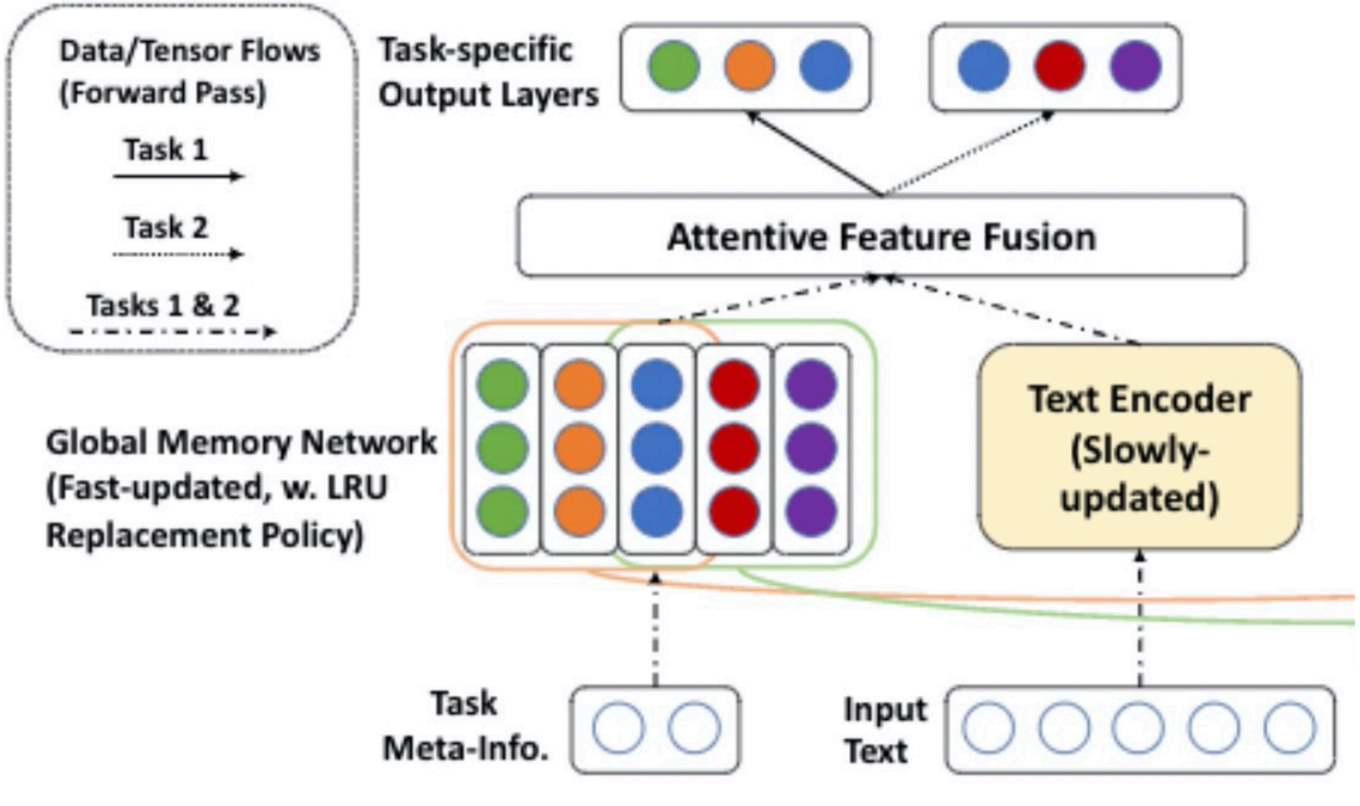
- Training meta-learners that can adapt to a variety of tasks with little training data available

✓Pre-trained Language Models

MeLL: Basic Model Structure



MeLL (Training Time)



a) MeLL (Training Time)

Algorithm 1 MeLL Training Procedure

// Initial Learning Stage

Initialize global memory G based on $\mathcal{D}_1, \mathcal{D}_2, \cdots \mathcal{D}_N$.

while not converge **do**

  Sample a task $\mathcal{T}_n$ from $\mathcal{T}_1, \mathcal{T}_2, \cdots \mathcal{T}_N$.

  Read a batch $\{(x_{n,i}, y_{n_i})\}$ from $\mathcal{D}_n$.

  Run through BERT to obtain representations $\{Q(x_{n,i})\}$.

  Read global memory G with the task meta-info. $\mathcal{Y}_n$ and text representations $\{Q(x_{n,i})\}$ to generate features $\{Att(x_{n,i})\}$ and pass them to the output layer f_n.

  Update parameters of f_n, G and the text encoder by back propagation.

end while

Create local memories $L_1, L_2, \cdots, L_N$ for $\mathcal{T}_1, \mathcal{T}_2, \cdots \mathcal{T}_N$, with all parameters frozen.

// Lifelong Learning Stage (Assume task $\mathcal{T}_j$ arrives, $j > N$.)

Update global memory G based on $\mathcal{D}_j$ w. LRU replacement.

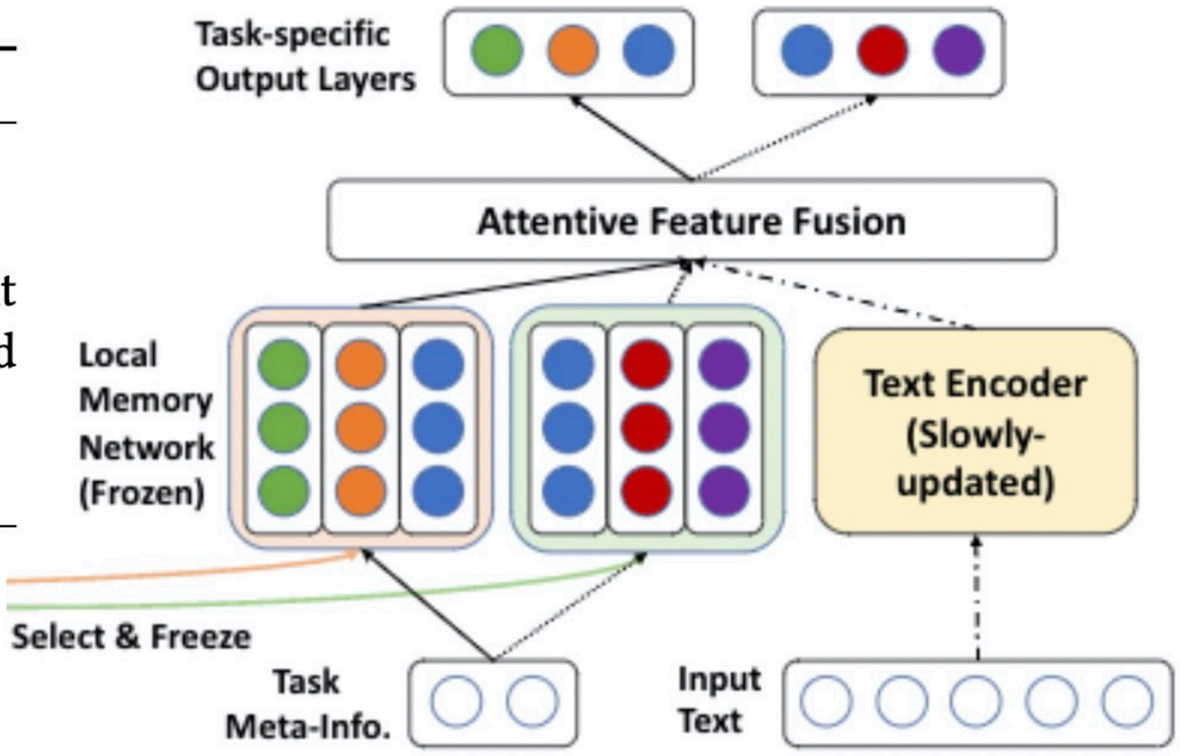
Train the model with a new task-specific output layer f_j and a smaller learning rate on BERT. Parameters of f_n, G and BERT are updated.

Create local memory L_j for $\mathcal{T}_j$ with all parameters frozen.

MeLL (Inference Time)

Algorithm 2 MeLL Inference Procedure

1: Read a batch $\{(x_{n,i})\}$ from an unlabeled dataset of task $\mathcal{T}_n$.
2: Run through BERT to obtain representations $\{Q(x_{n,i})\}$.
3: Read local memory L_n with the task meta-info. $\mathcal{Y}_n$ and text representations $\{Q(x_{n,i})\}$ to generate features $\{Att(x_{n,i})\}$ and pass them to the task-specific output layer f_n.
4: Make predictions $\{\hat{y}_{n,i}\}$ based on $f_n(Att(x_{n,i}))$.



b) MeLL (Inference Time)

Global and Local Memory Networks

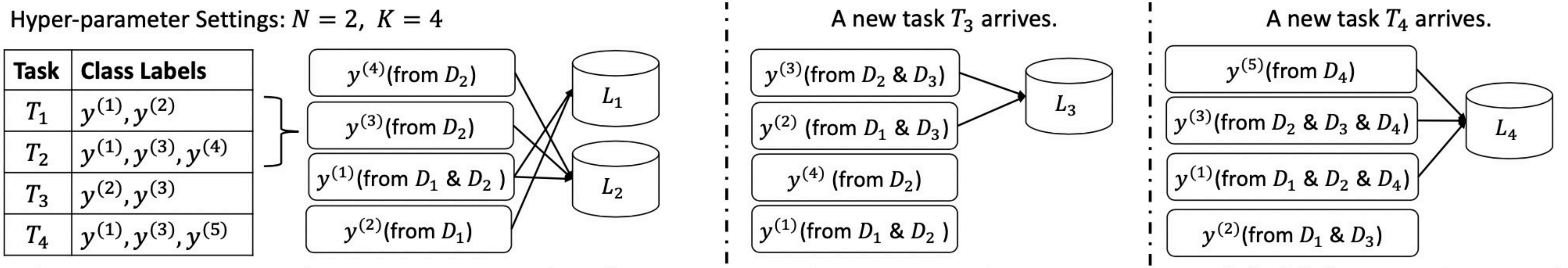
✓Global Memory Network

- Each “slot” stores the “centroid” representation for each class.

Initial Stage
$$G_N^{(m)} = \frac{1}{|\mathcal{T}^{(m)}|} \sum_{\mathcal{T}_n \in \mathcal{T}^{(m)}} \frac{1}{|\mathcal{D}_n^{(m)}|} \sum_{(x_{n,i}, y_{n,i}) \in \mathcal{D}_n^{(m)}} Q(x_{n,i})$$

Update Rule
$$G_j^{(m)} = (1-\gamma) G_{j-1}^{(m)} + \frac{\gamma}{|\mathcal{D}_j^{(m)}|} \sum_{(x_{n,i}, y_{n,i}) \in \mathcal{D}_j^{(m)}} Q(x_{n,i})$$

- Replacement policy for “slots”: Least Recently Used (LRU)



a) Example Tasks & Class Labels　b1) Global Memory (Initial)　c1) Local Memories (Initial)　b2) Global Memory (T_3)　c2) New Local Memory (T_3)　b3) Global Memory (T_4)　c3) New Local Memory (T_4)

Feature Fusion and Model Output

✓Feature Fusion

- Attentive score $$\alpha^{(m)}(x_{n,i}) = \frac{Q(x_{n,i})^T \cdot G_n^{(m)}}{\sum_{y^{(\tilde{m})} \in \mathcal{Y}_n} \alpha^{(\tilde{m})}(x_{n,i})}$$

- Attentive features $$Att(x_{n,i}) = Q(x_{n,i}) + \sum_{y^{(m)} \in \mathcal{Y}_n} \alpha^{(m)}(x_{n,i}) \cdot G_n^{(m)}$$

Results from BERT encoder

Results from global memory

✓Model Output

- Each task has its own task-specific output layer.

Experiments (1)

✓Datasets

- TaskDialog-EUIC: built from three public query intent classification datasets
- Hotline-EUIC: a real-world e-commerce dataset for response intent classification in hotline agents

✓Experimental Settings

- bert-base-en (uncased) for TaskDialog-EUIC
- roberta-tiny-chinese for Hotline-EUIC

	TaskDialog-EUIC	Hotline-EUIC
#Train.	12,845	90,594
#Dev.	2,569	10,114
#Test	2,569	11,803
#Tasks	90	90
#Base tasks	30	30
#Distinct labels	26	71

Experiments (2)

- Examples of Hotline-EUIC

Domain	Task Description	User Response Intents
Map	Check whether the shop name is correct Check whether the shop is still open	{Yes, No, Other} {Open, Close, Not sure}
Health	Ask about the medication history Ask about the fasting plasma glucose	{1 Year, 1-3 Years, >3 Years} {Normal, Pre-diabetes, Diabetes}
Food takeout	Check if the customer is available to pick up the takeout Satisfaction survey	{ Available, Not available, Deliver as soon as possible } { Satisfied, Slow delivery, Food spilled, Not received }
Express delivery	Check if the customer is available to pick up the delivery Satisfaction survey	{ Available, Not available, Collect the parcels by others } { Satisfied, Slow delivery, Package damaged, Not received }

Experiments (3)

✓Overall Model Performance

Task	TaskDialog-EUIC				Hotline-EUIC			
Results	All tasks		New tasks		All tasks		New tasks	
	Accuracy	F1	Accuracy	F1	Accuracy	F1	Accuracy	F1
MTL (Upper-bound)*	0.9597	0.9590	0.9568	0.9562	0.9788	0.9480	0.9832	0.9523
Single*	0.9006	0.8974	0.9005	0.8969	0.9196	0.8685	0.9239	0.8814
Lifelong-freeze	0.9214	0.9194	0.9015	0.8988	0.9401	0.8798	0.9259	0.8501
Lifelong-seq	0.3140	0.2043	0.3447	0.2455	0.4517	0.3485	0.5272	0.4238
Lifelong-replay*	0.6225	0.5481	0.5485	0.4573	0.8215	0.8260	0.9420	0.8553
MeLL	**0.9379**	**0.9342**	**0.9271**	**0.9224**	**0.9673**	**0.9341**	**0.9675**	**0.9319**

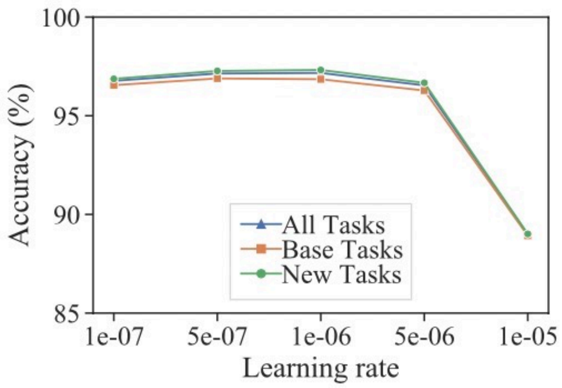
Experiments (4)

✓Ablation Study

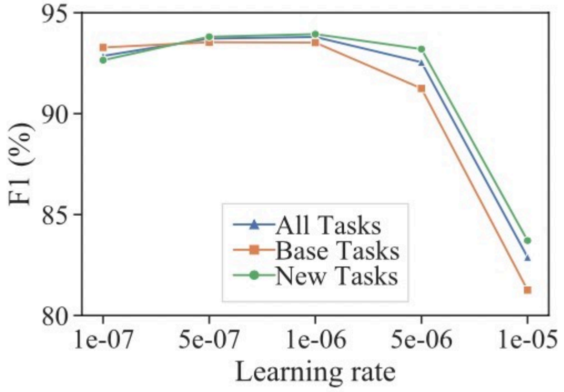
- The meta knowledge plays an important role in overall model performance.

Ablation	F1	Improv. Rate
MeLL	0.9341	N/A
w/o Meta knowledge	0.9178	-1.63%
w/o Slow learner	0.9269	-0.72%
w/o LRU replacement policy	0.9380	+0.39%

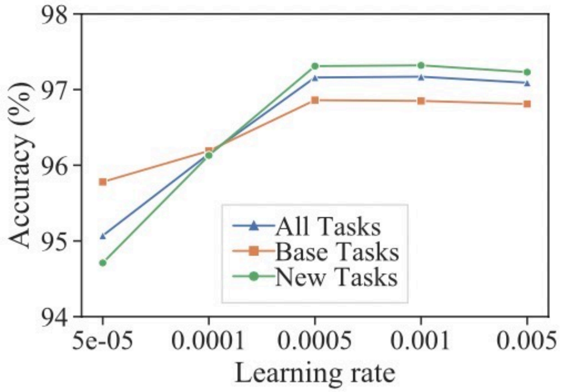
✓Parameter Analysis



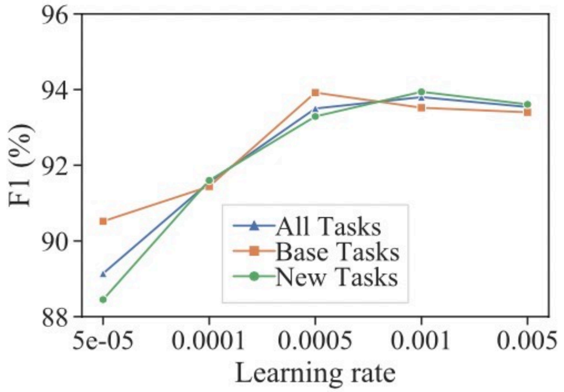
(a) Accuracy w.r.t the learning rate of the slow leaner.



(b) F1 w.r.t the learning rate of the slow leaner.



(c) Accuracy w.r.t the learning rate of the fast leaner.



(d) F1 w.r.t the learning rate of the fast leaner.

Experiments (5)

✓Online Deployment

- A/B test on AliMe hotline system
- Online system
  - Task-specific TextCNN models

Method	F1	Relative Improv.
Online system (Single)	0.8359	N.A.
MeLL (w. LRU)	**0.9079**	8.61%

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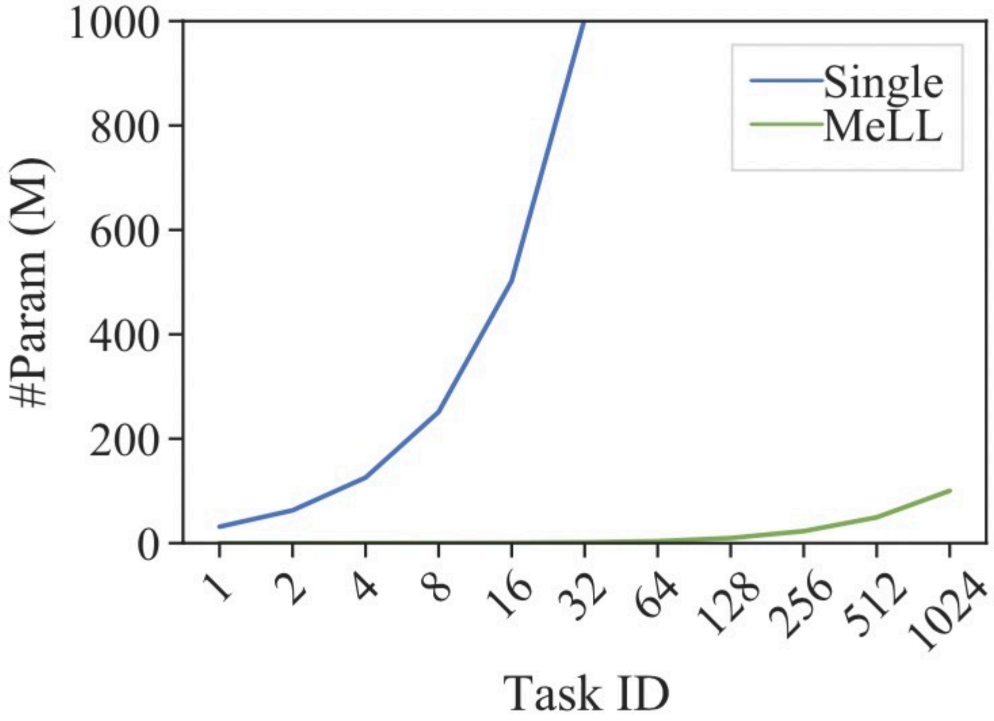
✓Salability Analysis

- Number of parameters w. the number of tasks



Conclusion

✓We present the MeLL framework to address large-scale extensible user intent classification.

✓Experiments and online A/B test show that MeLL consistently outperforms strong baselines.

✓Future work:

- How MeLL be employed to solve other tasks and support other applications.

THANKS

--------- Q&A Section --------