A Simple Hash-Based Early Exiting Approach For Language Understanding and Generation

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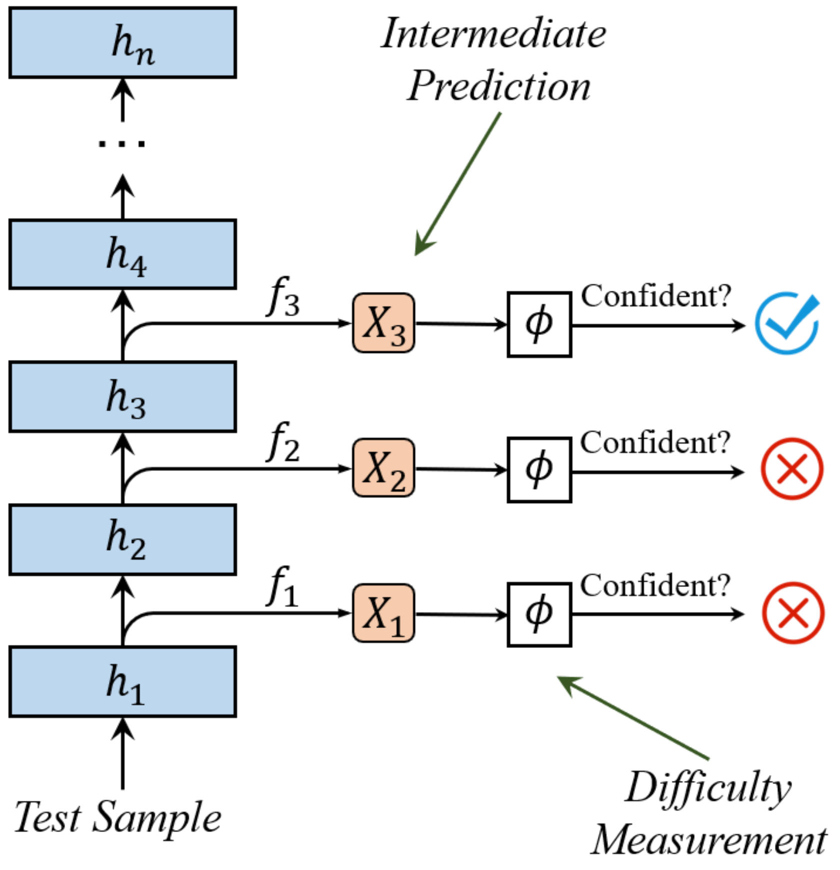
Findings of ACL 2022

Background

- **Early Exiting**
  - Allows instances to exit at early layers according to the **estimation of difficulty**



Background

- **Early Exiting**
  - Allows instances to exit at early layers according to the **estimation of difficulty**
- **How to Estimate Instance Difficulty?**
  - Heuristic metrics, e.g. entropy, maximum softmax score···
    - **Examples**: DeeBERT, FastBERT, PABEE, etc.
    - **Problem**: Suffers from generalization and thresholding tuning.
  - Learning to predict instance difficulty
    - **Example**: Learn-to-exit (Xin et al., EACL 2021)
    - **Problem**: **Can instance difficulty really be learned? (Our initial motivation)**

Can Instance Difficulty Be Learned?

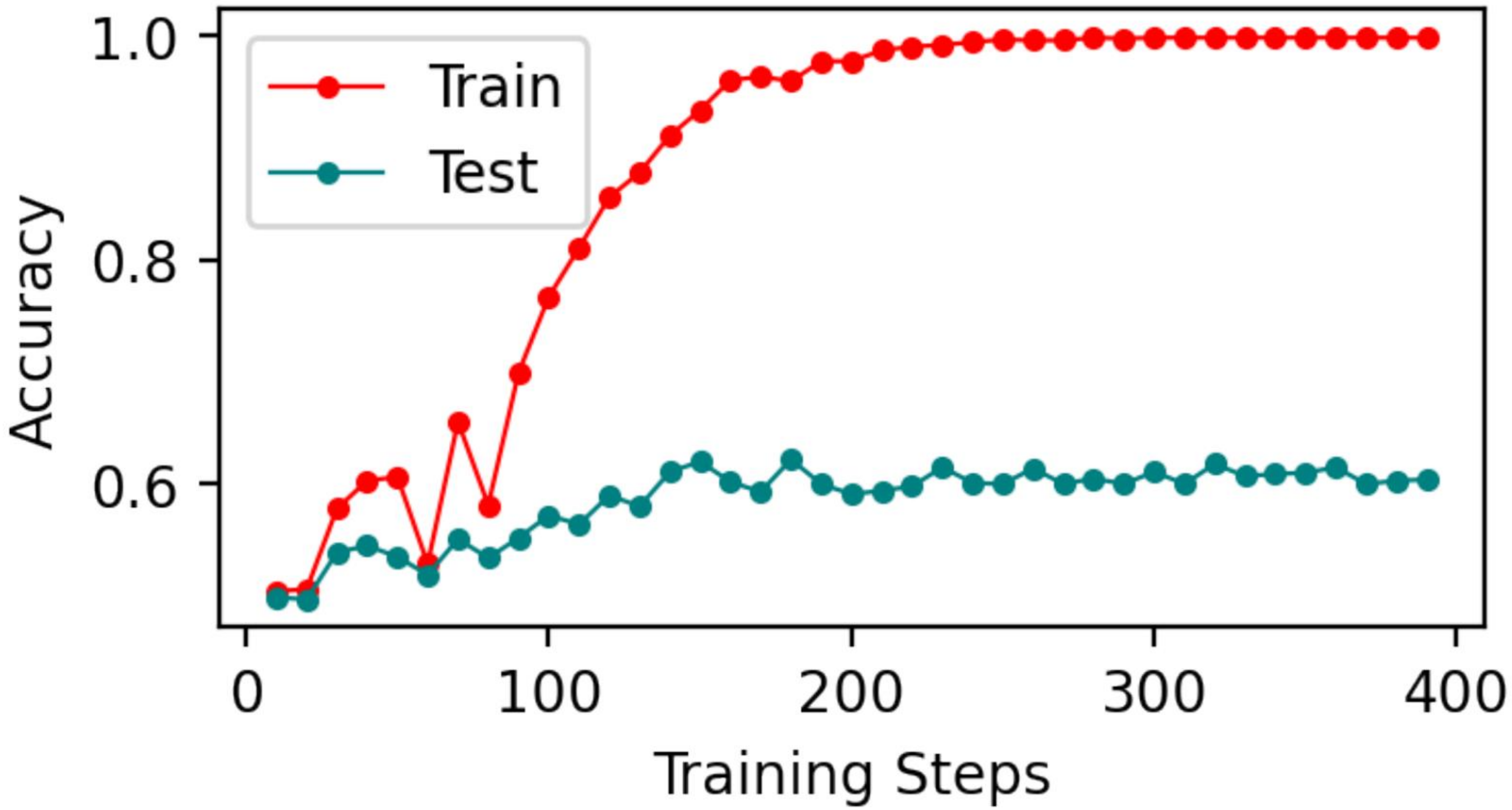
- **How Can We Say Instance Difficulty Can/Cannot Be Learned?**
  - **Step 0:** Define instance difficulty.
  - **Step 1**: We need some "difficulty" datasets.
  - **Step 2**: We use the training set to train a neural model and see if it can generalize to the test set.
- **Step 0 - Two Kinds of Difficulty**
  - **Human-defined difficulty**
    - Measures how difficult for human to judge its label.
  - **Model-defined difficulty**
    - Measures how difficult for a well-trained model to predict its label.

Human-defined Difficulty

- **Step 1: Data Construction**
  - In SNLI, the labels are determined by the majority of the crowd-sourced annotators. If there is no majority for an instance, its label would be “unknown".
  - We collect 1,119 “unknown” instances as **difficulty instances**, and randomly sample 1,119 **simple instances** from the SNLI training set.
  - Now, we have 2,238 instances with two labels (simple or difficult), and randomly sample 1,238 instances with balanced labels as **training set** and use the rest 1k instances as the **test set**.
- **Step 2: Training Models to Predict Instance Difficulty**
  - We train a `BERT-base-uncased` with a linear classifier on the top.

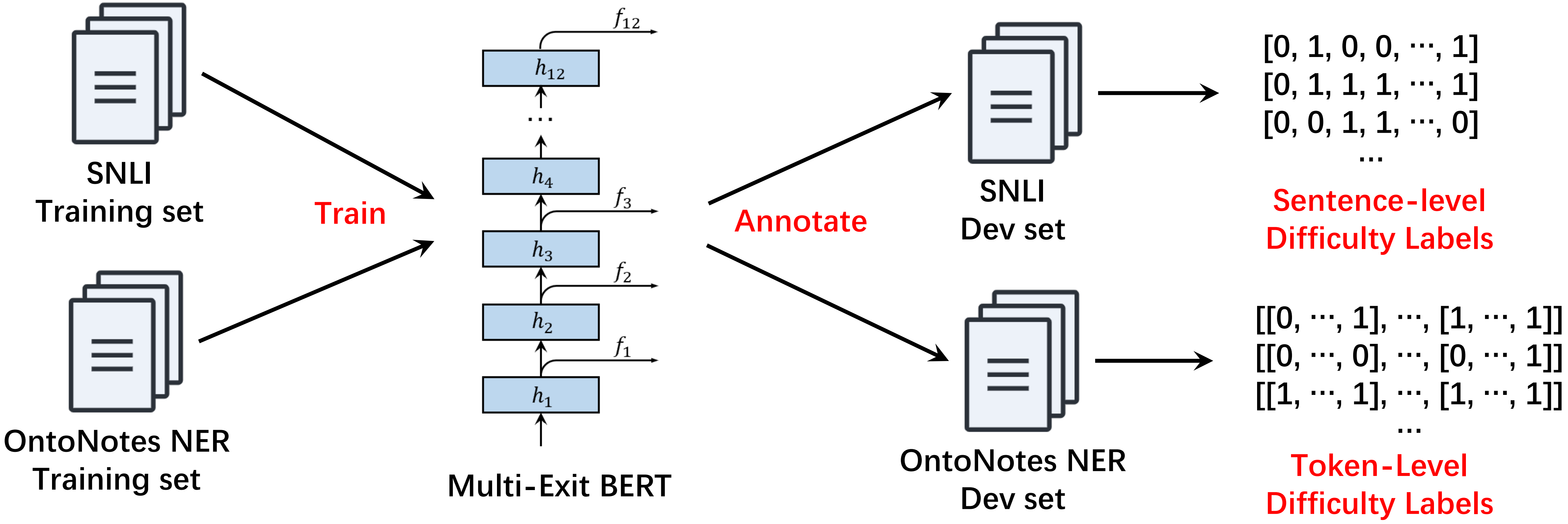
Human-defined Difficulty

- **Can We Learn to Predict Human-defined Difficulty?**
- **Almost no!**



Model-defined Difficulty

- **Step 1: Data Construction**
  - **Idea**: An instance can be defined as a difficult one if it can not be correctly predicted by a well-trained model.

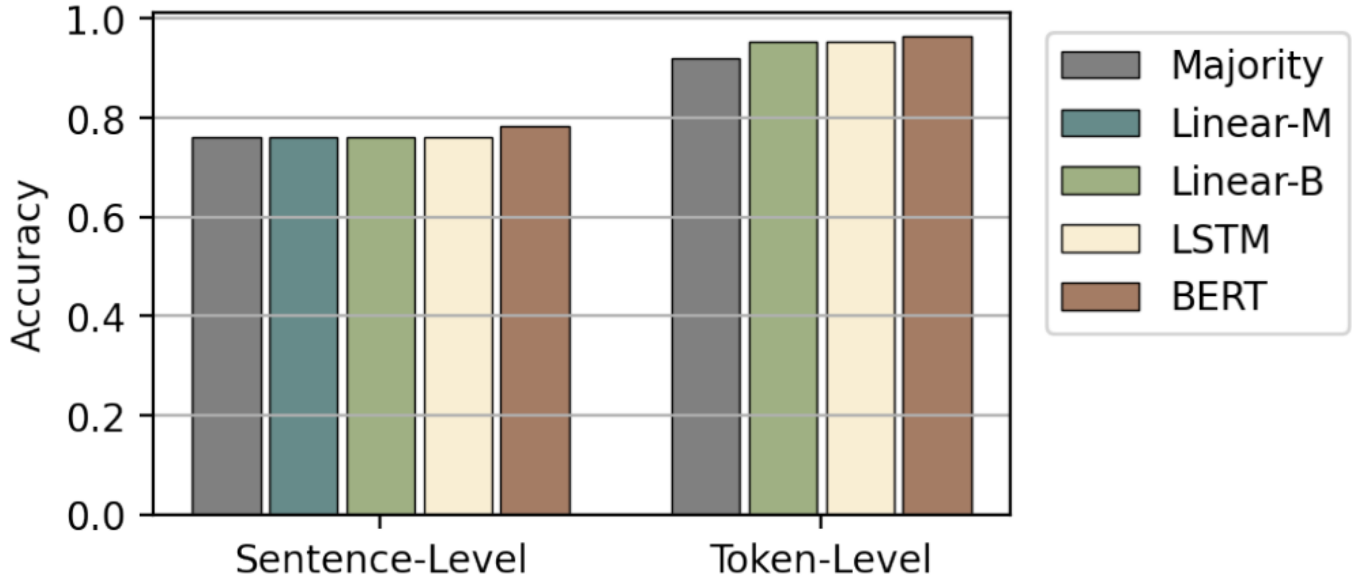


Model-defined Difficulty

- **Step 1: Data Construction**
  - **Idea**: An instance can be defined as a difficult one if it can not be correctly predicted by a well-trained model.
- **Step 2: Training Models to Predict Instance Difficulty**
  - **Majority**: Always predicts the majority class for each label.
  - **Linear-M**: A multi-classification linear layer that takes as input the average pooled word embeddings and outputs the exiting layer (1~12)
  - **Linear-B**: A binary classification linear layer that takes as input the hidden states at each BERT layer and outputs the difficulty label at this layer (0/1)
  - **LSTM**: Takes as input the instance and outputs the exiting layer (1~12)
  - **BERT**: Takes as input the instance and outputs the exiting layer (1~12)

Model-defined Difficulty

- **Can We Learn to Predict Model-defined Difficulty?**
- **Almost no!**



Model	Precision	Recall	F1 Score
Sentence-Level Difficulty			
Majority	60.5	36.7	45.7
Linear-M	54.8	42.1	47.6
Linear-B	52.9	45.3	48.8
BiLSTM	54.5	45.2	49.4
BERT	61.1	49.9	54.9
Token-Level Difficulty			
Majority*	-	-	-
Linear-B	56.6	38.7	46.0
BiLSTM	46.8	39.9	43.0
BERT	65.6	44.6	53.1

HashEE: Hash Early Exiting

- **What Is Unnecessary and What Works?**
  - **On the one hand,** our experiments show that instance difficulty is hard to be predicted.
  - **On the other hand,** learn-to-exit methods have achieved competitive results.
  - **There must be something works and it has nothing to do with estimating instance difficulty.**
  - Let's take a closer look at the learn-to-exit module

$$P(y|x) = \sum_{\substack{d \in D \\ \uparrow \\ \text{Difficulty (implies Architecture)}}} P(y|x,d)\underbrace{P(d|x)}_{\substack{\uparrow \\ \text{Learn-to-exit module}}}$$

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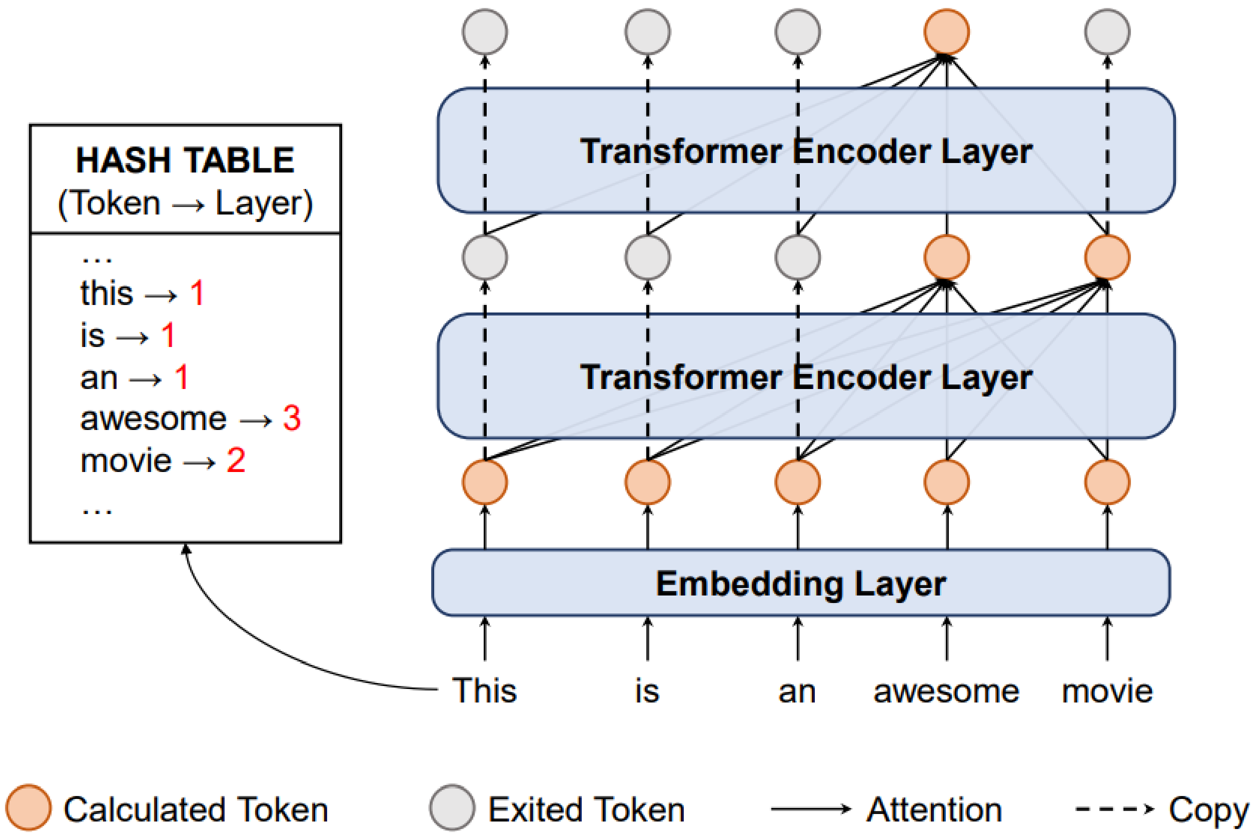
  - Let's take a closer look at the learn-to-exit module
  - **Consistency hypothesis:** *If a training instance x_i is predicted to exit at layer l, then an inference instance x_j that is similar with x_i should exit at layer l, too.*

↓

Can we just replace the neural learn-to-exit module with a simple hash function?

HashEE: Hash Early Exiting

- **HashEE**
  - **Assign tokens to fixed exiting layers using a hash function.**
  - **Considered hash functions:**
    - Random Hash
    - Frequency Hash
    - MI Hash
    - Clustered Hash
  - **Can be used for both NLU and NLG**



Experiments on NLU

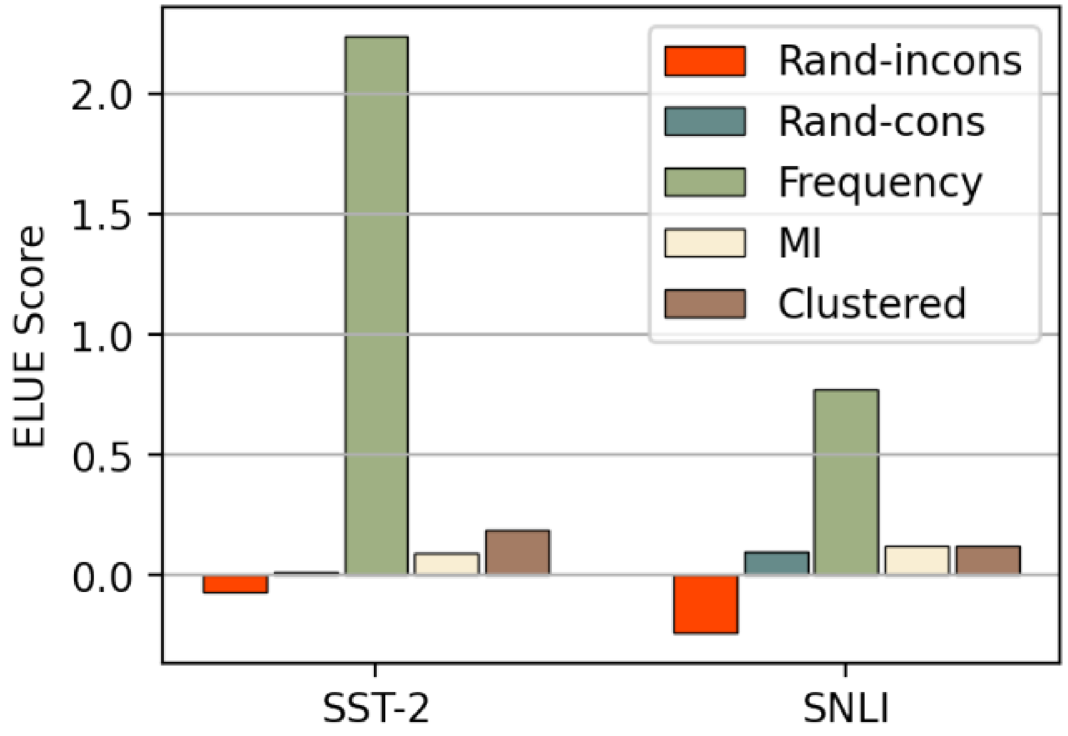
- **State-of-the-art on ELUE (A Benchmark for Efficient NLP)**

Models	**SST-2** (8.5k)	**IMDb** (20.0k)	**SNLI** (549.4k)	**SciTail** (23.6k)	**MRPC** (3.7k)	**STS-B** (5.7k)	**ELUE Score**
Pre-Trained Language Models							
BERT-3L	79.3 (4.0×)	88.4 (4.0×)	87.1 (4.0×)	84.3 (4.0×)	76.0 (4.0×)	75.8 (4.0×)	-3.70
ALBERT-3L	82.4 (3.6×)	90.7 (3.9×)	87.8 (3.7×)	87.5 (3.9×)	80.0 (3.6×)	79.1 (3.9×)	-1.59
RoBERTa-3L	81.8 (4.1×)	90.7 (4.2×)	88.0 (3.8×)	84.9 (3.9×)	75.6 (3.9×)	67.5 (3.9×)	-2.17
ElasticBERT-3L	84.1 (4.0×)	91.8 (4.0×)	89.3 (4.0×)	91.9 (4.0×)	83.1 (4.0×)	83.5 (4.0×)	0.00
Static Models							
DistilBERT	84.8 (2.0×)	92.0 (2.0×)	89.2 (2.0×)	89.7 (2.0×)	83.8 (2.0×)	81.7 (2.0×)	-2.55
TinyBERT	<u>85.3</u> (2.0×)	89.0 (2.0×)	89.3 (2.0×)	90.0 (2.0×)	**84.7** (2.0×)	**85.0** (2.0×)	-2.20
HeadPrune	84.8 (1.3×)	84.7 (1.5×)	87.8 (1.5×)	88.3 (1.5×)	77.8 (1.5×)	74.8 (1.5×)	-6.85
BERT-of-Theseus	84.4 (2.0×)	90.7 (2.0×)	<u>89.4</u> (2.0×)	<u>92.1</u> (2.0×)	82.4 (2.0×)	**85.0** (2.0×)	-2.55
Dynamic Models							
DeeBERT	78.9 (3.4×)	79.5 (4.1×)	48.1 (3.6×)	71.9 (3.4×)	79.1 (3.5×)	-	-
FastBERT	82.7 (3.7×)	**92.5** (3.5×)	88.8 (3.5×)	89.0 (3.6×)	80.3 (4.2×)	-	-
PABEE	83.1 (2.9×)	91.6 (3.4×)	88.7 (3.1×)	90.7 (3.3×)	75.2 (3.5×)	80.1 (3.2×)	-1.31
CascadeBERT	82.4 (3.8×)	91.8 (3.7×)	89.0 (3.6×)	91.7 (3.8×)	78.8 (3.8×)	-	-
BERxiT w/ BERT	71.8 (2.2×)	85.0 (2.8×)	88.4 (3.6×)	80.3 (3.4×)	74.9 (4.0×)	57.8 (4.0×)	-6.12
BERxiT w/ ElasticBERT	72.6 (4.4×)	91.2 (4.0×)	84.7 (3.9×)	91.0 (4.0×)	78.6 (4.3×)	81.5 (4.0×)	-3.90
Ours							
HashEE	**85.5** (**4.8**×)	<u>92.4</u> (**6.2**×)	**89.6** (**4.4**×)	**92.3** (**5.1**×)	<u>84.0</u> (**4.8**×)	84.3 (**4.6**×)	**1.20**

Experiments on NLU

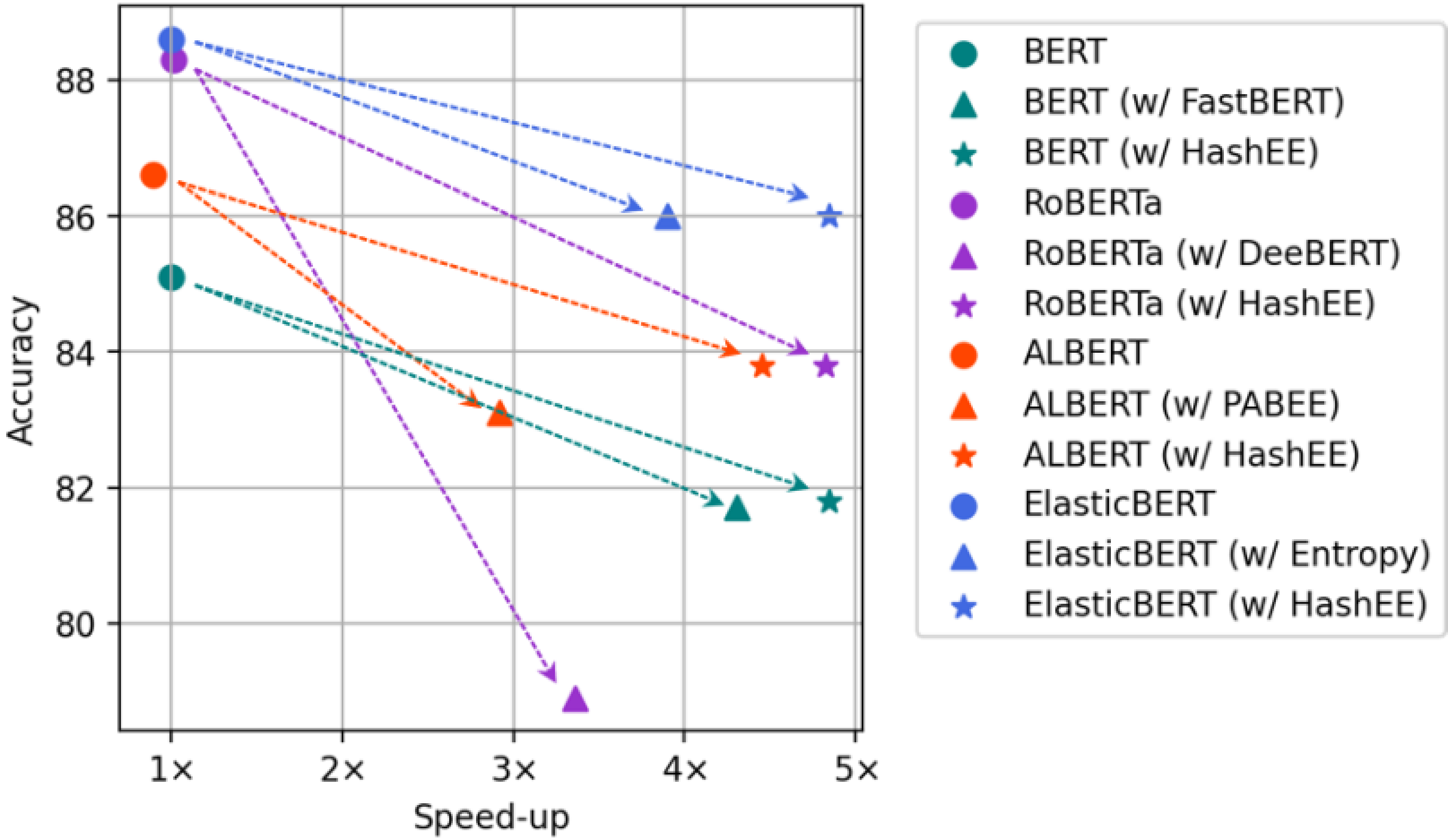
- **Effect of Hash Functions**

Hash Functions	Speed -up	SST-2 (8.5k)	SNLI (549.4k)	MRPC (3.7k)
Backbone: ElasticBERT-6L				
Rand-incons	3.0×	85.5 (±0.53)	89.7	85.0 (±0.22)
Rand-cons	3.0×	85.7 (±0.45)	90.1	86.3 (±0.67)
Frequency	4.9×	85.5 (±0.41)	89.6	84.0 (±0.27)
MI	3.3×	85.5 (±0.49)	90.0	86.0 (±0.23)
Clustered	3.0×	85.7 (±0.50)	90.2	86.3 (±0.47)
Backbone: ElasticBERT-12L				
Rand-incons	1.6×	85.7 (±0.38)	89.6	86.6 (±0.45)
Rand-cons	1.5×	86.5 (±0.37)	90.2	87.4 (±0.34)
Frequency	2.8×	85.6 (±0.37)	89.8	84.4 (±0.17)
MI	1.8×	86.6 (±0.17)	90.1	87.2 (±0.66)
Clustered	1.5×	87.0 (±0.54)	90.1	87.3 (±0.48)



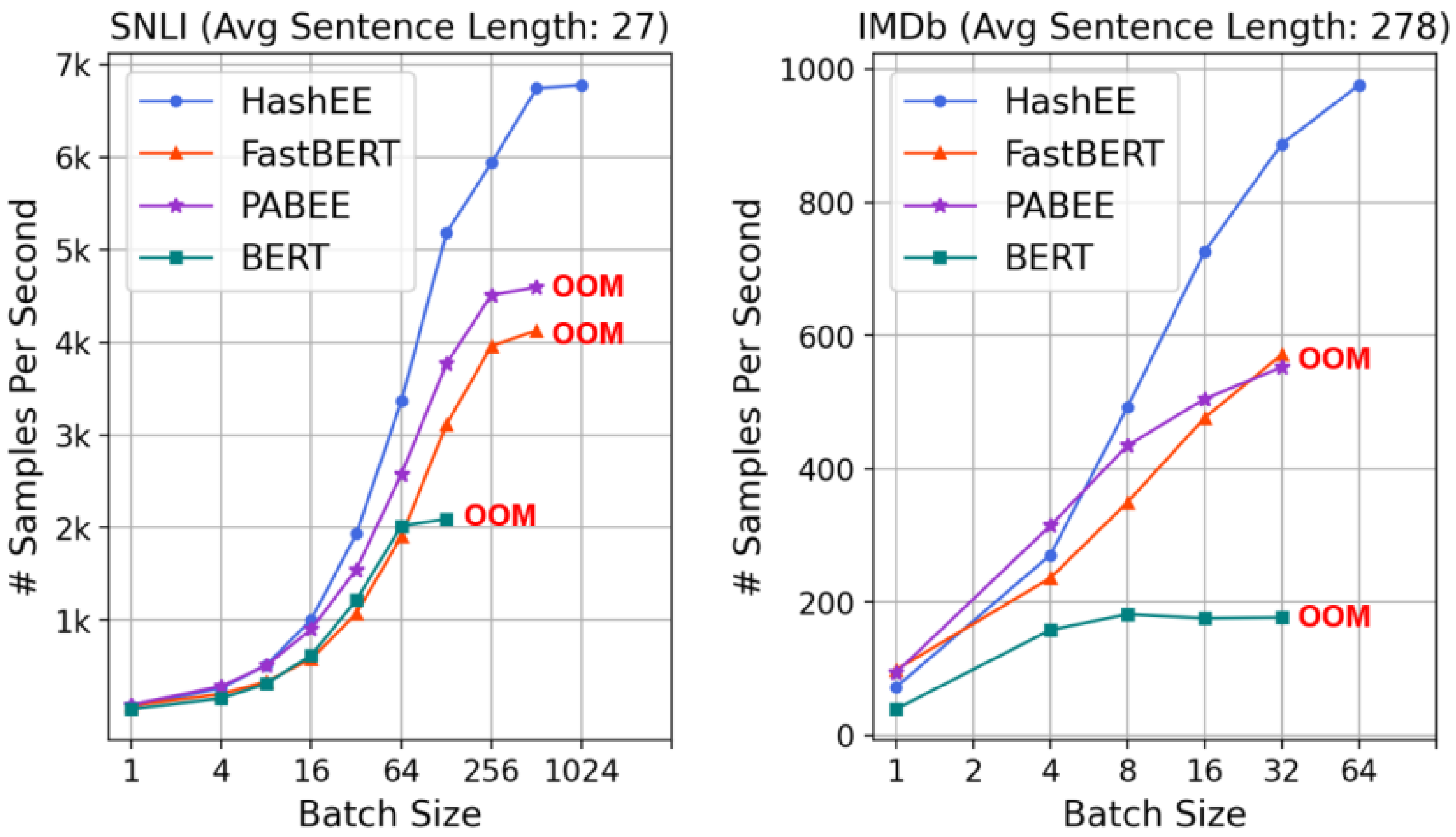
Experiments on NLU

- **Effect of Backbones**



Experiments on NLU

• **Comparison of Actual Inference Time**



Experiments on NLG

- **Results on 4 Summarization Datasets**

Model	Speed-up			English		Chinese	
	Enc.	Dec.	Total	Reddit	CNN/DM	CSL	TTNews
BART	1.0×	1.0×	1.0×	29.71/9.91/23.43	44.16/21.28/40.90	64.49/52.48/61.81	53.84/38.09/49.85
DAT	1.0×	0.5×	0.8×	27.02/**8.89/22.68**	40.30/17.77/37.53	-	-
BART-6L	2.0×	**1.4**×	**1.8**×	26.22/6.82/21.05	40.02/16.60/36.82		-
HashEE w/ BART	**3.3**×	1.0×	**1.8**×	**28.77**/8.52/21.97	**41.04/18.41/37.65**	-	-
CPT	1.0×	1.0×	1.0×	-	-	65.49/53.82/62.96	53.48/37.59/49.82
CPT-6L	2.0×	**1.2**×	1.9×	-	-	52.29/39.35/50.06	50.89/33.75/45.42
HashEE w/ CPT	**2.3**×	1.0×	**2.2**×	-	-	**62.42/49.96/59.15**	**52.67/35.31/46.97**

Thanks!