A Meta-framework for Spatiotemporal Quantity Extraction from Text

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amazon



HOORAY DATA

NEWS BREAK



Microsoft

Input Document

Extraction

1. Spatiotemporal Quantity Extraction

We propose a meta-framework STEQE for quantity extractions, which includes quantity span, type, spatial and temporal groundings.

2.Our Contribution

(A) We argue that spatiotemporal quantity extraction is important but challenging.

Important: provide rapid response to evolving situations (covid-19) and automatic extraction for sociopolitical analysis (elections).

Challenging: rarely studied by previous work, existing models are not sufficient.

- (B) A meta-framework STEQE which includes problem definitions and a reusable extraction pipeline for domains and tasks.
- (C) Annotated datasets on three example sociopolitical events: Covid-19, Black Lives Matter protests, and 2020 California wildfires.
- (D) Experiments on existing models' performance on spatiotemporal quantity extraction, analysis and future directions.

4. Data Collection and Statistics

We use the STEQE pipeline to annotate three example datasets on Covid-19, BLM protests, and California wildfires for experiments and showcasing the pipeline. All domains go through the same annotation pipeline.

Domain	#Q Typing	#Q Space	#Q Time	#Q Test
Covid	1.5k	3.4k	4.3k	500
BLM	4k	1.5k	1.6k	500
Wildfire	2k	2k	1.6k	500

Document Creation Time: 2020-08-27

Title: 104 New USC Student Coronavirus Cases

Text: Log Angeles, CA – The number of coronavirus cases confirmed among USC students continued rising Thursday, with the university announcing [104] new cases over the past four days.

Type: Confirmed Coronavirus Cases

Spatial Grounding: United States -> California -> Los Angeles -> USC

Temporal Grounding: [2020-08-23, 2020-08-26]

Figure 1: An example document, quantity extraction, type recognition and spatiotemporal grounding.

3. STEQE Formulation

Raw Document

Quantity Recognition [DCT] [Title $t_1, t_2, t_3, ...$] [Body Text $b_1, b_2, ..., q_1, q_2, ..., q_m, ..., b_n$]

Time Span Location

protests ***

Quantity Recognition: Finds a special type of numbers that are associated with events

- Non-quantity numbers: Date/Time, Duration, Entity names...
- Exclude article words and ordinal numbers

Quantity Typing: Domain-specific semantic types

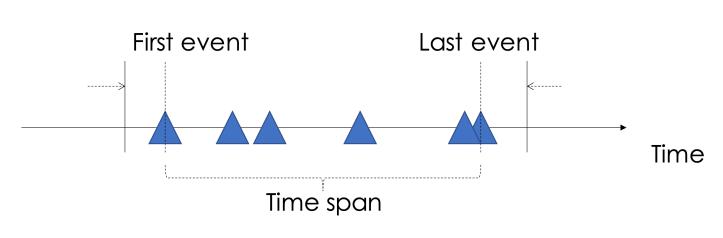
Assume single-typing, ignore rate and money quantities

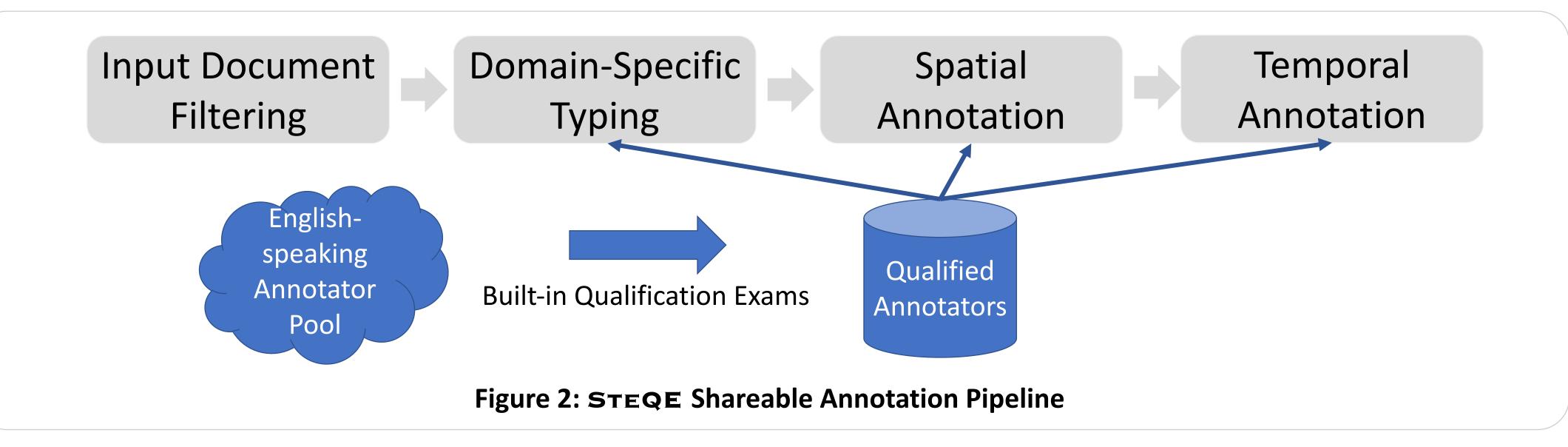
Spatial Grounding: Hierarchical country->state->city->free-span

South Portland, Maine – A facility for people with cognitive disabilities reports having [six] cases

Temporal Grounding:

- Best start/end timepoint estimation based on events
- Overall number: there have been [3 million] cases so far





5. Experiment Setup

Typing: accuracy

Spatial Grounding: Exact Match (city/state level) **Temporal Grounding:**

- overall num ending on DCT (binary)
- non-overall num start/end EM

End-to-end evaluation:

Spatial EM-city + Temporal binary

Supervision: in-domain / all-domain

Naïve Baselines:

- Typing: predict most popular type.
- Spatial: predict the nearest location mention in text, relative to the quantity span.
- Temporal: predict overall num ending on DCT.
- End2end: same as the spatial and temporal.

Our Model: T5 with labels as output sequences T5 gold output T5 input Typing Physical ..to <MARKER> 440 square kilometers.. Model measurements Spatial US, CA, ..to <MARKER> 440 square kilometers.. Model Los Angeles

6. Experiment Results **Spatial Exact Match (city)** Typing Accuracy ■ In-Domain ■ All-Domain Naïve ■ In-Domain ■ All-Domain 100 100 60 60 CalFire CalFire Covid BLM Covid **BLM** In-Domain All-Domain All-Domain In-Domain https://github.com/steqe 80 60 **End-to-end** Non-overall Number End Time EM Code & Data 60 40 40 20 CalFire BLM CalFire Covid BLM Covid

Takeaways:

- T5 achieves usable performance in some settings but has room for improvement.
- All-domain supervision is generally better, especially in more difficult settings.