# Improving Event Duration Question Answering by Leveraging Existing Temporal Information Extraction Data



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#### Introduction

**Duration Question Answering:** McTACO (Zhou et.al, 2019)

If you have ever heard, "Eat a good breakfast", thats why. How long does it take to **eat breakfast**?

- 15 minutes
- ✓ plausible
- several days
- × not plausible
- 20 minutes
- ✓ plausible

The performance of modern pre-trained NLP models for this task is still far behind humans due to limited training data.

There are plenty of auxiliary resources containing duration information, e.g. UDS-T dataset (Vashishtha et.al., 2019), that can be used to improve McTACO.

However, a straightforward two-stage fine-tuning is less likely to succeed since there are discrepancy between the two tasks:

- UDS-T : Duration Unit Classification
- McTACO: Duration Question Answering

We need to bridge the discrepancy between the two tasks.

### **Duration Task Recasting**

We bridge the discrepancy by recasting Duration Information Extraction dataset into Question Answering.

#### **UDS-T Duration Classification**

# Their worker even cleaned 3 of my windows and changed a lightbulb for me. event: changed label: minutes 78 88 event: cleaned label: hours

**Duration Span Timeline** 

#### **Recasting Steps:**

- 1. Irrelevant Contexts Removal
- 2. Question Generation
- 3. Candidate Answer Generation
  - Positive answer generation
  - Negative answer generation

#### **UDS-T Duration QA**

Their worker even cleaned 3 of my windows and changed a lightbulb for me.

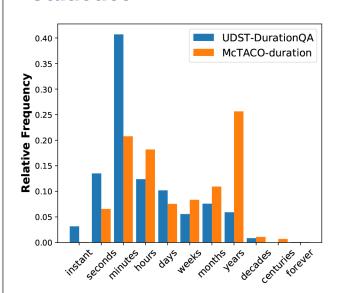
How long does it take for their worker to clean 3 of my windows?

- 2 hours
- ✓ plausible
- a few hours
- ✓ plausible

plausible or not

- several years4 months
- not plausiblenot plausible

#### **Statistics**



The duration distribution of our recast data is relatively similar to McTACO, except for *minutes* and *years*.

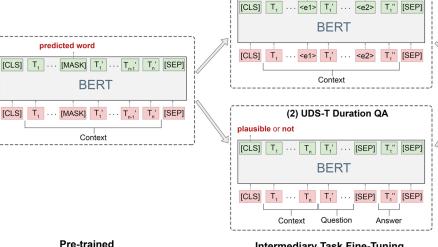
#### Number of QA pairs

train +	dev	test
McTACO-duration: 1.1k		3.0k
UDST-DurationQA: 39.9k +	+ 4.9k	4.8k

## **Experiments**

100





Language Model

Intermediary Task Fine-Tuning (1) or (2)

(1) UDS-T Duration Classification

duration label duration label

Target Task Fine-Tuning (McTACO Duration QA)

**BERT** 

#### Results

Model	EM	F1
RoBERTa-large → McTACO-duration	40.45	67.42
RoBERTa-large → UDS-T (duration cls.) → McTACO-duration	39.49	64.95
RoBERTa-large → UDST-DurationQA (unit only) → McTACO-duration	42.78	66.97
RoBERTa-large → UDST-DurationQA → McTACO-duration	45.86	70.52

# -Additional Experiments

Are the setups that leverage two-stage fine-tuning more effective than multi-task learning?

Model	EM	F1
Two-stage Fine-tuning	45.86	70.52
Multi-task Learning	41.72	66.93

How does our proposed method compare to a SOTA pretrained temporal common sense language model?

Model	EM	F1
TACOLM (Zhou et. al., 2020) → McTACO	34.60	-
BERT-base → McTACO	33.76	60.98
BERT-base → UDST-DurationQA → McTACO	36.52	63.22