Progressive Continual Learning for Spoken Keyword Spotting

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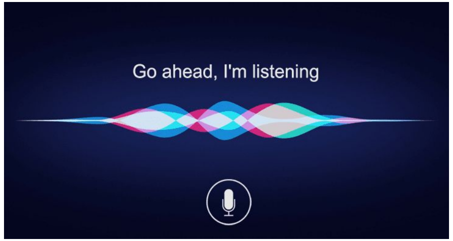
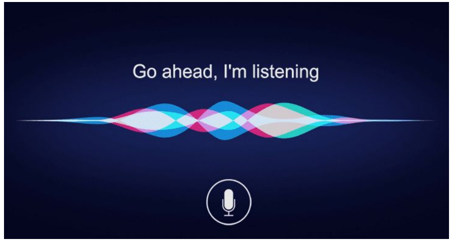
Background: Voice Assistants/Word Spotting (KWS)



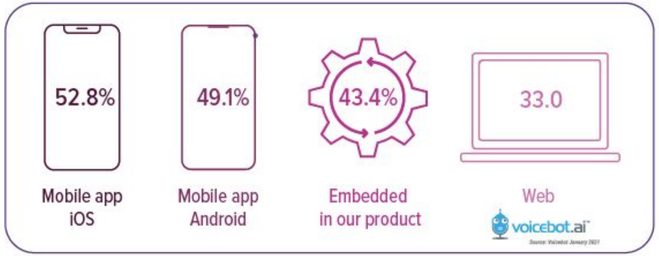
Intelligent voice assistants are,

- **everywhere** around us.
- awakened by specific speech **keywords (KWS)**.

Background: Voice Assistants/Word Spotting (KWS)



Where Marketers are Deploying Voice Capabilities to Engage Customers [1]



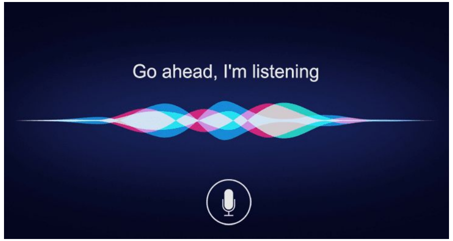
Intelligent voice assistants are,

- **everywhere** around us.
- awakened by specific speech **keywords**.
- mostly deployed in **edge/mobile** devices.

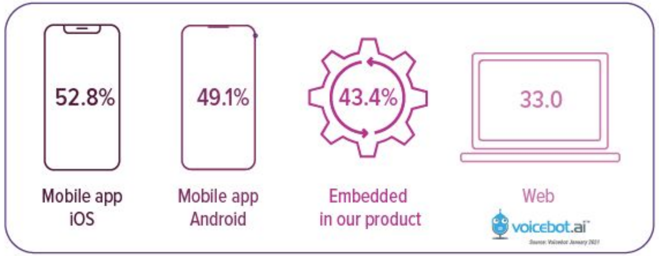
Limited Computational Resource.

[1] https://voicebot.ai/2021/03/29/where-custom-voice-assistants-are-deployed-in-2021/

Motivation



Where Marketers are Deploying Voice Capabilities to Engage Customers [1]



Limited vocabularies in KWS models.

Cannot **deal with unknown words** without a large pre-trained model.

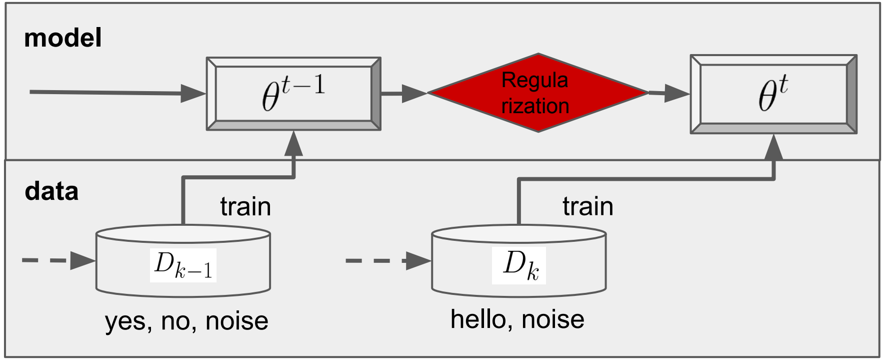
Limited Computational Resource

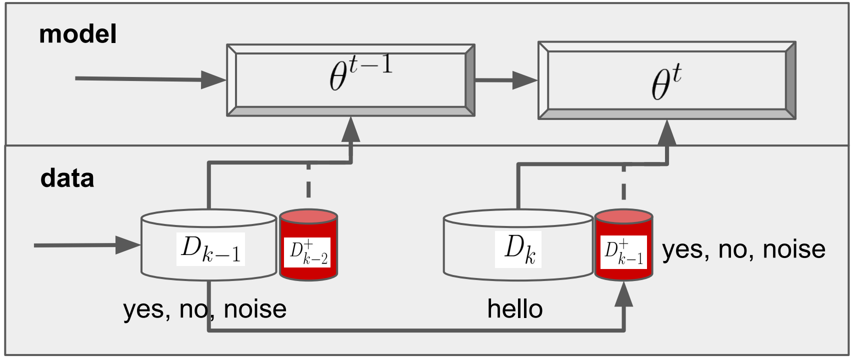
(small memory, slow training speed, etc).

[1] https://voicebot.ai/2021/03/29/where-custom-voice-assistants-are-deployed-in-2021/

Related Works: Continual Learning

Continual Learning Methods





Regularization-based Methods

- Elastic Weight Consolidation (EWC) [3]
- Synaptic Intelligence (SI) [4]

Replay Methods

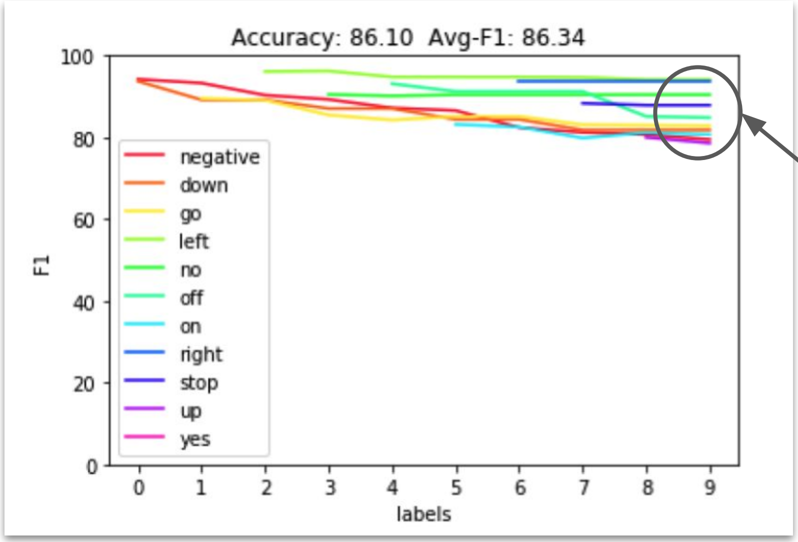
- Naive Rehearsal
- Gradient Episodic Memory (GEM) [5]

[3] https://arxiv.org/abs/1612.00796 (James Kirkpatrick et al, Overcoming catastrophic forgetting in neural networks; *PNAS'17*)
[4] https://arxiv.org/abs/1703.04200 (Friedemann Zenke et al, Continual Learning Through Synaptic Intelligence; *ICML'17*)
[5] https://arxiv.org/abs/1706.08840 (David Lopez-Paz et al, Gradient Episodic Memory for Continual Learning; *NeurIPS'17*)

Related Works: Fine-tuning

Fine-tuning the KWS model on unknow keywords

[2]



Learning new keywords sequentially

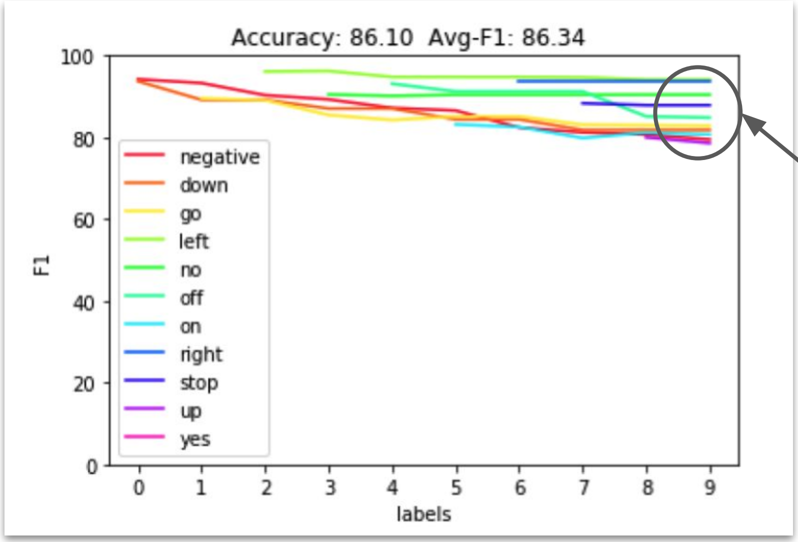
forgetting issue!
(*even with a **large** speech pre-trained model)

[2] https://arxiv.org/abs/2106.02443 (Awasthi et al, Teaching keyword spotters to spot new keywords with limited examples; *InterSpeech'21*)

Related Works: Gaps

Fine-tuning the KWS model on unknow keywords

[2]



Learning new keywords sequentially

limited **the learning ability** for more words.

forgetting issue!
(*even with a **large** speech pre-trained model)

higher **memory footprint**.

[2] https://arxiv.org/abs/2106.02443 (Awasthi et al, Teaching keyword spotters to spot new keywords with limited examples; *InterSpeech'21*)

Progressive Continual Learning for KWS (PCL-KWS)

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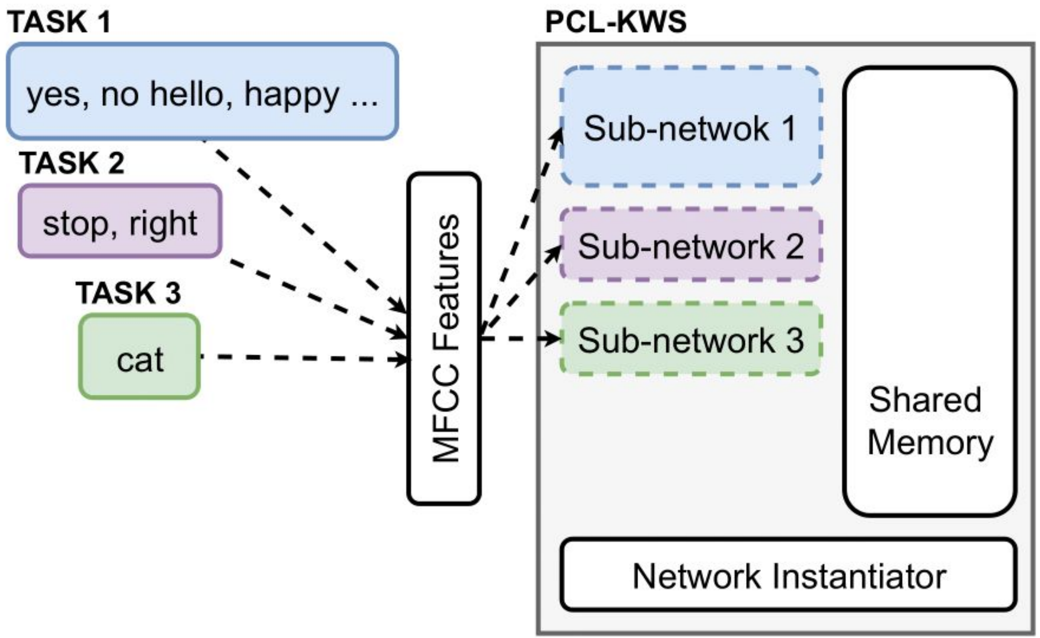
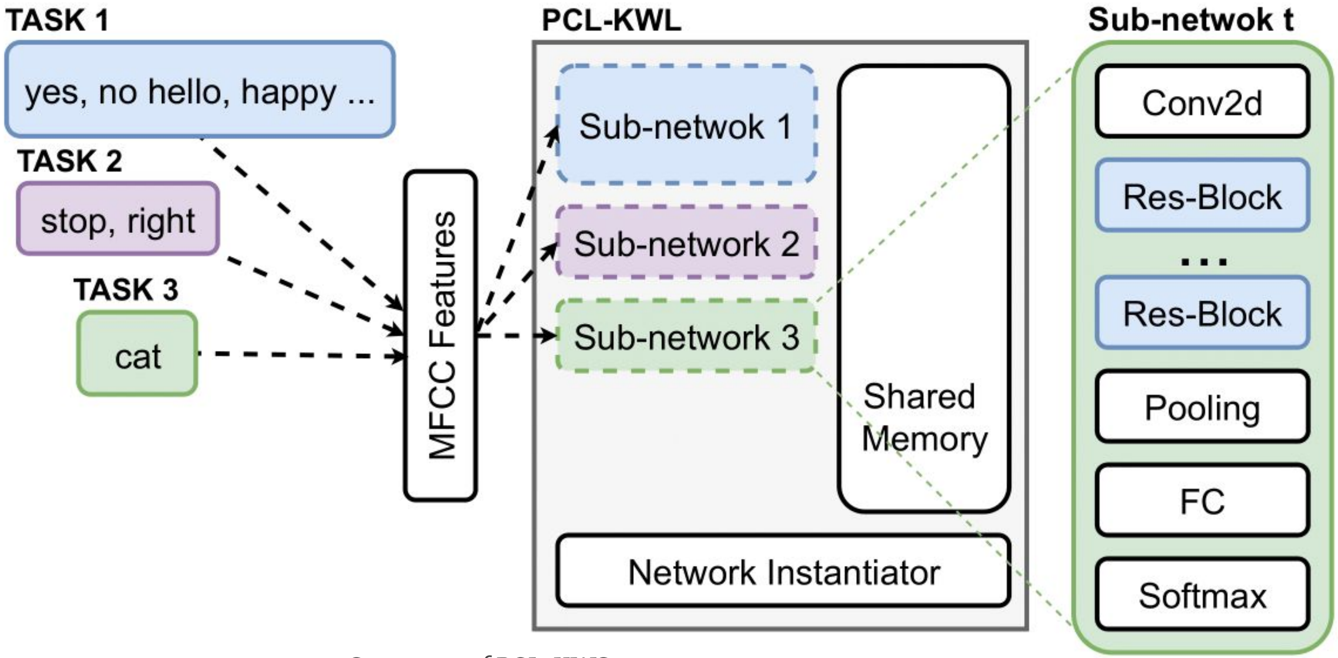
Progressive model expanding



Structure of PCL-KWS

Progressive Continual Learning for KWS (PCL-KWS)

Progressive model expanding

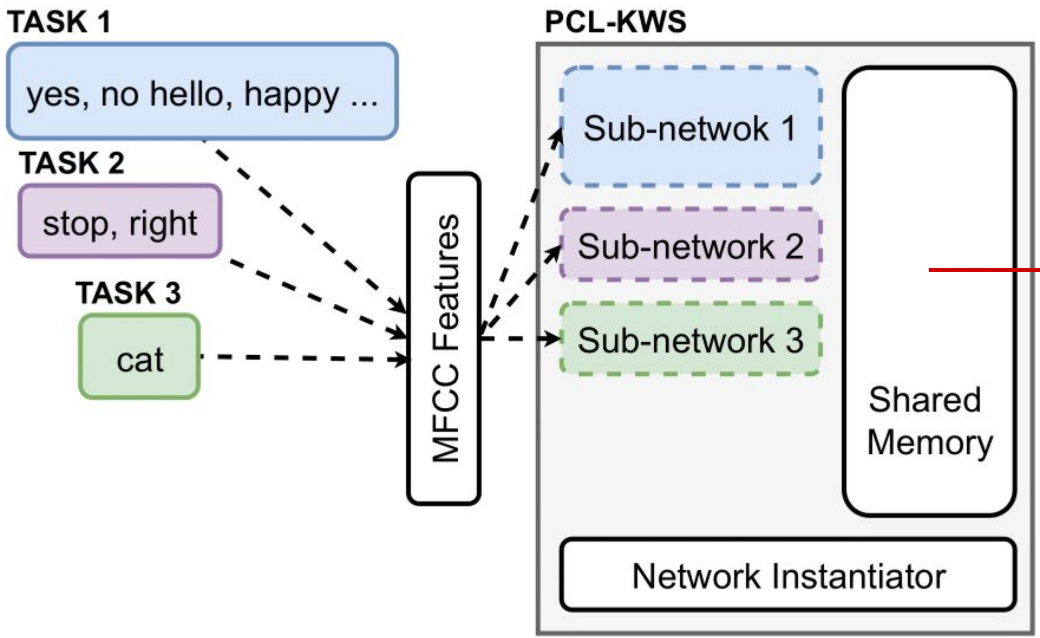


Structure of PCL-KWS

classification layers dedicated for each task (one or more keywords).

Progressive Continual Learning for KWS (PCL-KWS)

Progressive model expanding



Structure of PCL-KWS

store the learned features of previously learned tasks.

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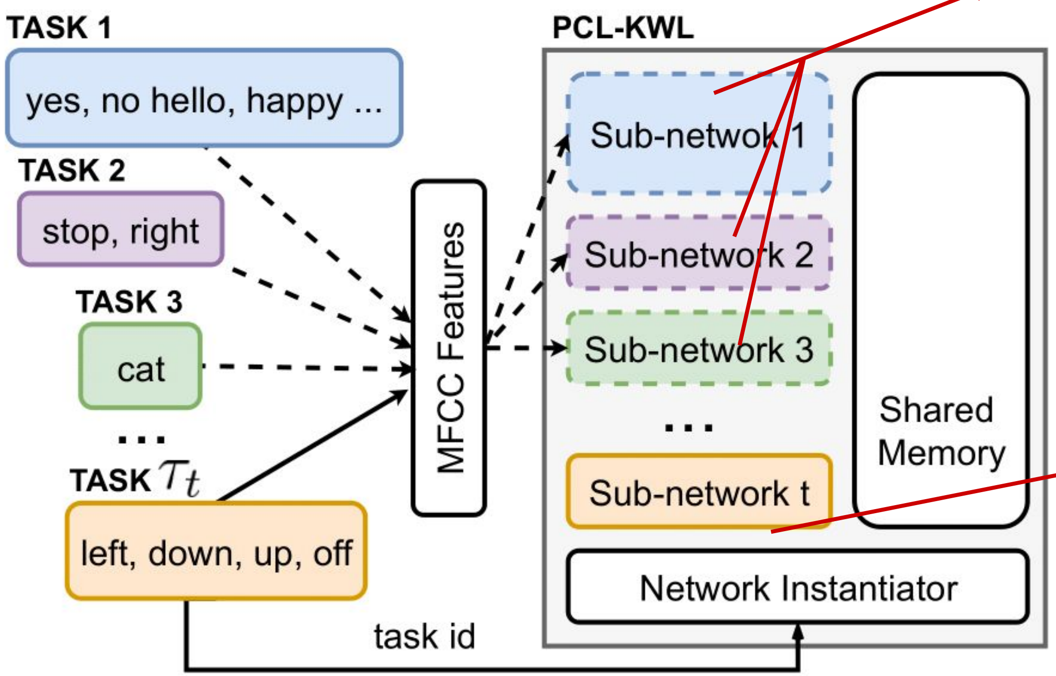
Progressive model expanding

frozen while learning new keywords.

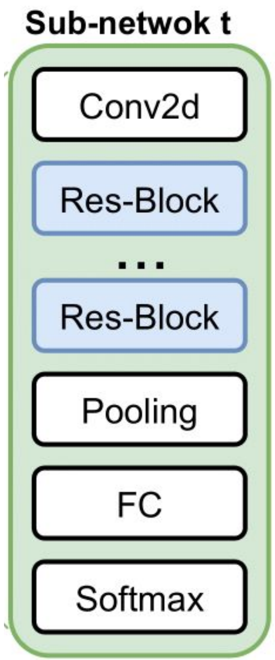


create a sub-network according to the new keyword learning task.

Structure of PCL-KWS

Progressive Continual Learning for KWS (PCL-KWS)

Keyword-aware Network Scaling Mechanism



Structure of Sub-network

$$\{16, 24, 32, 48\} * \alpha_t$$

dynamic width multiplier

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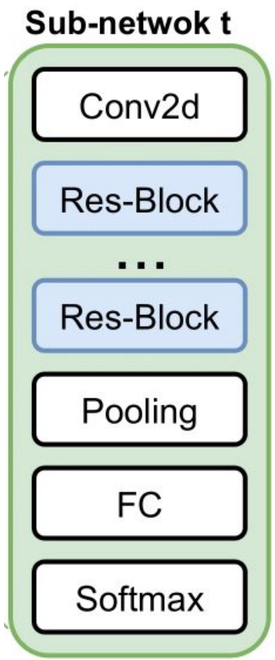
Keyword-aware Network Scaling Mechanism



Structure of Sub-network

$$\{16, 24, 32, 48\} * \alpha_t$$

dynamic width multiplier (factor)

$$\alpha_t = \mu \frac{C_t}{C_0}, (\mu > 0)$$

determined by the new keyword numbers, and the pre-trained keywords.

Evaluation & Insights

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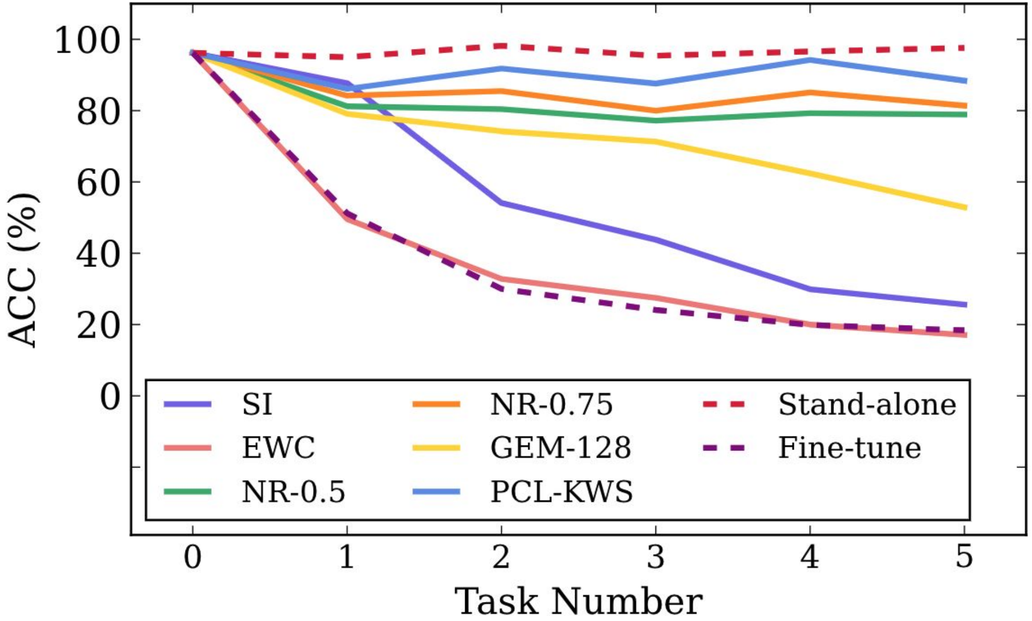
Comapre with Continual Learning Baselines



The overall accuracy (%) with the number of learned tasks (each has 3 keywords from Google Speech Commands Dataset)

Stand-alone: separate model for each task.

Fine-tune: without continual learning.

from PCL-KWS:

1. near upper-bound performance.
2. better than all CL baselines.

Evaluation & Insights

Comapre with Continual Learning Baselines

	Accuracy (average of all tasks)	Speed (per-epoch training time)	Memory (extra parameters + buffer size)
Fine-tune (Lower-bound)	0.39	109.2s	N.A
Regularization-based (EWC, SI)	0.45	133.5s	67.69K
Replay-based (NR, GEM)	0.73	506.9s	132.4M
PCL-KWS (Ours)	**0.91**	97.4s	**25.5K**
Stand-alone (Upper-bound)	0.94	123.3s	617.8K

Regularization-based:

- **High** training speed.
- **Low** memory footprint.
- **Poor** accuracy.

Replay-based:

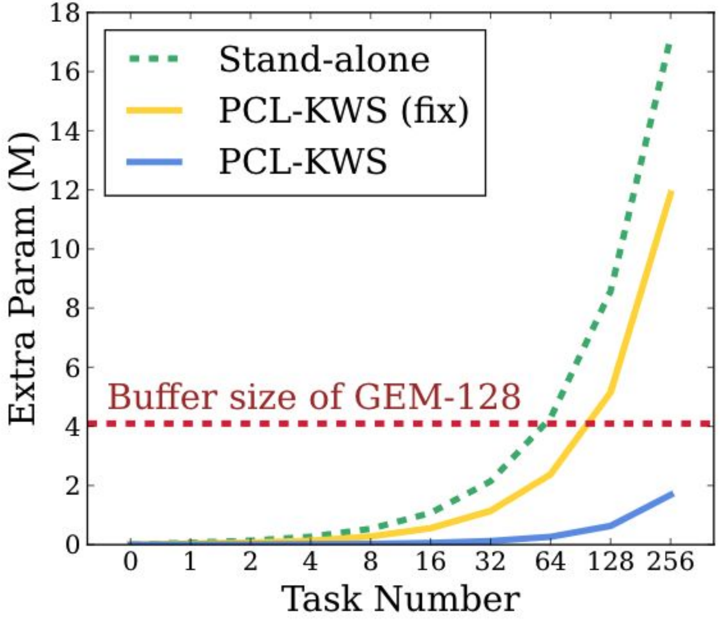
- **Low** training speed.
- **High** memory footprint.
- **Good** accuracy.

PCL-KWS:

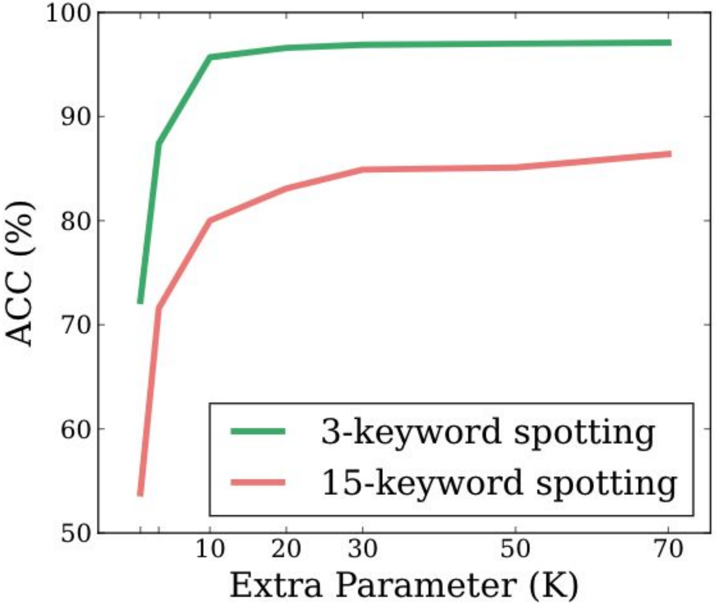
- **High** training speed.
- **Low** memory footprint.
- **Good** accuracy.

Evaluation & Insights

Parameter Growth Rate of PCL-KWS



(a)



(b)

Summary

- Apply various continual learning methods for spoken keyword spotting incremental learning.
- Proposed PCL-KWS, a novel continual learning strategy designed for small-footprint KWS.
  - Compare with regularization-based methods, PCL-KWS has better CL performance.
  - Compare with replay-based methods, PCL-KWS has better system efficiency.
- Introduced a keyword-aware network scaling mechnichsm to reduce the parameter growth rate.

Thanks