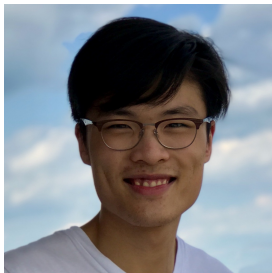
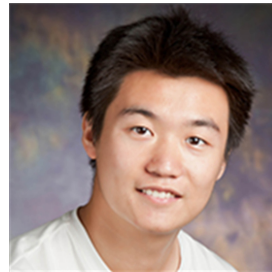




Temporal Common Sense Acquisition with Minimal Supervision



Ben Zhou



Qiang Ning*

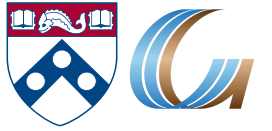


Daniel Khashabi*



Dan Roth

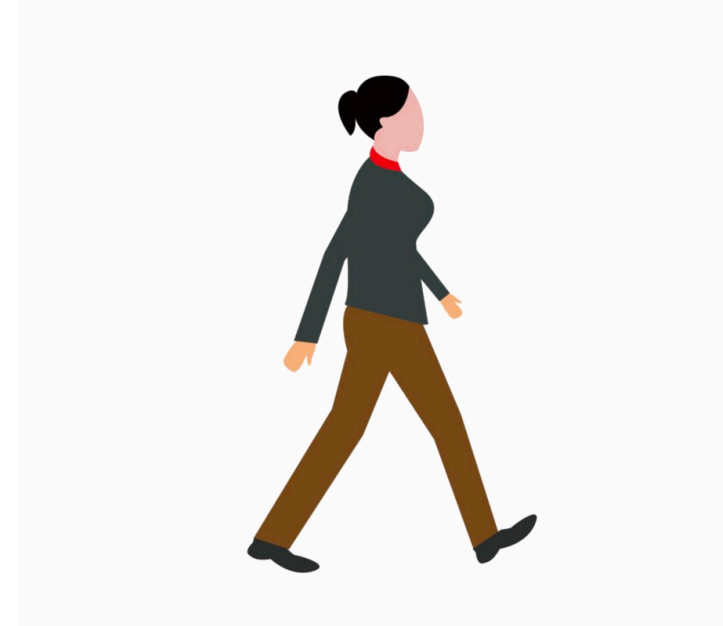
Time and Common Sense



- Choose from “*will*” or “*will not*”

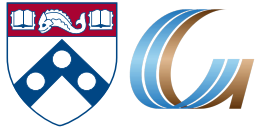


Dr. Porter is **taking a vacation** and
___ be able to see you soon.



Dr. Porter is **taking a walk** and
___ be able to see you soon.

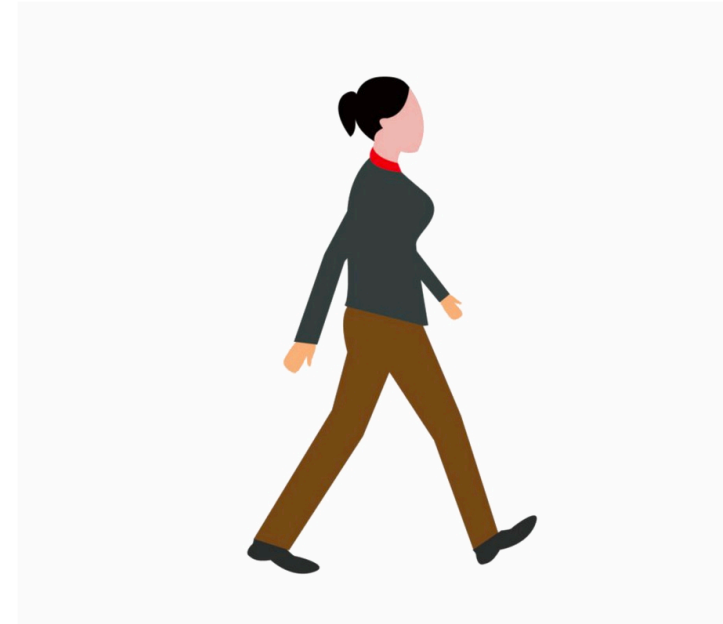
Time and Common Sense



- Choose from “*will*” or “*will not*”

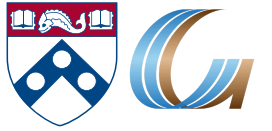


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Time and Common Sense



- Choose from “*will*” or “*will not*”

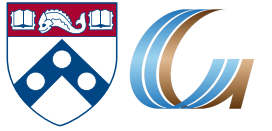


Dr. Porter is **taking a vacation** and will not be able to see you soon.



Dr. Porter is **taking a walk** and ____ be able to see you soon.

Time and Common Sense



- Choose from “*will*” or “*will not*”

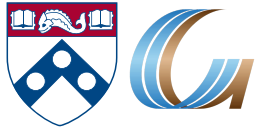


Dr. Porter is **taking a vacation** and will not be able to see you soon.



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Time and Common Sense



- Choose from “*will*” or “*will not*”

www.iconexperience.com



Dr. Porter is **taking a vacation** and will not be able to see you soon.

Time:

- An important component for reading comprehension
- Commonsense-level understanding is required



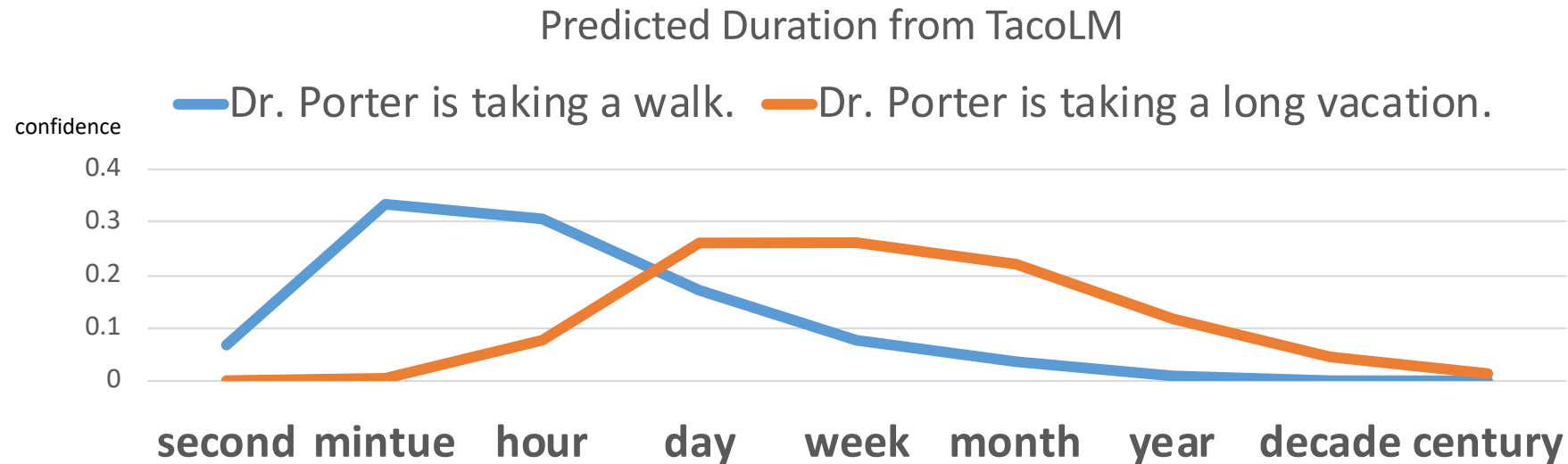
Dr. Porter is **taking a walk** and will be able to see you soon.

■ Time

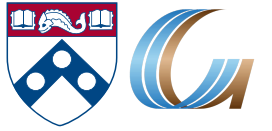
- ☐ An important component for reading comprehension
- ☐ Commonsense-level understanding is required

■ In this work

- ☐ TacoLM – A general LM that is aware of time and temporal common sense
 - Minimal Supervision



Time and Common Sense



■ Time

- ☐ An important component for reading comprehension
- ☐ Commonsense-level understanding is required

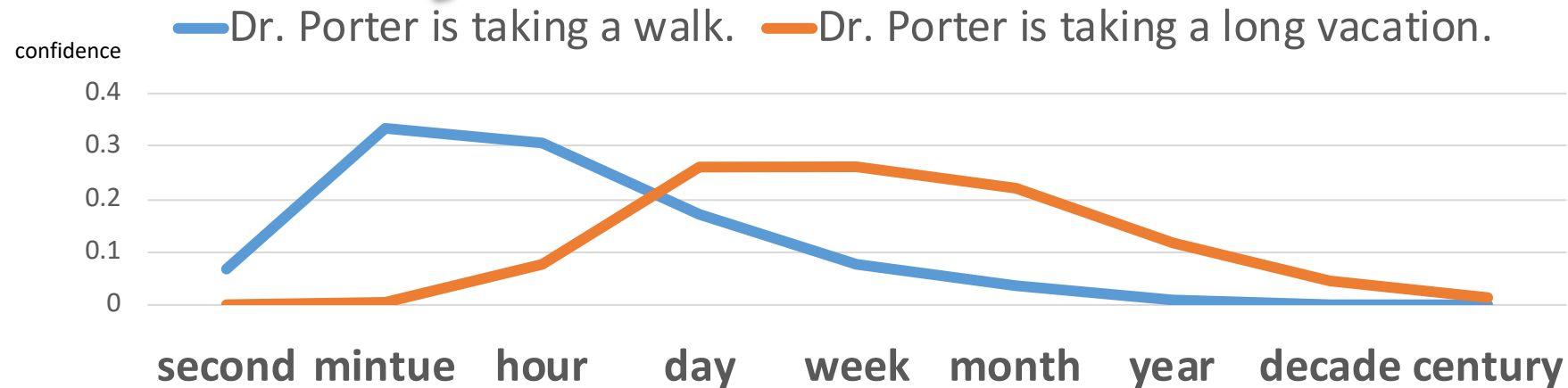
■ In this work

- ☐ TacoLM - aware of time and temporal common sense

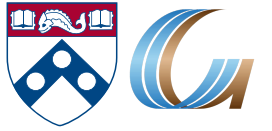
- Minim

Dr. Porter is
coming back
shortly.

Predicted Duration from TacoLM



Time and Common Sense



■ Time

- ☐ An important component for reading comprehension
- ☐ Commonsense-level understanding is required

■ In this work

☐ TacoLM

■ Minim

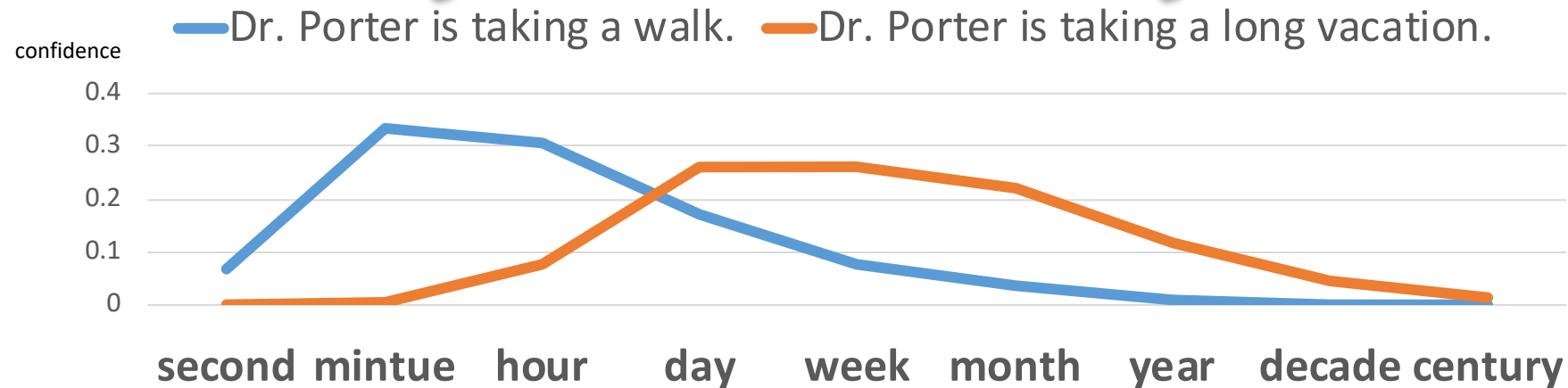
Dr. Porter is coming back shortly.

aware of time and

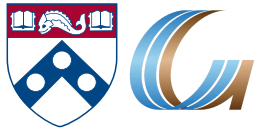
She may not be back for days.

sense

Predicted Duration from TacoLM



Acquiring Temporal Common Sense



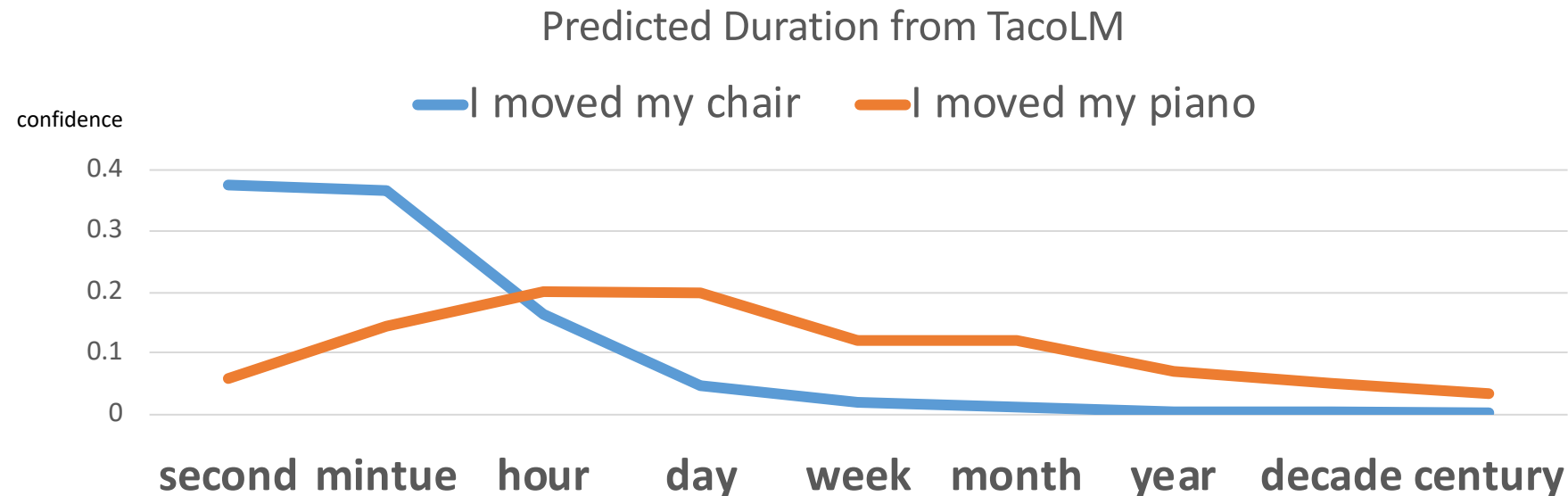
■ Challenging

□ Reporting Biases:

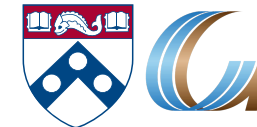
- people rarely mention the common sense to be efficient *"It took me 2 seconds to move my chair"*
- Sometimes highlight rarities *"It took me an hour to move my chair"*

□ Highly Contextual:


- The duration of "Move" depends on the object's weight/size.




TacoLM – the Big Picture



Step 1: Information Extraction

- 
- Use high-precision patterns to acquire temporal information
 - Unsupervised automatic extraction
 - Overcomes reporting biases with a large amount of natural text

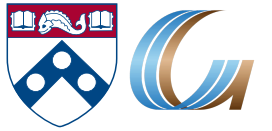
Step 2: Joint Language Model Pre-training

- 
- Multiple temporal dimensions
 - Duration \sim 1 / Frequency
- “I brush my teeth every morning”
- Duration of “brushing teeth” < morning
- Further generalization to combat reporting biases

Output: TacoLM- a time-aware general BERT

Goal: build a general time-aware LM with minimal supervision

Step 1: Information Extraction



Step 1: Information Extraction

Step 2: Joint Language Model Pre-training

Output: TacoLM- a time-aware general BERT

■ Use high-precision patterns based on SRL

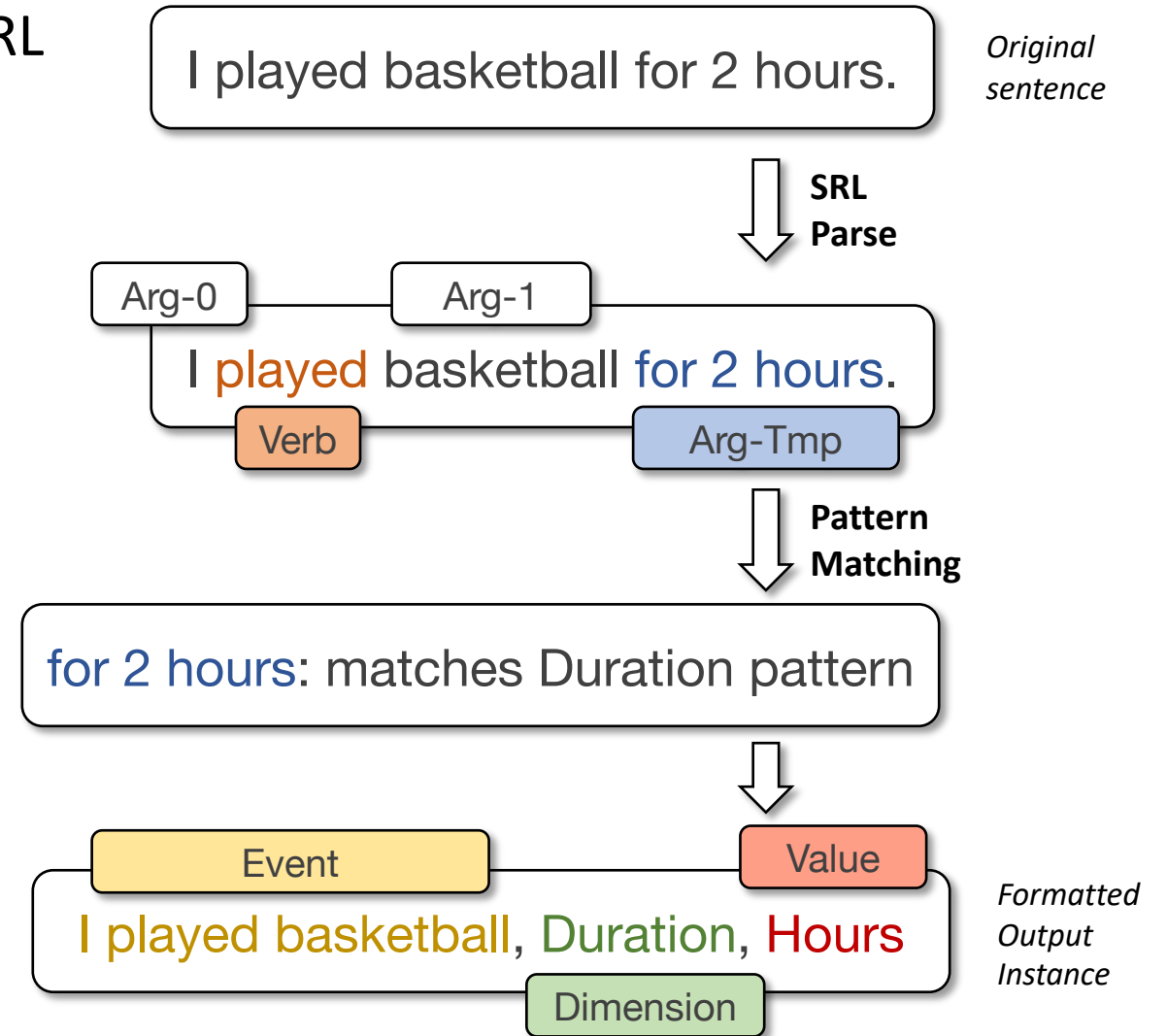
- ☐ Duration
- ☐ Frequency
- ☐ Typical Time
- ☐ Duration Upperbound
- ☐ Hierarchy

■ Labels

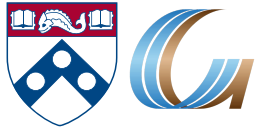
- ☐ Units (seconds, ... centuries)
- ☐ Temporal keywords (Monday, January, ...)

■ Output

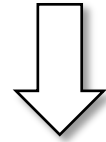
- ☐ 4.3M instances of
(event, dimension, value) tuple



Step 2: Language Model Pre-training



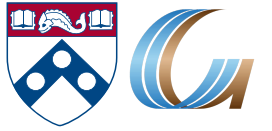
Step 1: Information Extraction



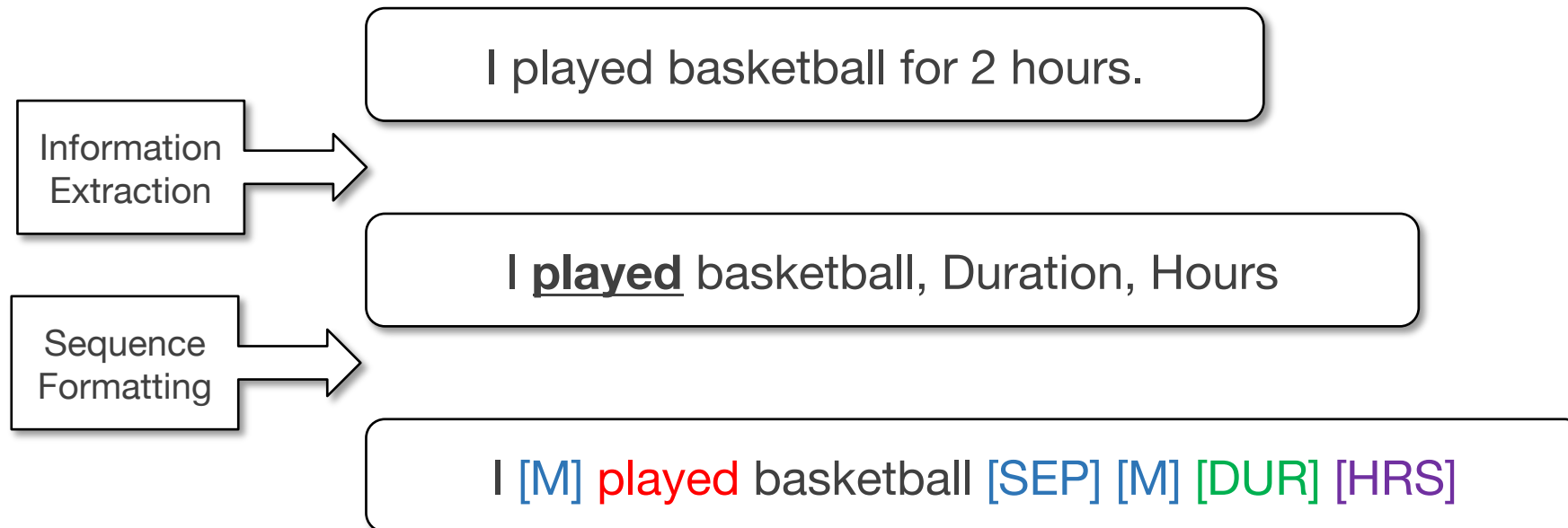
Step 2: Joint Language Model Pre-training

Output: TacoLM- a time-aware general BERT

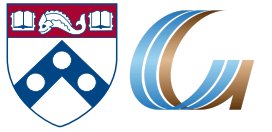
Sequence Classification



- Consider [Event] [Dimension] [Value] tuples in each instance
- [E1, E2, ... M, ET ... En, SEP, M, Dim, Val]
 - M is a special marker, same across all dimension/value
 - Dim is a marker for each dimension, Val is a marker for the value of the dimension
- With an example:



Joint Model with Masked LM



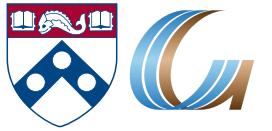
I [M] played basketball [SEP] [M] [DUR] [HRS]

- Baseline Model: Pre-trained BERT-base
- Main objective: mask some tokens and recover them
- How we mask:
 - With some probability, mask **temporal value** while keeping others

I [M] played basketball [SEP] [M] [DUR] [MASK]
 - Otherwise, mask a certain portion of E1...En while keeping **temporal value** unchanged

I [M] [MASK] [MASK] [SEP] [M] [DUR] [HRS]
 - $\text{Max} (P(\text{Event} | \text{Dim}, \text{Val}) + P(\text{Val} | \text{Event}, \text{Dim}))$; Preserving original LM capability
- Benefits:
 - Jointly learn **one** transformer towards **all** dimensions
 - Labels play a role in the transformer
 - One event may contain more than one (Dim + Val), so the model learns dimension relationships

Joint Model with Masked LM



I [M] played basketball [SEP] [M] [DUR] [HRS]

■ 1: Soft cross entropy for recovering Val

- If gold label is “hours”, the label vector \mathbf{y} for “minutes, hours, days” will be [0.16, 0.47, 0.25]

$$\hat{\mathbf{x}} = \log(\text{softmax}(\mathbf{x}))$$

$$\text{loss} = -\hat{\mathbf{x}}^\top \mathbf{y}$$

■ 2: Label weight adjustment

- Instances with “seconds” have higher loss than those with “years”

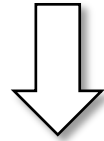
■ 3: Full event masking

- Instead of 15% used by BERT, we use 60% when masking E1, ... E_n to reduce biases

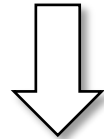
I [M] had a cup of [MASK] [SEP] [M] [TYP] [Evening] → MASK = coffee, because “cup of”

I [M] had [MASK] [MASK] of [MASK] [SEP] [M] [TYP] [Evening]

Step 1: Information Extraction

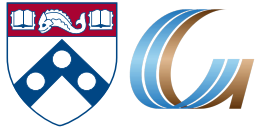


Step 2: Joint Language Model Pre-training

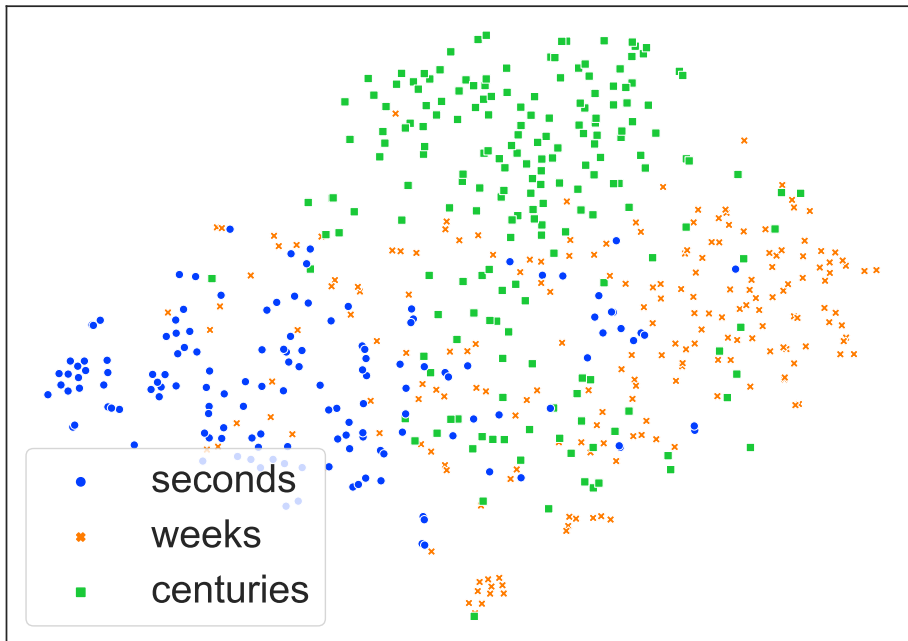


Output: TacoLM- a time-aware general BERT

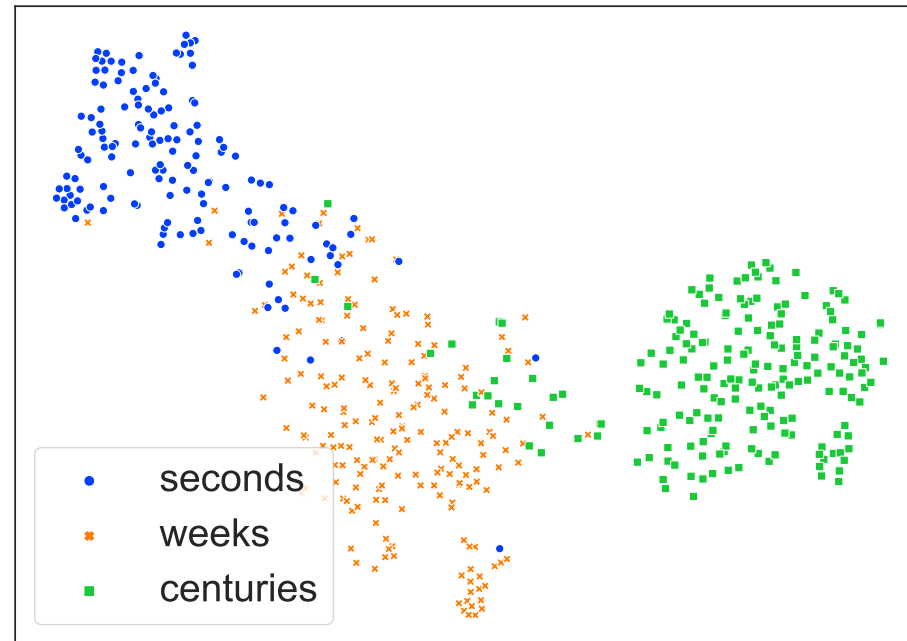
Evaluation: Intrinsic (Embedding space)



- A collection of events with duration of “seconds,” “weeks” or “centuries” (three extremes)
- BERT (left), Ours (right) representation on the event’s trigger
 - PCA + t-SNE to 2D visualization
- Our model separates the events much better (➔ our model is aware of time)

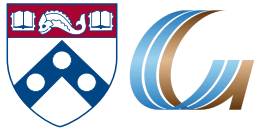


BERT

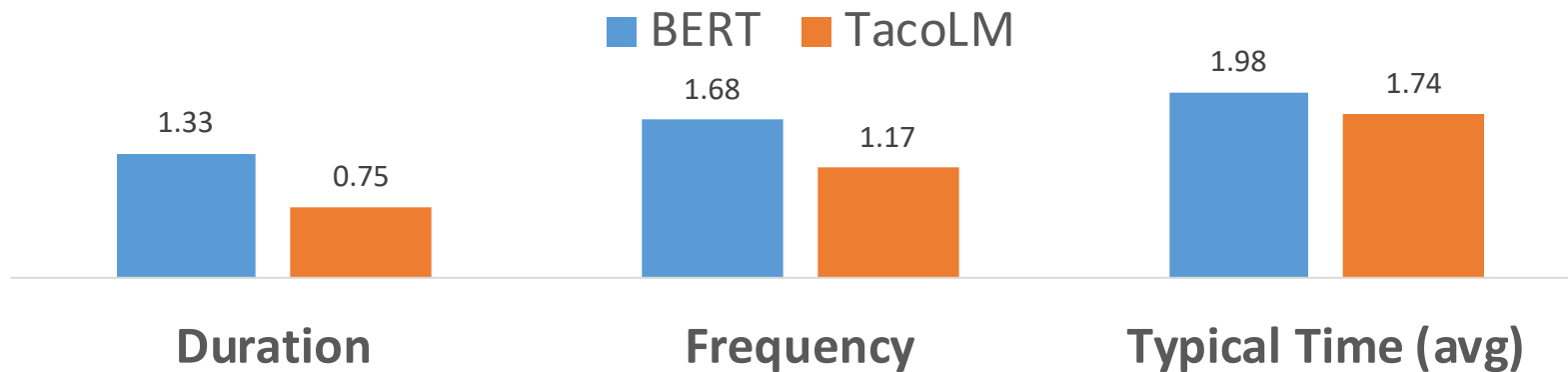


TacoLM

Evaluation: Intrinsic (Quantitatively)

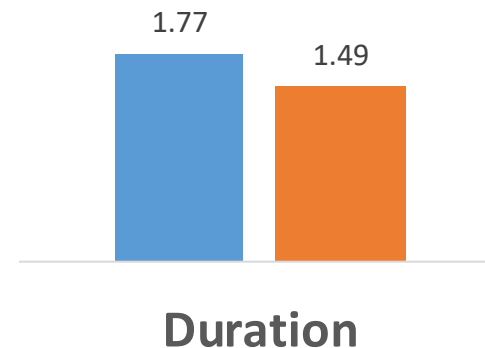


- Metric: Distance to gold label
 - Dist (seconds, hours)=2, Dist (minutes, hours)=1
 - **Lower the better**
- RealNews [Zellers et al. 2019]: no document overlap
 - Raw corpus + MTurk annotation

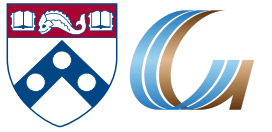


19% average improvement

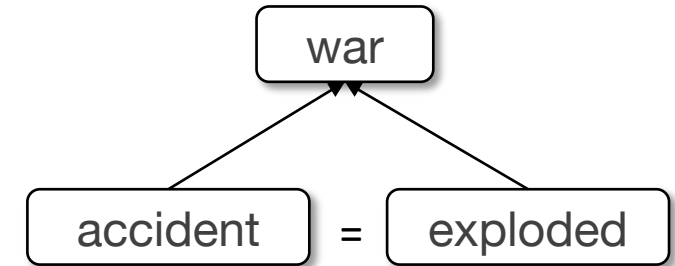
- UDS-T [Vashishtha et al. 2019]: duration only



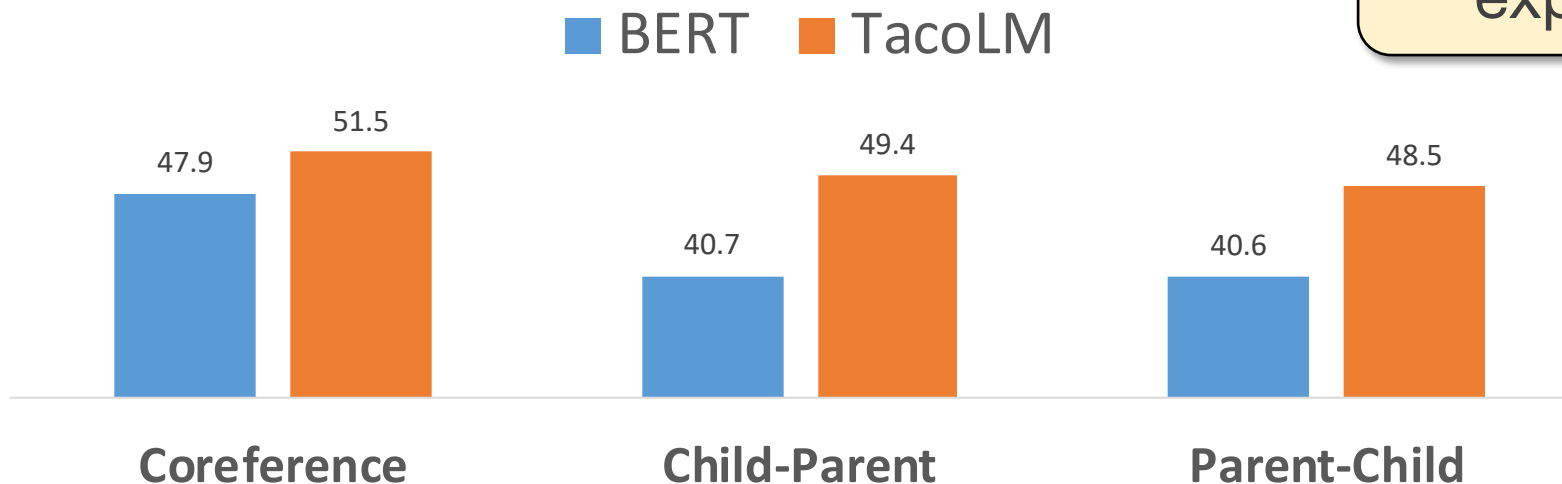
Evaluation: Extrinsic



- Use as a general language model with finetuning
- Task: Identify event-event hierarchical relations
 - HiEVE [Glavas et al. 2014]
 - Child-Parent / Parent-Child / Coreference
 - A bomb **exploded**. This is the sixth **accident** since the **war** started.
- Model (finetuned):
 - Sentence pair classification
- Results (F1, **higher the better**)



More Intrinsic/Extrinsic experiments in the paper!



Conclusion - TacoLM



■ Time-aware with minimal supervision

I played basketball for 2 hours

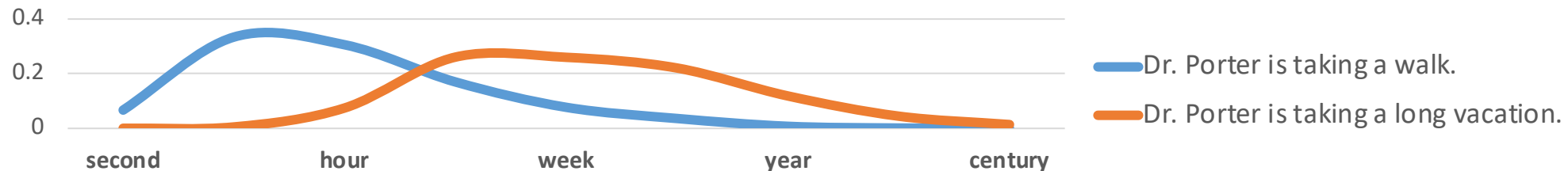
■ Joint pre-training over multiple temporal dimensions

Frequency of “brushing teeth” = every morning

Duration of “brushing teeth” < morning

■ Able to directly predict events’ duration, frequency or typical time

- ☐ 19% better on direct prediction tasks
- ☐ Bell-shaped predictive distributions
- ☐ Differentiates fine grained event contexts



■ Works as a general language model

- ☐ 8% improvement on child-parent event relation extraction

Thank you!
Code & Data:

<https://github.com/CogComp/TacoLM>