TLP: A Deep Learning-Based Cost Model for Tensor Program Tuning

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Introduction

- Tensor program tuning is a non-convex optimization problem that need to search.
- In searching, we need to know the performance of every tuned program.
  - [S1] We can measure online.
  - [S2] We can measure in advance and save in a table then look up.
  - [S3] We can predict online.

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  - [S3] We can predict online.
- S1 is too slow.
- S2 is impractical.
- So study on S3.

Introduction

- **Main problem:** program tuning is expensive on time consumption.
- **Goal:** reduce the tuning time and also keep tuning performance.

- Contribution1: A new cost model based on deep learning - TLP.
  - Extract features from the schedule primitives.
  - Take primitives as embeddings and the cost predicting task becomes a **natural language regression task**.

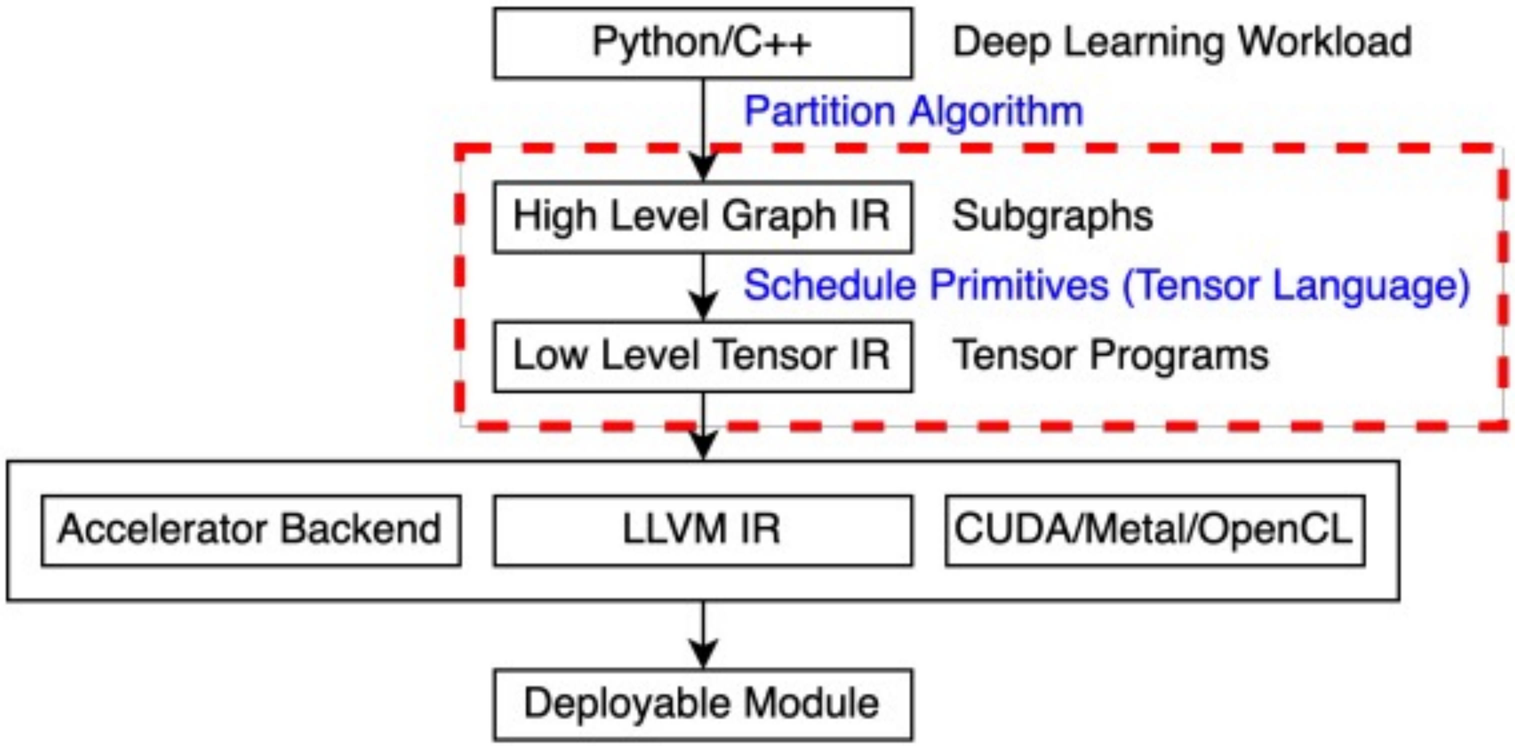
Introduction

- **Subordinate problem**: cross-hardware unavailability of cost model.
- **Goal**: cost model can perform well cross various hardware with few training data.

- Contribution2: A novel method to train cost model with cross-hardware availability based on multi-task learning – MTL-TLP.
  - Extend TLP model to a multi-task learning model aka. MTL-TLP.

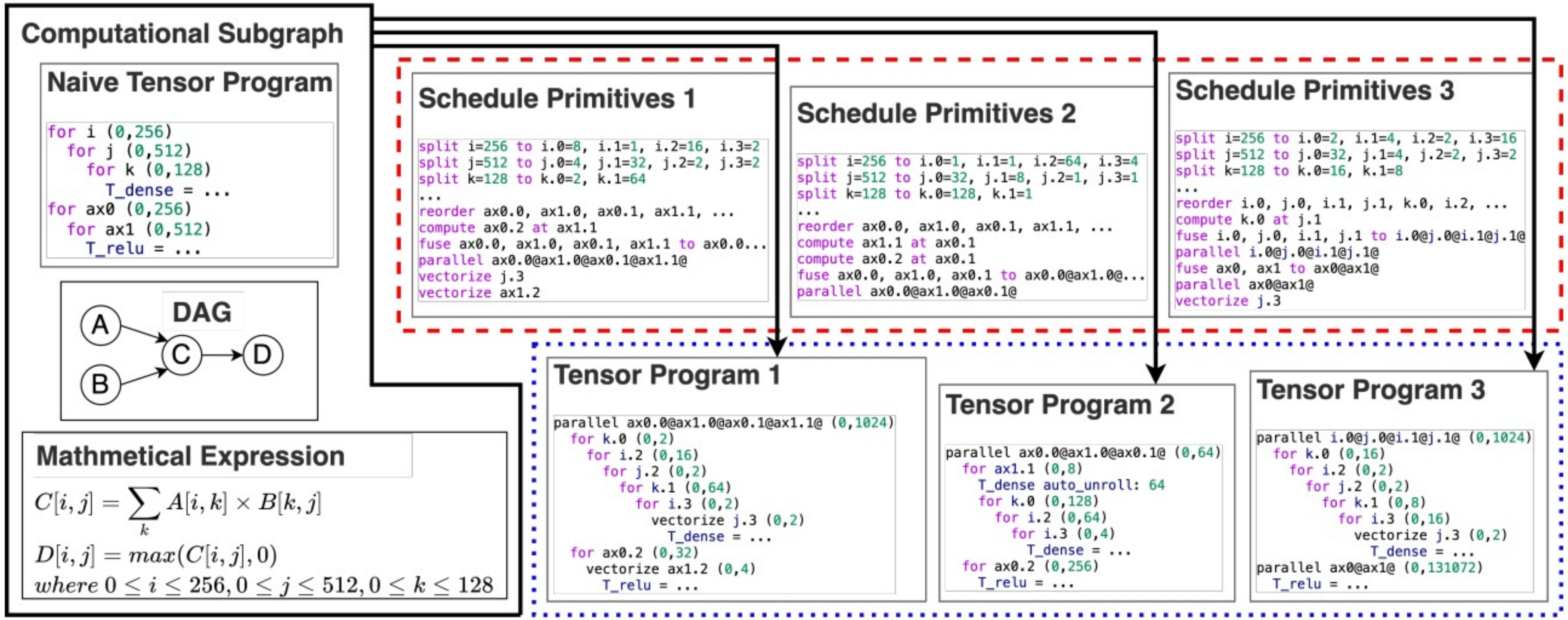
Background

- Deep learning program tuning



Background

- Deep learning program tuning



Background

- Cost models

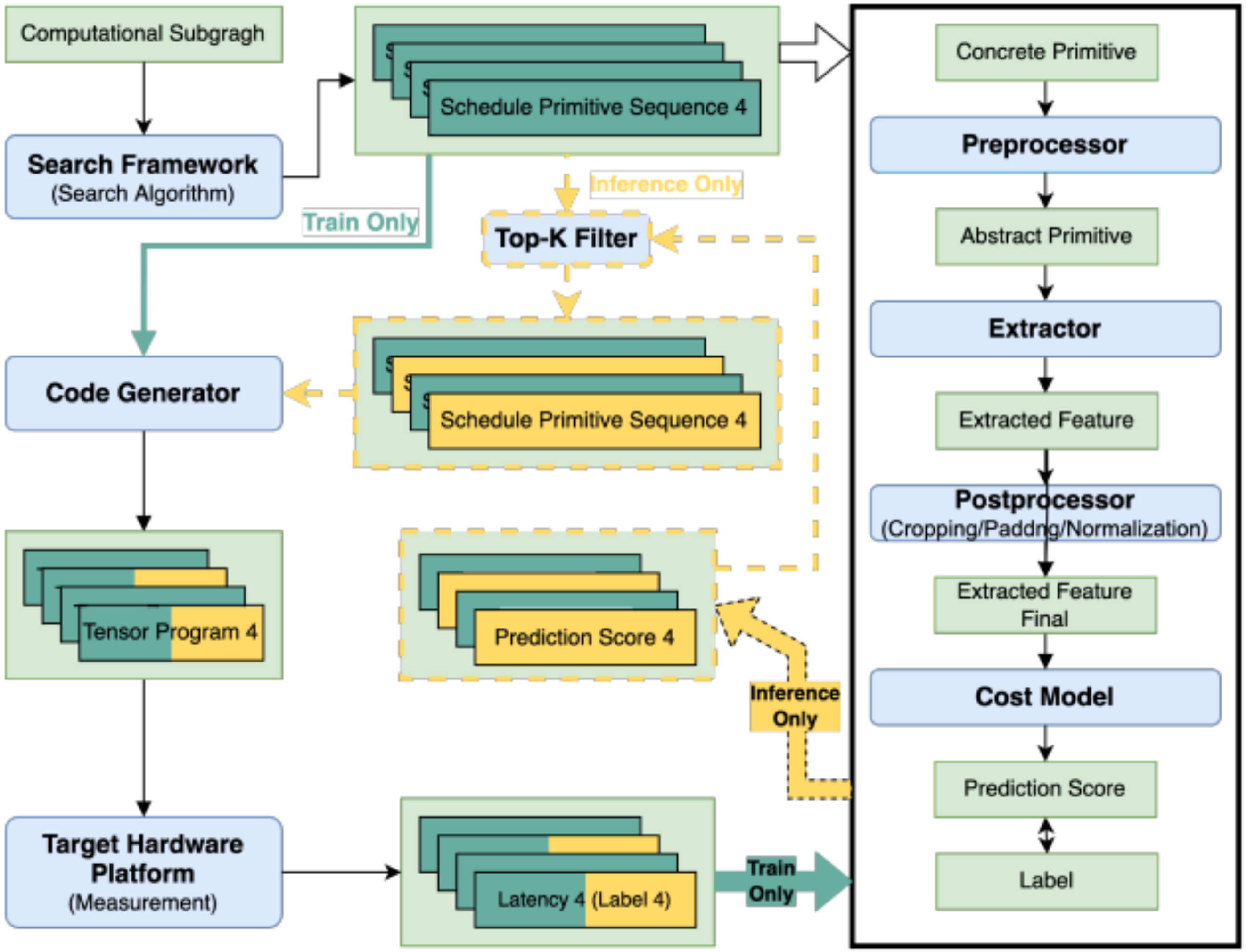
Cost Model	Representative Works
Empirical Formula Cost Model	Halide16 [25]
Online Learning Cost Model	AutoTVM [11], Ansor [38], Chameleon [2], FlexTensor [40], Halide20 [1, 3]
Offline Learning Cost Model	TenSet, TIRAMISU cost model, The work of Benoit Steiner et al. [30]

Hard to modeling.

Extra overhead in tuning.

Extract features from tensor program.

System overview



TLP

- Extract features from primitive schedules.
  - Avoid generating tensor programs and reduce tuning time.
  - Features from primitive schedules are enough for predicting.

(PrimitiveSequence)	S	$::=$	p^*
(Primitive)	p	$::=$	τ (id | num)*
(PrimitiveType)	$\mathbf{T} \ni \tau$	$::=$	split | reorder | fuse | ...
(NameParam)	id		
(Number)	num		

(a) Abstract Schedule Primitive Sequence

(Features) $f = F(p) \quad ::= \quad F_1(\tau)\ (F_2(\text{id}) | F_3(\text{num}))^*$

F : Primitive $\longrightarrow$ Features

F_1 : PrimitiveType $\longrightarrow$ OnehotVector

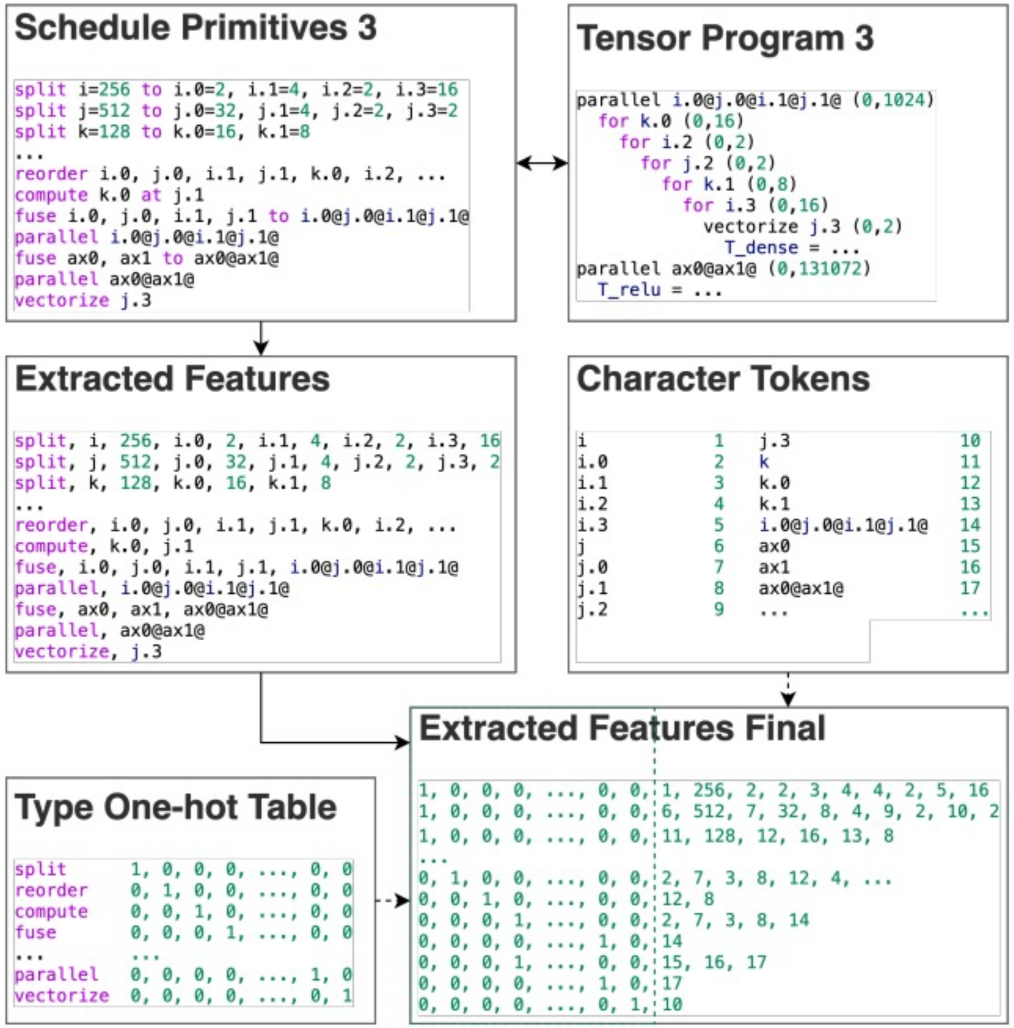
F_2 : NameParam $\longrightarrow$ Token

F_3 : Number $\longrightarrow$ Number

(b) TLP Extractor

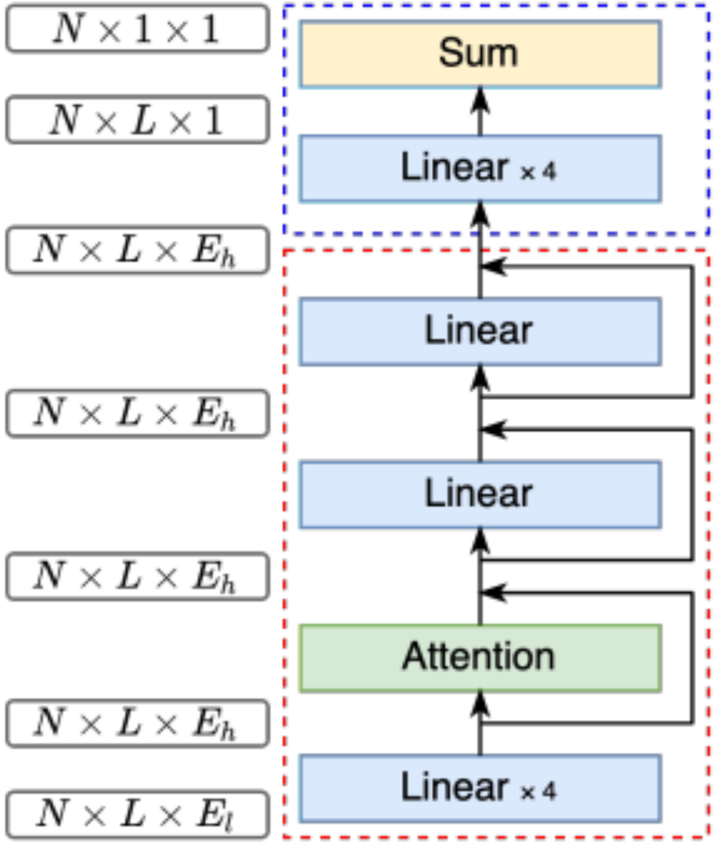
TLP

- Extraction processing



TLP

- Cost model



Train on TenSet dataset.
Using MSE loss or rank loss.

TLP

- Performance

$$top - k = \frac{\sum_m \sum_s min\_latency_{m,s} \times weight_{m,s}}{\sum_m \sum_s \min\left(latency_{m,s,i}\right) \times weight_{m,s}}, 1 \le i \le k$$

s: subgraph index
m: model index
i: predicting rank
weight_m,s: the number of times the subgraph s appears in model m

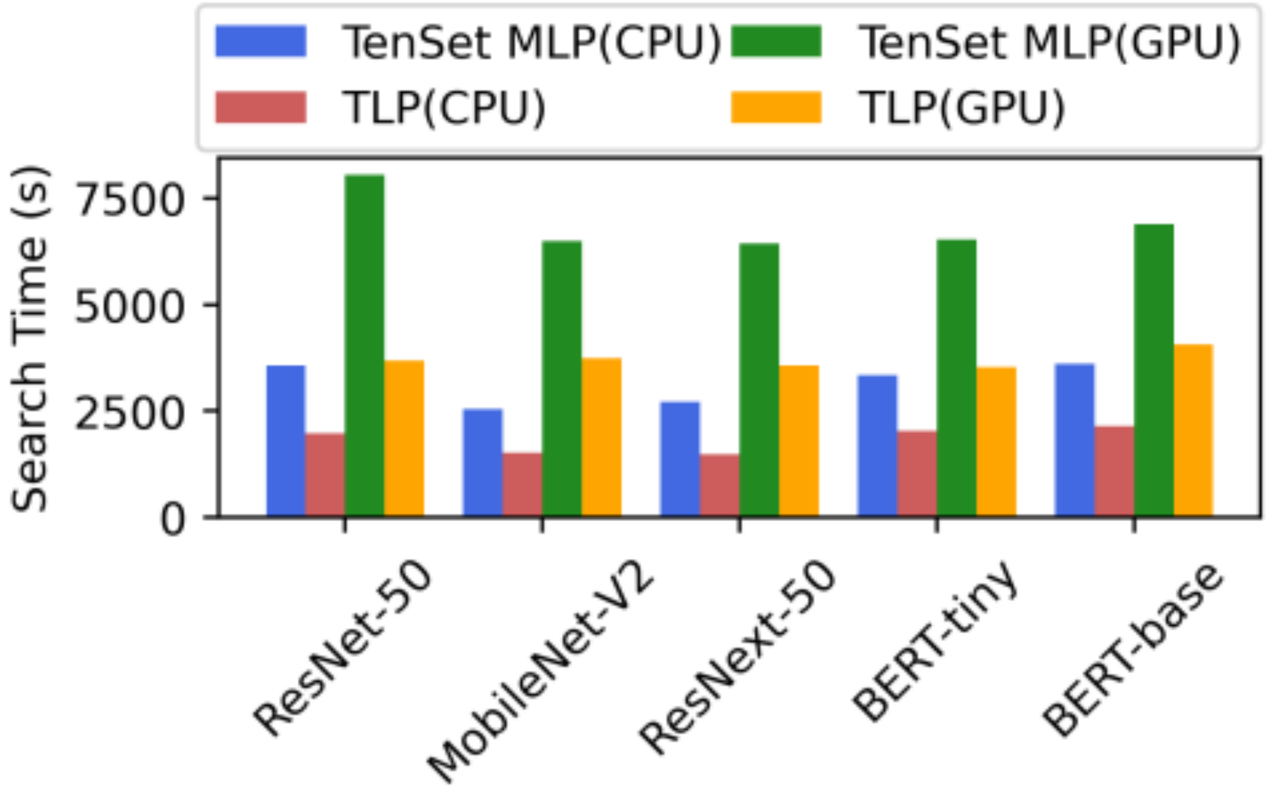
TLP

- Performance

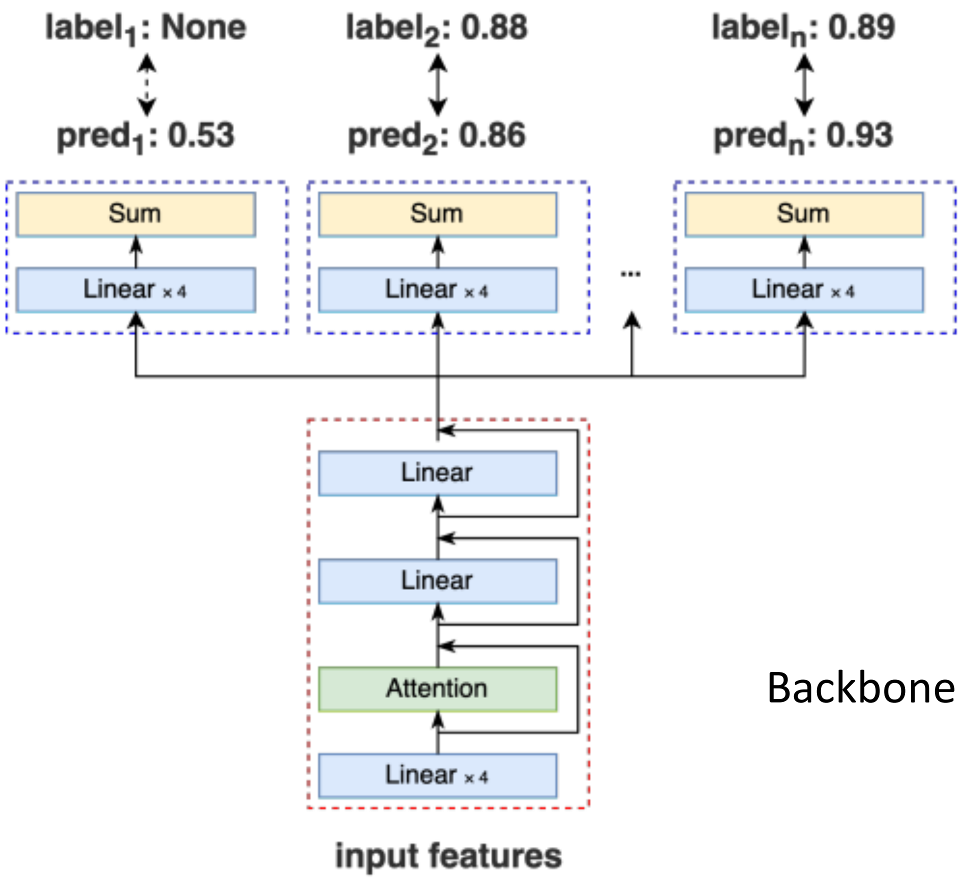
	TenSet		Ours	
	Top-1 Score	Top-5 Score	Top-1 Score	Top-5 Score
Intel Platinum 8272CL @ 2.60GHz (16 cores)	0.8748	0.9527	**0.9194**	**0.9710**
Intel E5-2673 v4 @ 2.30GHz (8 cores)	0.8332	0.8977	**0.8941**	**0.9633**
AMD EPYC 7452 @ 2.35GHz (4 cores)	0.8510	0.9175	**0.9055**	**0.9494**
ARM Graviton2 (16 cores)	0.7799	0.9049	**0.8207**	**0.9226**
Intel i7-10510U @ 1.80GHz (8 cores)	0.7776	0.8590	**0.8473**	**0.9427**
NVIDIA Tesla K80	**0.9083**	0.9629	0.9059	**0.9741**
NVIDIA Tesla T4	0.8757	**0.9528**	**0.8847**	0.9250

TLP

Tune 2000 times:



MTL-TLP



Each head is work for a specific platform.

Backbone is shared cross platforms.

MTL-TLP

		Top-1 Score	Top-5 Score
E5-2673	500K	0.6647	0.8848
E5-2673 Platinum-8272	500K ALL	0.8741	0.9385
E5-2673 Platinum-8272 EPYC-7452	500K ALL ALL	**0.8901**	**0.9520**
E5-2673 Platinum-8272 EPYC-7452 Graviton2	500K ALL ALL ALL	0.8753	0.9302

		Top-1 Score	Top-5 Score
i7-10510U Platinum-8272	500K ALL	**0.8413**	0.9202
i7-10510U E5-2673	500K ALL	0.8331	**0.9672**
i7-10510U EPYC-7452	500K ALL	0.8082	0.9122
i7-10510U Graviton2	500K ALL	0.7711	0.8909

		Top-1 Score	Top-5 Score
Tesla T4	500K	0.7971	0.8984
Tesla T4 Tesla K80	500K ALL	**0.8876**	**0.9373**

Inspiration

- AI achievements transfer to system.

- **An idea**: I think the method is relied on the programmer for character name is designed by programmer and has logical relationship between different codes. [Possible Solution] Maybe an extra preprocessing that formatting schedule primitives can work.

Thank You!

Mar 9, 2023

Presented by Mengyang Liu