Adversarial Knowledge Transfer from Unlabeled Data

    

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Problem Overview

Brief Statement

How to transfer knowledge from internet-scaled unlabeled data to improve the performance of given visual recognition task?

Motivation

- Machine learning approaches are data hungry
- Manual data collection is tedious and expensive
- Collected data should have similar data distribution

Learning Paradigm

(a) Transfer Learning. (Source: Labeled, Target: Labeled)

Learning Paradigm

Source Data

Target Data

(a) Transfer Learning. (Source: Labeled, Target: Labeled)

(b) Unsup. Domain Adaptation. (Source: Labeled, Target: Unlabeled)

Learning Paradigm

Source Data | Target Data

(a) Transfer Learning. (Source: Labeled, Target: Labeled)

Source Data | Target Data

(c) Semi-Supervised Learning. (Source: Unlabeled, Target: Labeled)

(b) Unsup. Domain Adaptation. (Source: Labeled, Target: Unlabeled)

Learning Paradigm

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(d) AKT (ours). (Source: Unlabeled, Target: Labeled)

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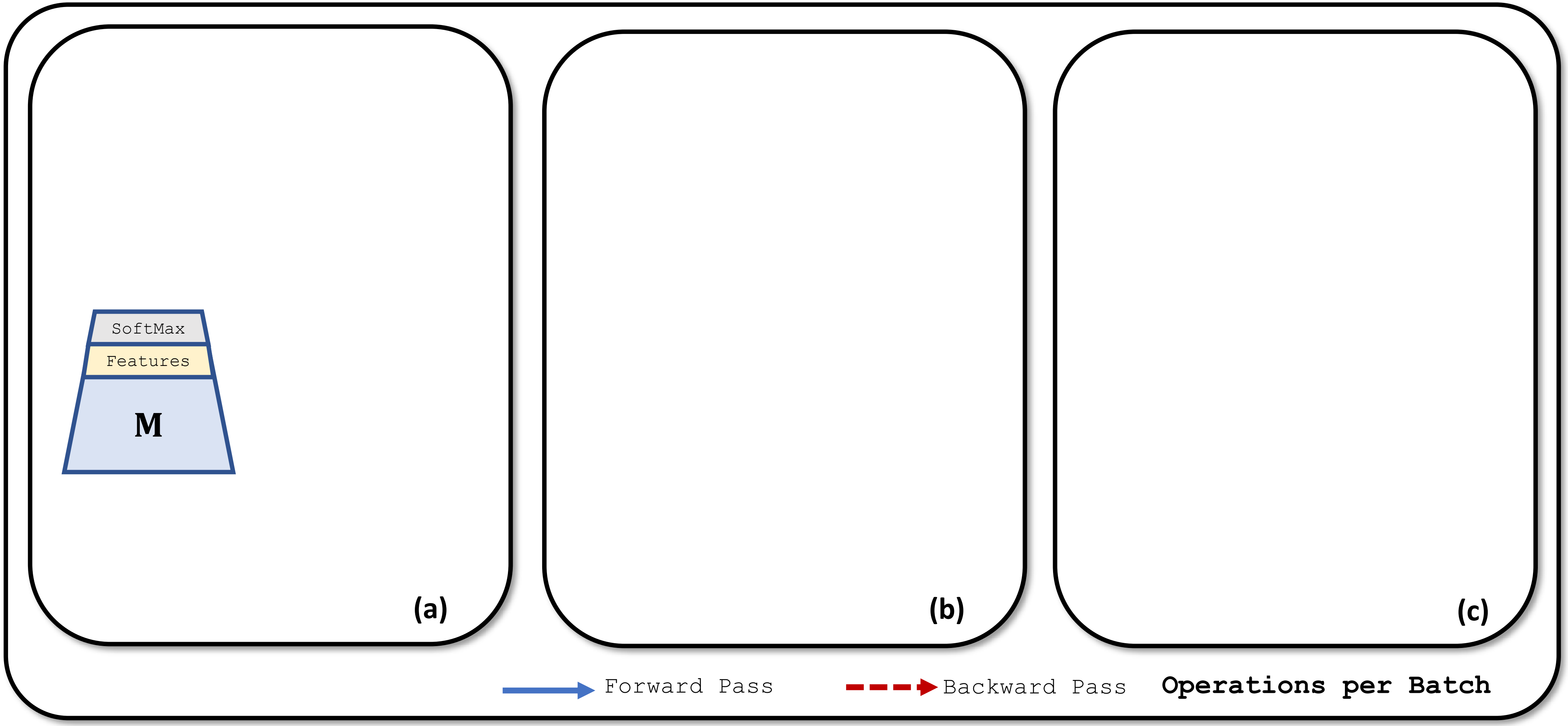
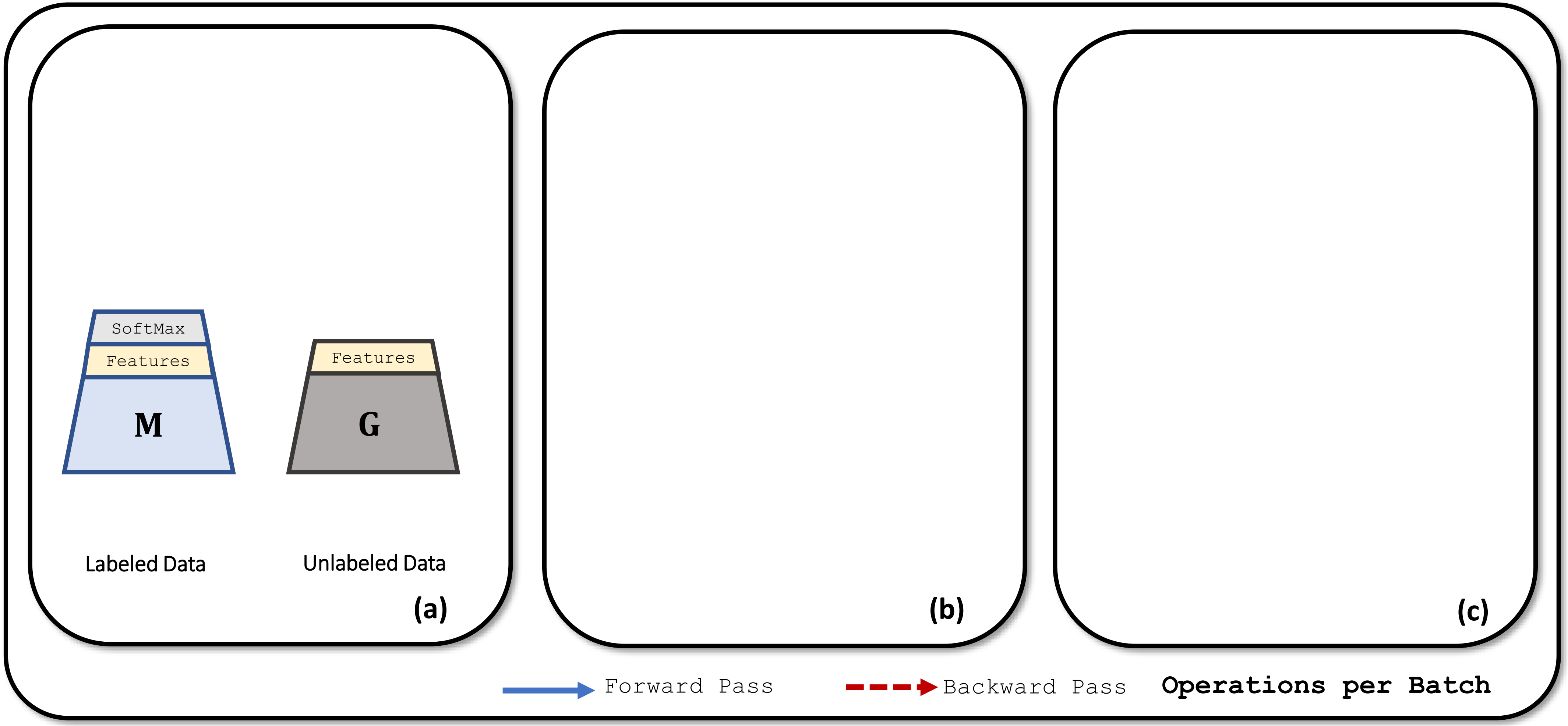
(d) AKT (ours). (Source: Unlabeled, Target: Labeled)

- ✓ Unlabeled data may have different data/label distribution
- ✓ Without defining a pretext task as in Self-Supervised Learning

Proposed Approach



Proposed Approach



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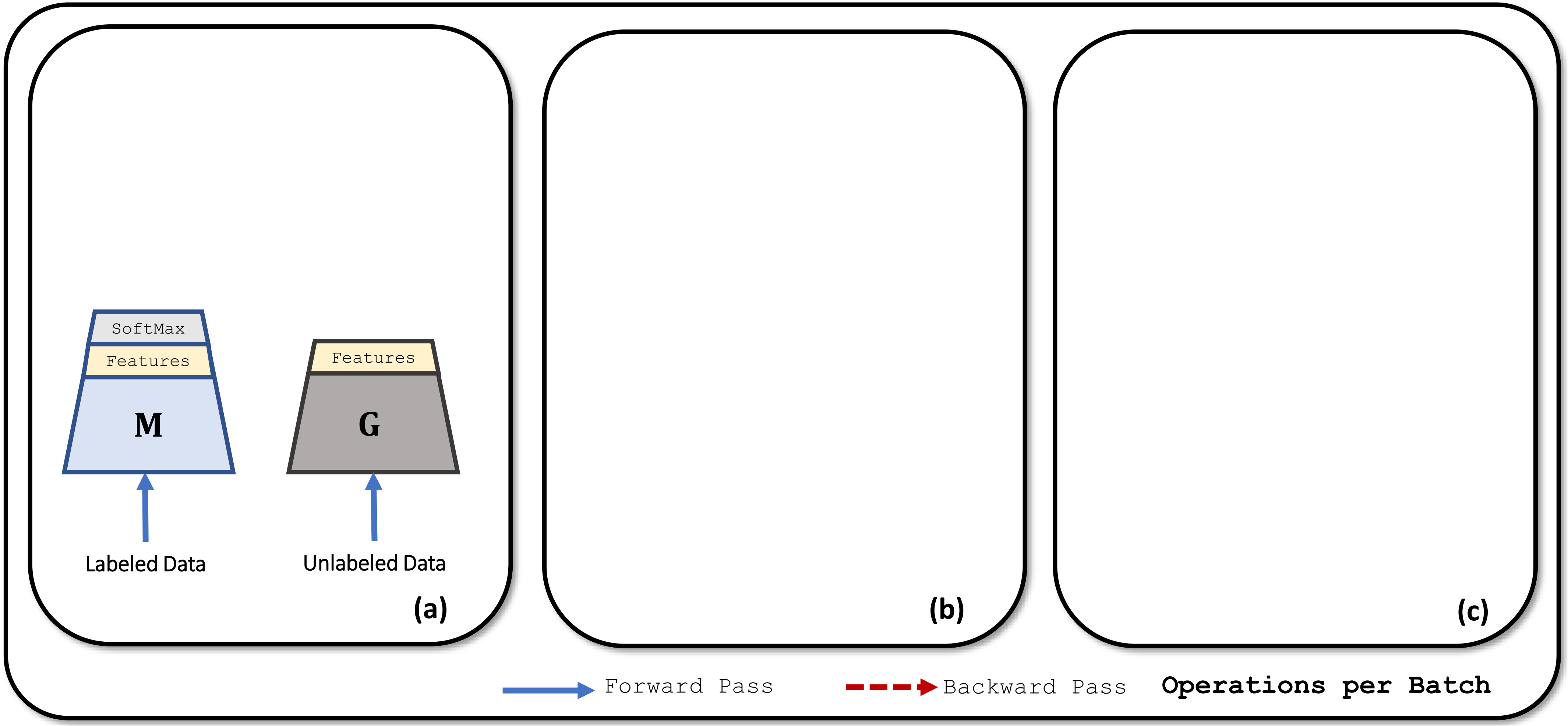

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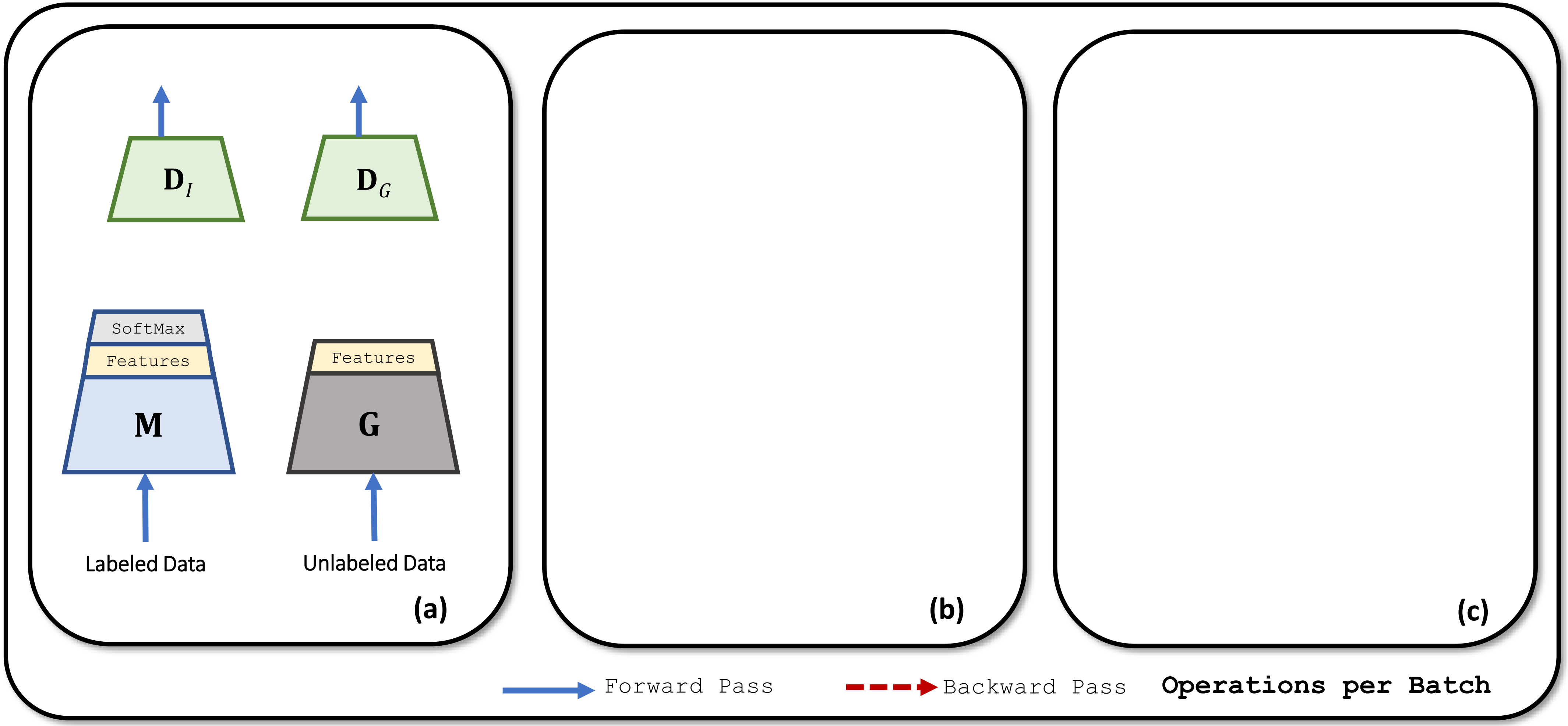

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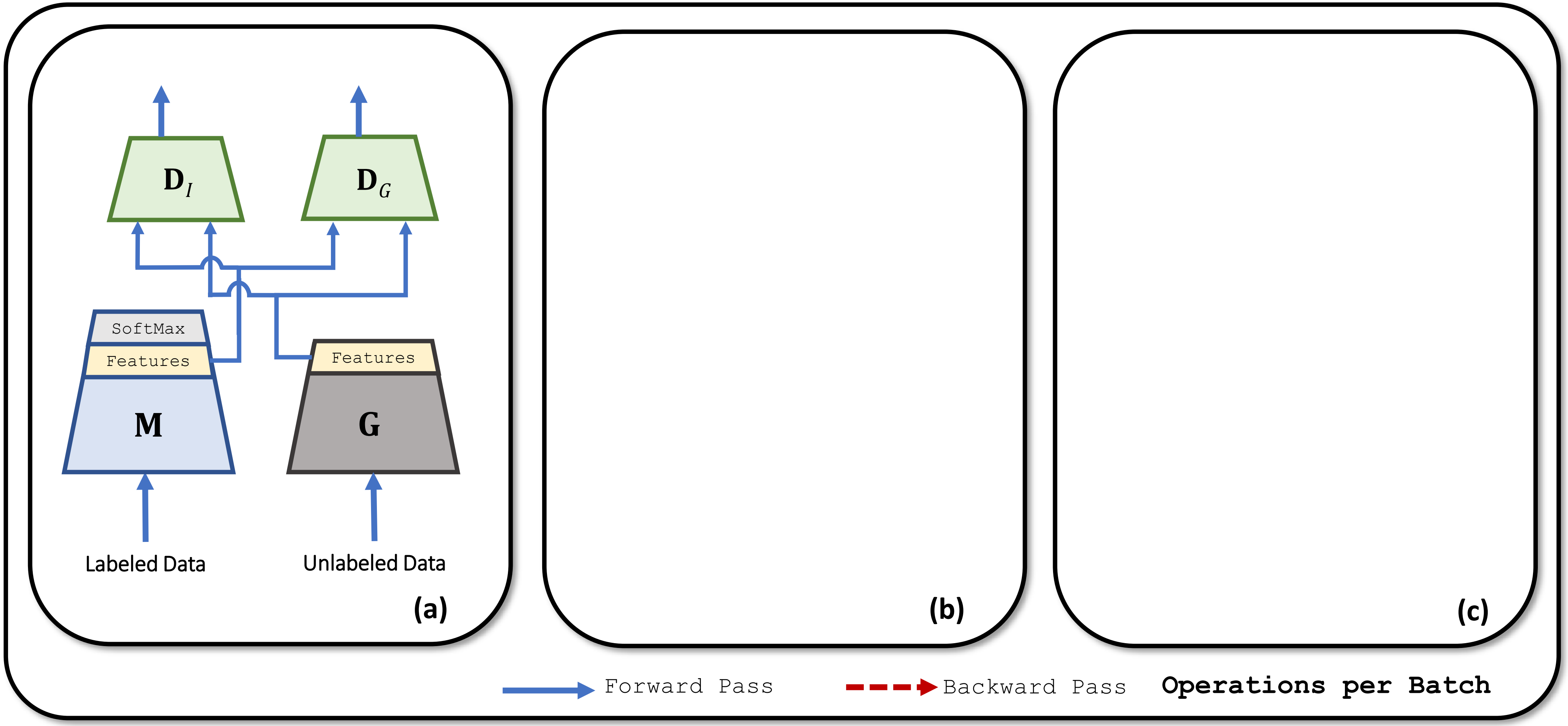

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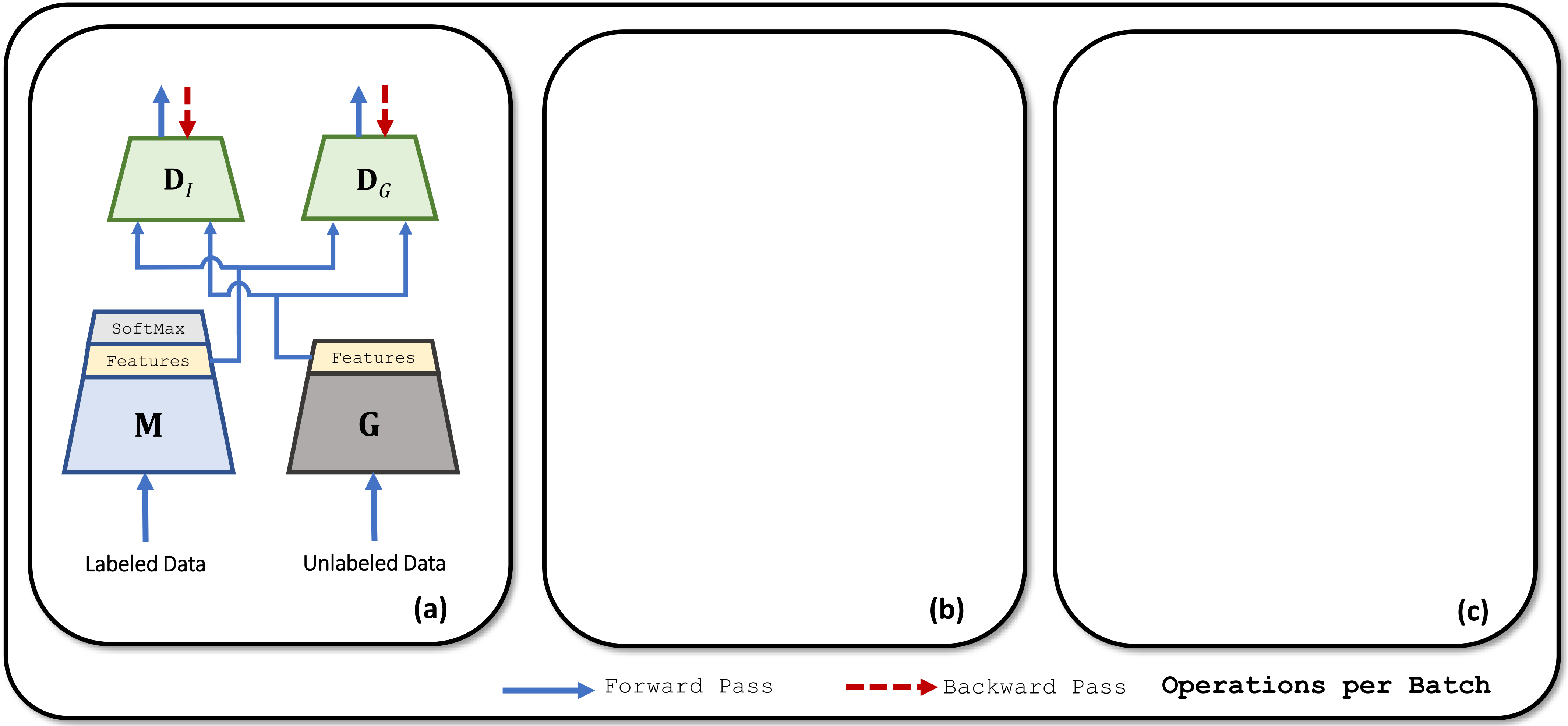

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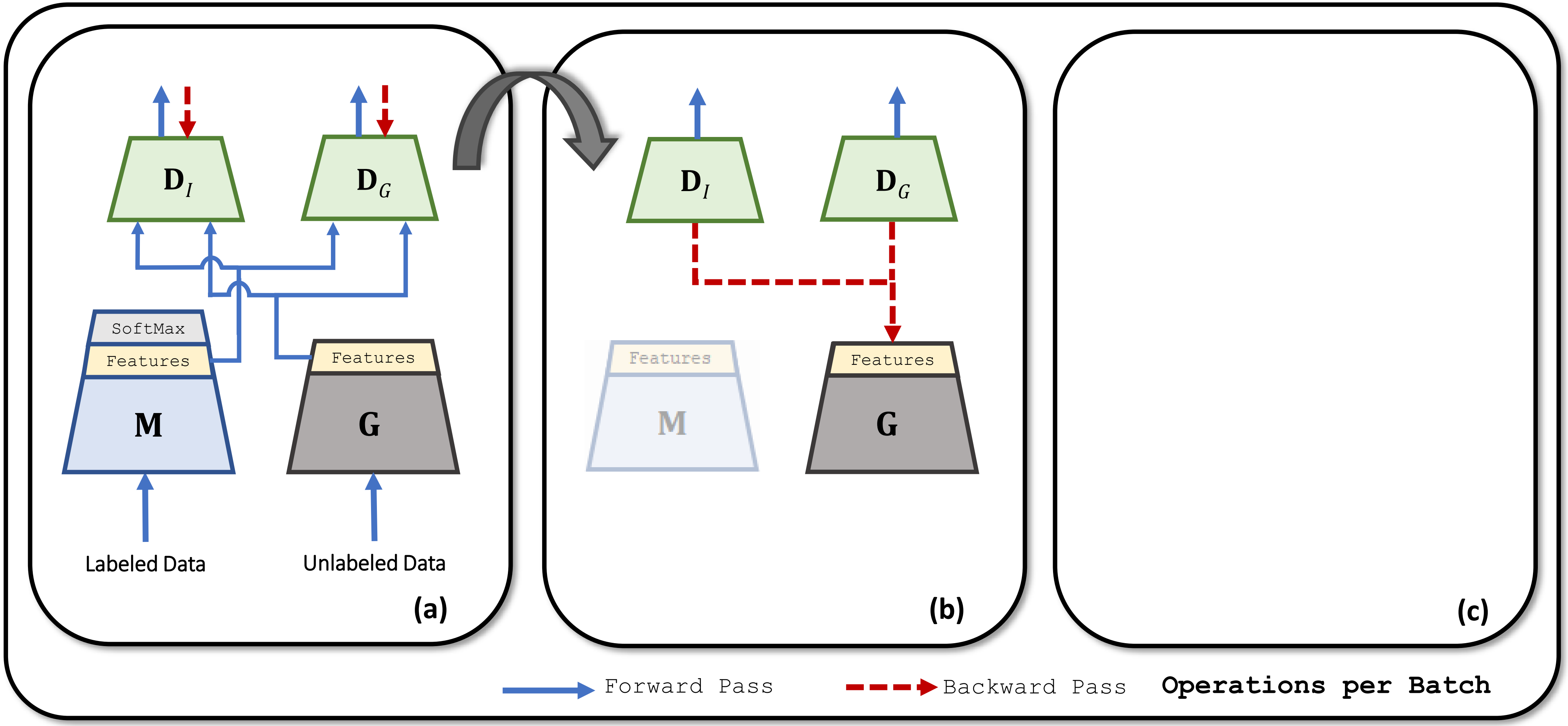

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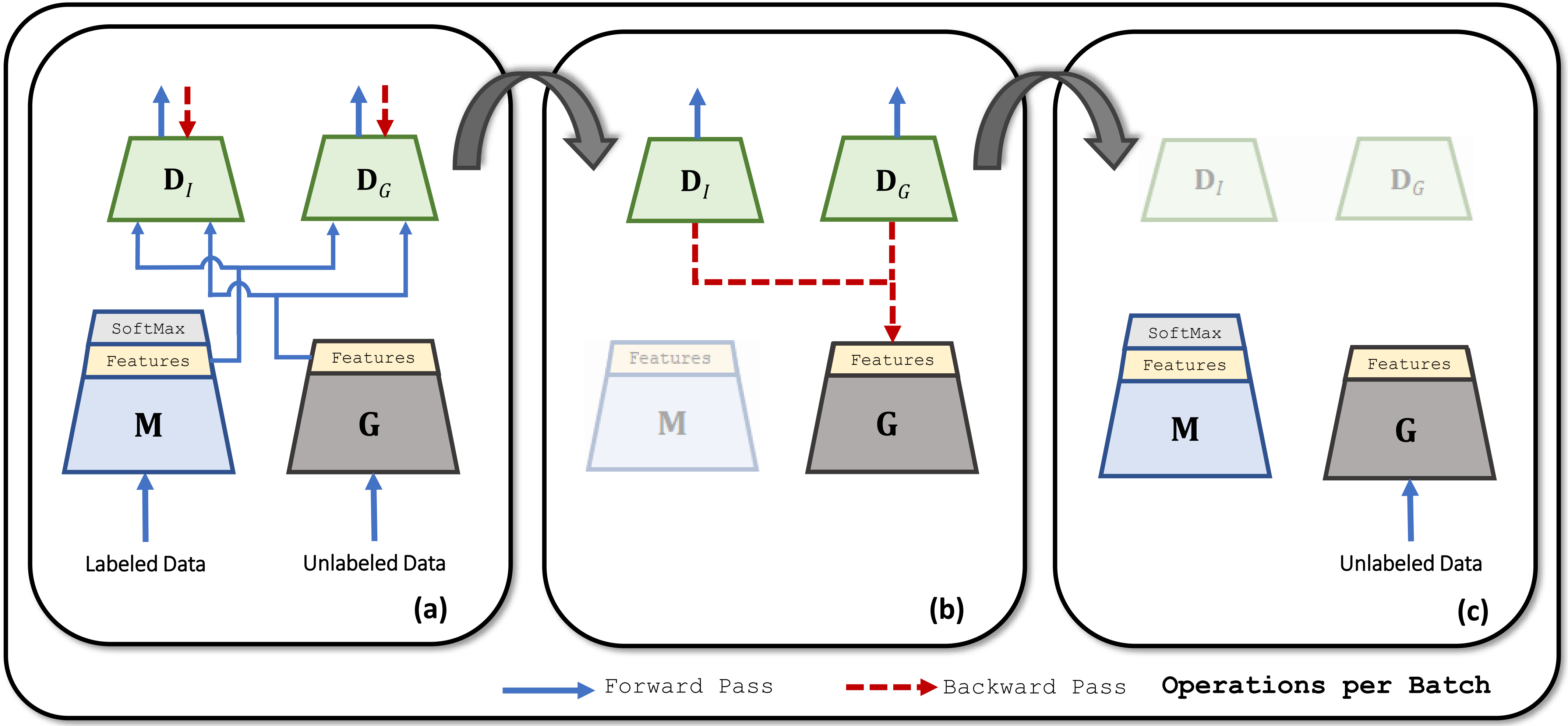
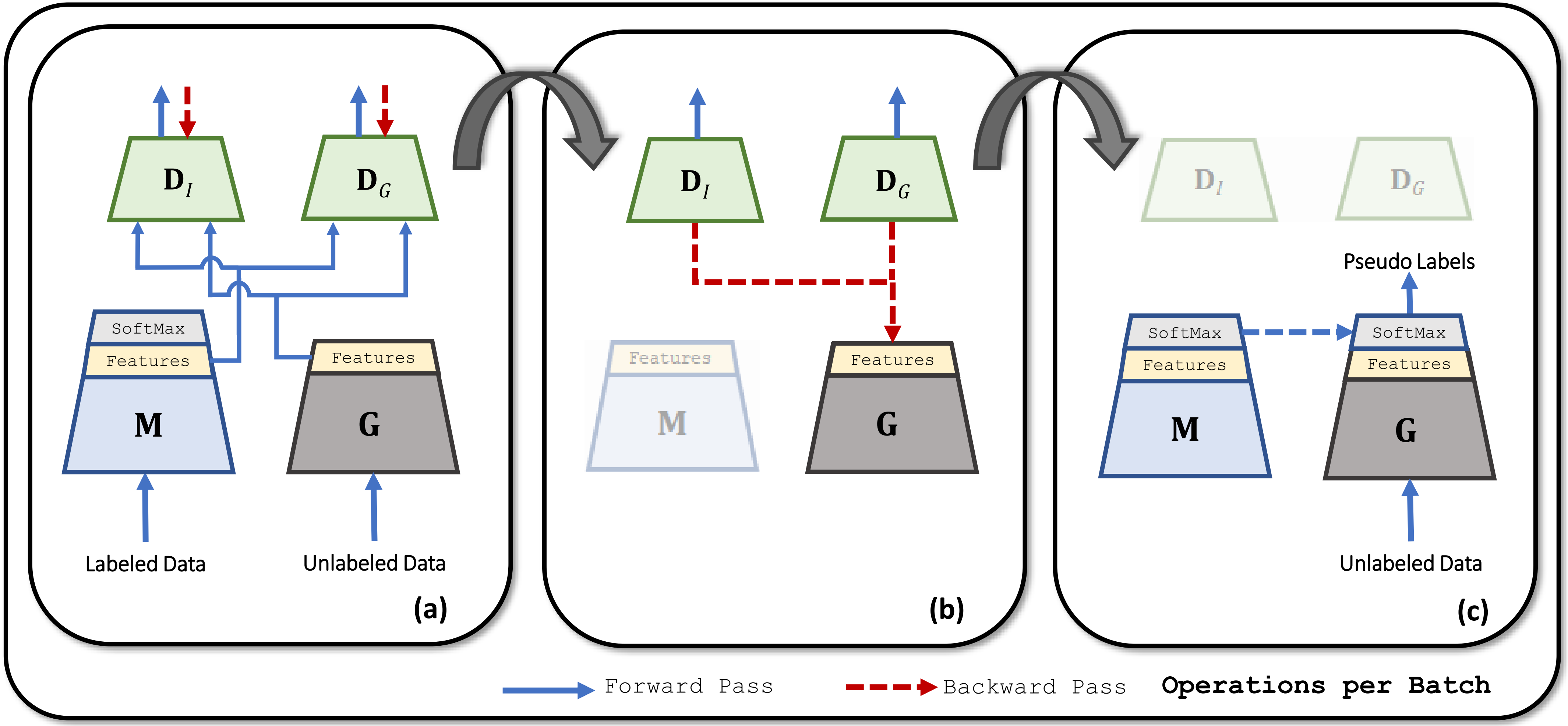


Proposed Approach



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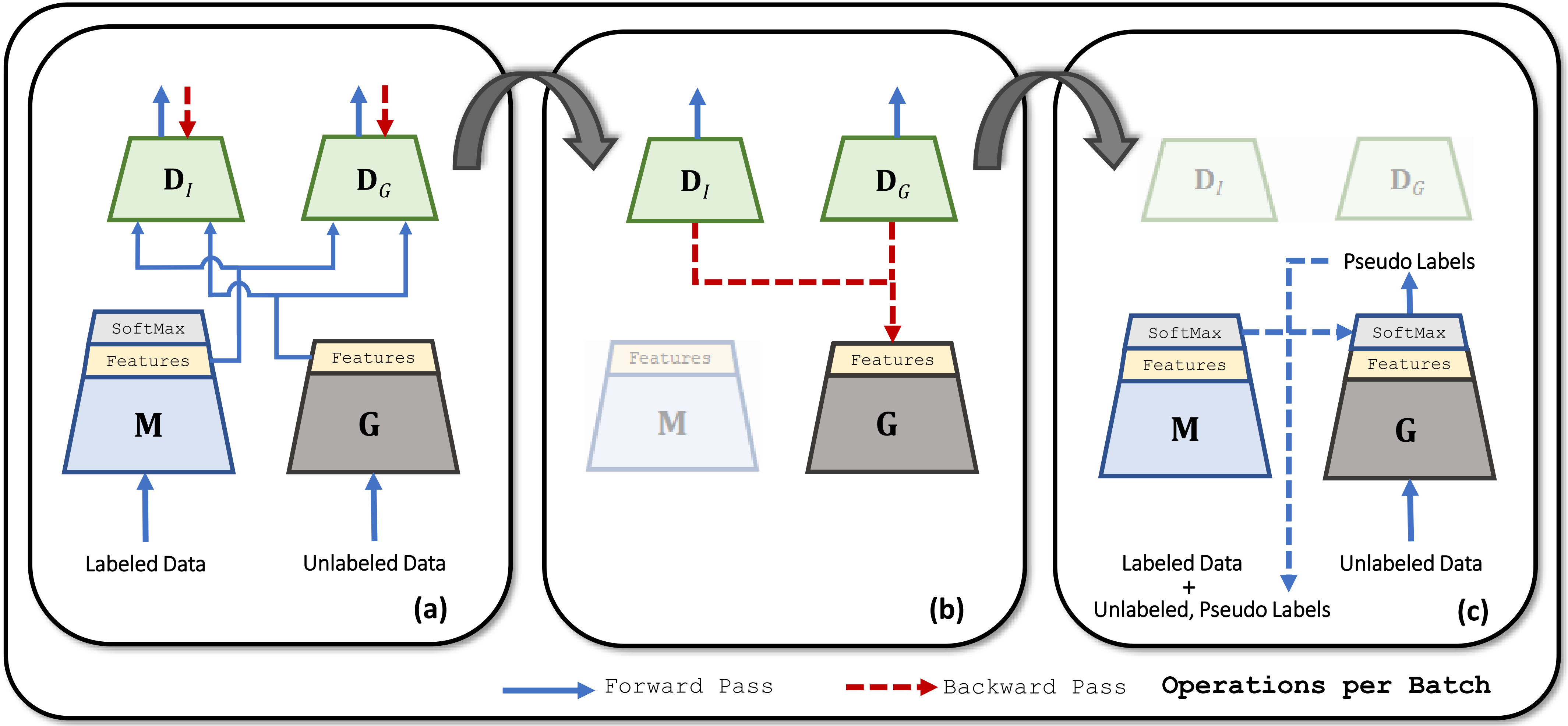

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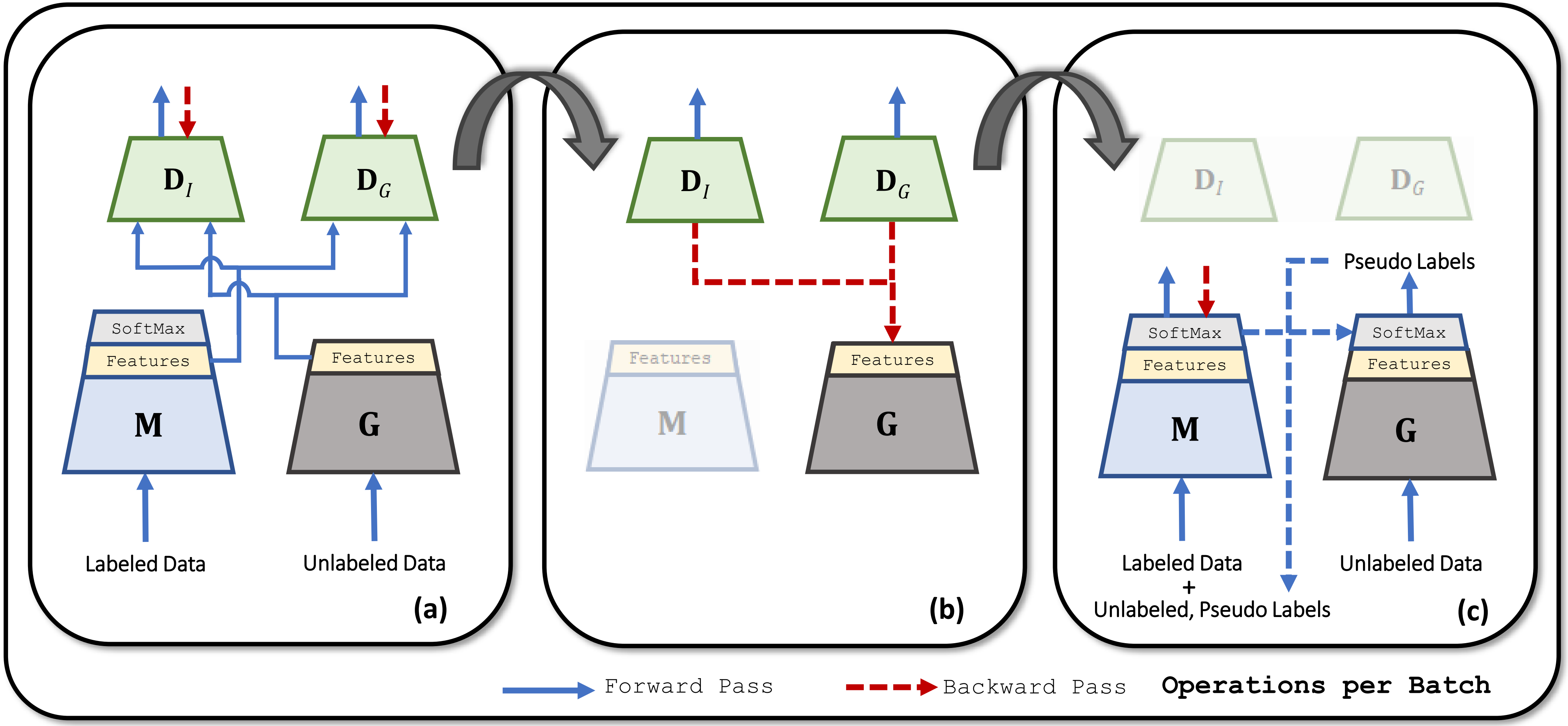

Results

- We perform various experiments on object recognition, character recognition and sentiment recognition.

Target: CIFAR-10 and Source: CIFAR-100	
Methods	Target Accuracy (%)
Scratch	92.49
Finetuning	93.27
Joint Training	93.32
Pseudo Labels [2]	92.85
Random Network [39]	92.37
Jigsaw [33]	75.85
Colorization [52]	92.57
Split-Brain [53]	92.60
AKT (Ours: only D_I)	93.04
AKT (Ours: with D_I and D_G)	**93.21**

Target: PASCAL-VOC and Source: ImageNet	
Methods	Target mAP (%)
Scratch	63.5
Finetuning	87.0
Joint Training	86.7
Pseudo Labels [2]	63.2
Random Network [39]	53.3
Jigsaw [33]	67.7
Jigsaw++ [34]	69.9
Colorization [52]	65.9
Split-Brain [53]	67.1
Rotation [12]	73.0
Rotation Decoupling [10]	74.5
AKT (Ours: only D_I)	76.9
AKT (Ours: with D_I and D_G)	**77.4**

Results

- Our approach generates reliable pseudo-labels

ImageNet Class	Top-3 Pseudo Label	Score
Fig. a. warplane	**aeroplane**, bird, car	86.67%
Fig. b. bike	**bicycle**, motorbike, person	88.46%

(a) Samples from class *aeroplane* from PASCAL-VOC experiment.

(b) Samples from class *bike* from PASCAL-VOC experiment.

Conclusions

- We propose a novel Adversarial Knowledge Transfer (AKT) framework for transferring knowledge from unlabeled data to the labeled data.
- Our approach does not require the unlabeled data to be from the same label space or data distribution as of the labeled data.
- Unlike, self-supervised methods our method doesn't require explicit pretext task making it highly efficient.
- Experiments on various recognition tasks show the efficacy of our proposed approach over state-of-the-methods.

Acknowledgement

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Thank you!

For more details: `https://agupt013.github.io/akt.html`