EQUATE : A Benchmark Evaluation Framework for Quantitative Reasoning in Natural Language Inference

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Abstract
Quantitative reasoning is an important component of reasoning that any intelligent natural language understanding system can reasonably be expected to handle. We present EQUATE (Evaluating Quantitative Understanding Aptitude in Textual Entailment), a new dataset to evaluate the ability of models to reason with quantities in textual entailment (including not only arithmetic and algebraic computation, but also other phenomena such as range comparisons and verbal reasoning with quantities). The average performance of 7 published textual entailment models on EQUATE does not exceed a majority class baseline, indicating that current models do not implicitly learn to reason with quantities. We propose a new baseline Q-REAS that manipulates quantities symbolically, achieving some success on numerical reasoning, but struggling at more verbal aspects of the task. We hope our evaluation framework will support the development of new models of quantitative reasoning in language understanding.

1 Introduction

Numbers play a vital role in our lives. We reason with numbers in day-to-day tasks ranging from handling currency to reading news articles to understanding sports results, elections and stock markets. As numbers are used to communicate information accurately, reasoning with them is an essential core competence in understanding natural language (Levinson, 2001; Frank et al., 2008; Dehaene, 2011). A benchmark task in natural language understanding is natural language inference (NLI)(or recognizing textual entailment (RTE)) (Cooper et al., 1996; Condoravdi et al., 2003; Bos and Markert, 2005; Dagan et al., 2006), wherein a model determines if a natural language hypothesis can be justifiably inferred from a given premise2. Making such inferences often necessitates reasoning about numbers. Consider the example,

P: After the deal closes, Teva will generate sales of about $7 billion a year, the company said.
H: Teva earns $7 billion a year

To conclude the hypothesis is inferable, a model must reason that since 99.6% of the precincts are counted, even if all the remaining precincts vote for Dewhurst, he would still fail to get 50% of the primary vote. Scant attention has been paid to building datasets to evaluate this reasoning ability. To address this gap, we present EQUATE (Evaluating Quantity Understanding Aptitude

RTE-QUANT
P: After the deal closes, Teva will generate sales of about $7 billion a year, the company said.
H: Teva earns $7 billion a year

AWP-NLI
P: Each of farmer Cunningham’s 6048 lambs is either black or white and there are 193 white ones.
H: 5855 of Farmer Cunningham’s lambs are black.

NEWSNLI
P: With 99.6% of precincts counted, Dewhurst held 48% of the vote to 30% for Cruz.
H: Lt. Gov. David Dewhurst fails to get 50% of primary vote.

REDDITNLI
P: Oxfam says richest one percent to own more than rest by 2016.
H: Richest 1% To Own More Than Half World’s Wealth By 2016 Oxfam.

Table 1: Examples drawn from four evaluation sets in the EQUATE framework.

2Often, this is posed as a three-way decision where the hypothesis can be inferred to be true (entailment), false (contradiction) or cannot be determined

*The indicated authors contributed equally to this work.
1EQUATE is freely available at https://goo.gl/Hwfu5Y
in Textual Entailment) (§3). EQUATE consists of five evaluation sets: Stress Test, AwpNLI, NewsNLI, RTE-Quant, RedditNLI, each featuring different facets of quantitative reasoning in textual entailment (Table 1) (eg: range comparisons, arithmetic reasoning, verbal reasoning involving quantities etc). The test sets contain synthetic data created by repurposing existing NLI and arithmetic word problem datasets, and natural data from news articles and social media. We evaluate the ability of existing state-of-the-art NLI models to perform quantitative reasoning (§4.1), by benchmarking 7 published models on EQUATE. Our results show that most models are incapable of quantitative reasoning, relying on lexical cues for prediction. Additionally, we build Q-REAS, a shallow semantic reasoning baseline for quantitative reasoning in NLI (§4.2). Q-REAS is effective on synthetic test sets which contain more quantity-based inference, but shows limited success on natural test sets which require deeper linguistic reasoning. However, the hardest cases require a complex interplay between linguistic and numerical reasoning. The EQUATE evaluation framework makes it clear where this new challenge area for textual entailment stands.

2 Related Work

NLI has attracted community-wide interest as a stringent test for natural language understanding (Cooper et al., 1996; Fyodorov; Glickman et al., 2005; Haghighi et al., 2005; Harabagiu and Hickl, 2006; Romano et al., 2006; Dagan et al., 2006; Giampiccolo et al., 2007; Zanzotto et al., 2006; Malakasiotis and Androutsopoulos, 2007; MacCartney, 2009; de Marneffe et al., 2009; Dagan et al., 2010; Angeli and Manning, 2014; Marello et al., 2014). Recently, the creation of large-scale datasets (Bowman et al., 2015; Williams et al., 2017; Khot et al., 2018) spurred the development of many neural models (Parikh et al., 2016; Nie and Bansal, 2017; Conneau et al., 2017; Balazs et al., 2017; Chen et al., 2017a; Radford et al., 2018). However, recent work has identified biases in some datasets (Gururangan et al., 2018; Poliak et al., 2018), which neural models exploit as shallow cues for prediction instead of doing expected reasoning for the task (Glockner et al., 2018; Naik et al., 2018). Naik et al. (2018) find that model inability to do numerical reasoning causes 4% of errors made by state-of-the-art models. Previously, Marneffe et al. (2008) found that in a corpus of real-life contradiction pairs collected from Wikipedia and Google News, 29% contradictions arise from numeric discrepancies, and in many Recognizing Textual Entailment (RTE) datasets, numeric contradictions made up 8.8% of contradictory pairs. Sammons et al. (2010); Clark (2018) present a thorough analysis of types of reasoning required for inference, arguing for a systematic knowledge-oriented approach by evaluating specific semantic analysis tasks, identifying quantitative reasoning in particular as an area models should concentrate on. Our work takes the first step towards addressing this, by presenting an evaluation framework and a closer examination of quantitative reasoning in NLI.

While to the best of our knowledge, prior work has not studied quantitative reasoning in NLI, Roy (2017) propose a model for a related subtask called quantity entailment, which aims to determine if a given quantity can be inferred from a sentence. In contrast, general-purpose textual entailment considers if a given sentence can be inferred from another. We focus on general-purpose textual entailment. Our work also relates to solving arithmetic word problems (Hosseini et al., 2014; Mitra and Baral, 2016; Zhou et al., 2015; Upadhyay et al., 2016; Huang et al., 2017; Kushman et al., 2014a; Koncel-Kedziorski et al., 2015; Roy and Roth, 2016; Roy, 2017; Ling et al., 2017). Word problems emphasize arithmetic reasoning, and the requirement for linguistic reasoning and world knowledge is limited as the text is concise, straightforward, and self-contained(Hosseini et al., 2014; Kushman et al., 2014b). Our work provides a testbed that evaluates basic arithmetic reasoning while also incorporating the complexity of natural language.

3 Quantitative Reasoning in NLI

Our interpretation of “quantitative reasoning” draws from cognitive testing and education (Stafford, 1972; Ekstrom et al., 1976), which considers it “verbal problem-solving ability”. While inextricably linked to mathematics, it is an inclusive skill involving everyday language rather than a specialized lexicon. To excel at quantitative reasoning, one must interpret quantities expressed in language, perform basic calculations and judge their accuracy, and justify quantitative
Table 2: An overview of the test sets included in EQUATE, a benchmark evaluation framework for quantitative reasoning in textual entailment. Column S indicates whether data is synthetic or natural. RedditNLI:Stress Test are 3-class (entailment, neutral, contradiction) while RTE-Quant;NewsNLI;AwpNLI entailments (entails=yes/no).

| Test Set      | Size | Classes | S | Data Source | Annotation Source | Quantitative Phenomena |
|---------------|------|---------|---|-------------|-------------------|------------------------|
| Stress Test   | 7500 | 3       | ✓ | AQuA-RAT    | Automatic          | Quantifiers            |
| RTE-Quant     | 166  | 2       | X | RTE2-RTE4   | Experts            | Arithmetic, World knowledge, Ranges, Quantifiers |
| AwpNLI        | 722  | 2       | ✓ | Arithmetic Word Problems | Automatic          | Arithmetic |
| NewsNLI       | 1000 | 2       | X | CNN         | Crowdworkers       | Ordinality, Quantifiers, Arithmetic, World Knowledge, Magnitude, Ratios |
| RedditNLI     | 250  | 3       | X | Reddit      | Experts            | Range, Arithmetic, Approximation, Verbal |

claims using both verbal and numeric reasoning. Based on these requirements, natural language inference lends itself as a test bed for the study of quantitative reasoning. Conversely, the ability to quantitatively reason is important for NLI (Sammons et al., 2010; Clark, 2018). Motivated by this interplay, we present the EQUATE (Evaluating Quantity Understanding Aptitude in Textual Entailment) framework.

### 3.1 The EQUATE Dataset

EQUATE consists of five NLI test sets featuring quantities. These sets (Table 2) are drawn from diverse sources and exhibit a wide range of quantitative reasoning phenomena. Some sets are controlled synthetic tests (§3.2; §3.4) to examine model ability to handle phenomena such as quantifiers, approximations or arithmetic reasoning. EQUATE also includes tests featuring text from news articles and social media (§3.3; §3.5; §3.6) to examine reasoning about quantities expressed verbally in the wild. Two main restrictions are imposed during test creation. First, we remove all sentences with temporal reasoning, since specialized knowledge is needed to reason about time. Secondly, we focus on sentences containing quantity mentions with numerical values.

### 3.2 Stress Test

We include the numerical reasoning stress test from (Naik et al., 2018) as a sanity check. It requires models to match entities from hypothesis to the premise, and reason with quantifiers.

### 3.3 RTE-Quant

This test set is constructed from the RTE sub-corpus for quantity entailment (Roy, 2017), originally drawn from the RTE2-RTE4 datasets (Dagan et al., 2006). The original sub-corpus conflates temporal and quantitative reasoning. Pairs requiring temporal reasoning are discarded, resulting in a set of 166 entailment pairs.

### 3.4 AwpNLI

To evaluate arithmetic ability of NLI models, we repurpose data from arithmetic word problems (Roy and Roth, 2016) which have characteristic structures. First, they establish a world and optionally update its state. Then, a question is posed about the world. This structure forms the basis of our pair creation process (Fig 1). World building and update statements form the premise. A hypothesis template is generated by first identifying modal/auxiliary verbs in the question, and subsequent verbs, which we refer to as secondary verbs. We identify the agent in the sentence and conjugate the secondary verb in present tense followed by the identified unit to form the final template. For every template, the correct guess is used to create an entailed hypothesis. Contradic-
Figure 1: The construction of the AwpNLI dataset.

Figure 2: Overview of Q-REAS baseline.
Table 3: Input, output and variable definitions for the ILP framework used in our quantity comparator-combiner module

1. **OpenAI Transformer (OpenAI):** unsupervised pretraining through a transformer-based language model (Vaswani et al., 2017) trained on 7000 books, followed by task-specific finetuning to obtain state-of-the-art performance on the MultiNLI dataset (Radford et al., 2018).

4.2 Q-REAS Baseline

Figure 2 presents an overview of the Q-REAS baseline for quantitative reasoning in NLI. The model manipulates quantity representations symbolically to decide the entailment relation and is weakly supervised, using only the final entailment label as supervision. This baseline has four stages: Quantity mentions are extracted and parsed into semantic representations called NUMSETS (§4.2.1, §4.2.2); compatible NUMSETS are extracted (§4.2.3) and composed (§4.2.4) to form justifications; Justifications are analyzed to determine entailment labels (§4.2.5).

4.2.1 Quantity Segmenter

Inspired by (Barwise and Cooper, 1981), we consider quantities as having a number, a unit and an optional approximator. We extract quantity mentions by identifying all least common ancestor noun phrases from the constituency parse of the sentence that contain cardinal numbers.

4.2.2 Quantity Parser

Our quantity parser constructs a grounded representation for each quantity mention in the premise and hypothesis, henceforth known as a NUMSET. A NUMSET can also be a composition of other NUMSETS. A NUMSET consists of (val, unit) tuples with:

1. **val** ∈ [R, R]: quantity represented as range
2. **unit** ∈ S: unit noun associated with quantity

To extract values for a quantity, we extract cardinal numbers, recording contiguity. We normalize the number. We also handle simple ratios such as quarter, half etc, and extract bounds (eg: less than 10 apples is parsed to [−∞, 10) apples.) To extract units, we examine tokens adjacent to cardinal numbers.

4.2.3 Quantity Compositor

Our quantity combiner constructs a grounded representation for each quantity mention in the premise and hypothesis, henceforth known as a NUMSET. A NUMSET can also be a composition of other NUMSETS. A NUMSET consists of (val, unit) tuples with:

1. **val** ∈ [R, R]: quantity represented as range
2. **unit** ∈ S: unit noun associated with quantity

To extract values for a quantity, we extract cardinal numbers, recording contiguity. We normalize the number. We also handle simple ratios such as quarter, half etc, and extract bounds (eg: less than 10 apples is parsed to [−∞, 10) apples.) To extract units, we examine tokens adjacent to cardinal numbers.

4.2.4 Justification Generator

Our justification generator constructs a grounded representation for each justification and is weakly supervised, using only the final entailment label as supervision. This baseline has four stages: Justifications are extracted and composed (§4.2.4) to form justifications; Justifications are analyzed to determine entailment labels (§4.2.5).

4.2.5 Entailment Classifier

Our entailment classifier decides the entailment relation (Gururangan et al., 2018).
found, we assign the token in a numerical modifier relationship with the cardinal number, else we assign the nearest noun to the cardinal number as the unit. A quantity is determined to be approximate if the word in a adverbial modifier relation with the cardinal number appears in gazetteer. If approximate, range is extended to (+/-)2% of the current value.

4.2.3 Quantity Pruner

The pruner constructs “compatible” premise-hypothesis NUMSET pairs. Consider the pair “Insurgents killed 7 U.S. soldiers, set off a car bomb that killed four Iraqi policemen” and “7 US soldiers were killed, and at least 10 Iraqis died”. Our parser extracts NUMSETS corresponding to “four Iraqi policemen” and “7 US soldiers” from premise and hypothesis respectively. But these NUMSETS should not be compared as they involve different units. The pruner discards such incompatible pairs. Heuristics to detect unit-compatible NUMSET pairs include direct string

| Definitional Constraints |
|--------------------------|
| Range restriction        | $x_i < K$ or $x_i = M - 1$ for $i \in [0, L - 1]$ if $c_i = 1$ |
|                         | $x_i \geq K$ and $x_i < M$ for $i \in [0, L - 1]$ if $r_i = 1$ |
|                         | $x_i \geq M$ for $i \in [0, L - 1]$ if $o_i = 1$ |
| Uniqueness               | $c_i + r_i + o_i = 1$ for $i \in [0, L - 1]$ |
| Stack definition         | $d_0 = 0$ (Stack depth initialization) |
|                         | $d_i = d_{i-1} - 2o_i + 1$ for $i \in [0, L - 1]$ (Stack depth update) |

| Syntactic Constraints    |
|--------------------------|
| First two operands       | $c_0 + r_0 = 1$ and $c_1 + r_1 = 1$ |
| Last operator            | $x_{L-1} \geq N - 1$ (Last operator should be one of \{ =, \subseteq \}) |
| Last operand             | $x_{L-2} = M - 1$ (Last operand should be hypothesis quantity) |
| Other operators          | $x_i \leq N - 2$ for $i \in [0, L - 3]$ if $o_i = 1$ |
| Other operands           | $x_i < K$ for $i \in [0, L - 3]$ if $c_i = 1$ |
|                         | $x_i < M$ for $i \in [0, L - 3]$ if $r_i = 1$ |
| Empty stack              | $d_{L-1} = 0$ (Non-empty stack indicates invalid postfix expression) |
| Premise usage            | $x_i \neq x_j$ for $i,j \in [0, L - 1]$ if $o_i \neq 1, o_j \neq 1$ |

| Operand Access           |
|--------------------------|
| Right operand            | $op2(x_i) = x_{i-1}$ for $i \in [0, L - 1]$ such that $o_i = 1$ |
| Left operand             | $op1(x_i) = x_l$ for $i,l \in [0, L - 1]$ where $o_i = 1$ and $l$ is the largest index such that $l \leq (i - 2)$ and $d_l = d_i$ |

Table 4: Mathematical validity constraint definitions for the ILP framework used in our quantity composition module. Functions $op1()$ and $op2()$ return the left and right operands for an operator respectively.

4.2.4 Quantity Composition

The composition module detects whether a hypothesis NUMSET is justified by composing “compatible” premise NUMSETS. Our framework generates postfix arithmetic equations from premise NUMSETS, which justify the hypothesis NUMSET. Note, the set of possible equations is exponential in number of NUMSETS, making exhaustive generation intractable. A large number of equations are invalid as they violate constraints such as unit consistency. Thus, our framework uses integer linear programming (ILP) to constrain the equation space. It is inspired by prior work on algebra word problems, with some key differences:

1. **Arithmetic equations:** We focus on arithmetic equations instead of algebraic for NLI.

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9roughly”, “approximately”, “about”, “nearby”, “roundabout”, “around”, “cira”, “almost”, “approaching”, “pushing”, “more or less”, “in the neighborhood of”, “in the region of”, “on the order of”, “something like”, “give or take (a few)”, “near to”, “close to”, “in the ballpark of”. Like (Roy, 2017), we consider two units compatible if one is a nationality or a job and the other unit is synonymous with people, person or citizen/worker.

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8from WordNet.

9Lists of jobs, nationalities scraped from Wikipedia.

10Direct comparisons are incorporated by adding “=” as an operator.
2. **Range arithmetic:** Quantitative reasoning involves ranges, which are handled by representing them as endpoint-inclusive intervals and adding four operators (\(\cup, \cap, \setminus, \subseteq\))

3. **Hypothesis quantity-driven:** We optimize an ILP model for each hypothesis \(NUMSET\) because a sentence pair is marked “entailment” iff every hypothesis quantity is justified.

Table 3 describes ILP variables. We impose the following types of constraints:

1. **Definitional Constraints:** Ensure that ILP variables take on valid values by constraining initialization, range and update.
2. **Syntactic Constraints:** Assure syntactic validity of generated postfix expressions by limiting operator-operand ordering.
3. **Operand Access:** Simulate stack-based evaluation correctly by choosing correct operator-operand assignments.
4. **Type Consistency:** Ensure that all operations are type-compatible.
5. **Operator Consistency:** Force range operators to have range operands and mathematical operators to have single-valued operands.

Table 5: Linguistic consistency constraint definitions for the ILP framework used in our quantity composition module. Functions \(op1()\) and \(op2()\) return the left and right operands for an operator respectively.

| Type Consistency Constraints |
|------------------------------|
| **Type assignment** |
| \(t_i = TL[k]\) for \(i \in [0, L - 1]\) if \(c_i + r_i = 1\) and \(type(SL_i) = k\) |
| **Two type match** |
| \(t_i = t_a = t_b\) for \(i \in [0, L - 1]\) such that \(a_i = 1, x_i \in \{+, -, *, /, =\}\), \(\cap, \cup, \setminus, \subseteq\), \(a = op1(x_i), b = op2(x_i)\) |
| **One type match** |
| \(t_i \in \{t_a, t_b\}, t_a \neq t_b\) for \(i \in [0, L - 1]\) such that \(a_i = 1, x_i = *, a = op1(x_i), b = op2(x_i)\) |
| \(t_i = t_a \neq t_b\) for \(i \in [0, L - 1]\) such that \(a_i = 1, x_i = /, a = op1(x_i), b = op2(x_i)\) |

| Operator Consistency Constraints |
|----------------------------------|
| **Arithmetic operators** |
| \(c_a = c_b = 1\) for \(i \in [0, L - 1]\) such that \(a_i = 1, x_i \in \{+, -, *, /, =\}\), \(a = op1(x_i), b = op2(x_i)\) |
| **Range operators** |
| \(r_a = r_b = 1\) for \(i \in [0, L - 1]\) such that \(a_i = 1, x_i \in \{\cap, \cup, \setminus, \subseteq\}\), \(a = op1(x_i), b = op2(x_i)\) |
| \(r_b = 1\) for \(i \in [0, L - 1]\) such that \(a_i = 1, x_i = \subseteq, b = op2(x_i)\) |

5 Results and Discussion

Table 6 presents results on EQUATE. Neural models, particularly OpenAI excel at verbal aspects of quantitative reasoning (RTE-Quant, NewsNLI), whereas Q-REAS excels at numerical aspects (Stress Test, AwpNLI).

- **Neural Models on NewsNLI** To tease apart contributory effects of numerical and verbal reasoning in natural data, we experiment with NewsNLI. We extract all entailed pairs where a quantity appears in both premise
Table 6: Accuracies(%) of 9 NLI Models on five tests for quantitative reasoning in entailment. M and D represent models and datasets respectively. ∆ captures improvement over majority-class baseline for a dataset. Column Avg. reports the average accuracy(%) of each model across all 5 evaluation sets in EQUATE.

Table 7: Component-based error analysis(% of errors) of the Q-REAS baseline on EQUATE. S- quantity segmenter, Pa - quantity parser, Pr - quantity pruner, C- comparator and R- global reasoner.

| Dataset      | S | Pa | Pr | C  | R |
|--------------|---|----|----|----|---|
| Stress Test  | 5 | 70 | 0  | 18 | 7 |
| RTE-Quant    | 20| 38 | 3  | 8  | 0 |
| AwpNLI       | 5 | 28 | 26 | 31 | 10|
| NewsNLI      | 21| 42 | 21 | 0  | 6 |
| RedditNLI    | 37| 40 | 2  | 6  | 0 |

and hypothesis, and perturb the quantity in the hypothesis generating contradictory pairs. For example, the pair ‘In addition to 79 fatalities, some 170 passengers were injured.’ ‘The crash took the lives of 79 people and injured some 170’, ‘entailment’ is changed to ‘In addition to 79 fatalities, some 170 passengers were injured.’, ‘The crash took the lives of 77 people and injured some 170’, ‘contradiction’), assuming scalar implicature and event coreference. Our perturbed test set contains 261 pairs. On this set, OpenAI\textsuperscript{14} achieves an accuracy of 32.33\%, as compared to 71.26\% on the unperturbed set, highlighting reliance on quantities rather than verbal information. Closer examination reveals that OpenAI switches to predicting the ‘neutral’ category for perturbed samples instead of entailment, accounting for 51.7\% of it’s errors, possibly symptomatic of lexical bias issues (Naik et al., 2018).

\textbf{What Quantitative Phenomena Are Hard?} We sample 100 errors made by Q-REAS on each test in EQUATE (Table 7), to identify phenomena not addressed by simple quantity comparison. On natural datasets containing sentences with complex linguistic structure, the segmenter and parser cause most errors (66\% on average), indicating that identifying quantities, or parsing them into a representation is more difficult in these datasets. Conversely, the composition module has a higher error rate on synthetic data (24.5\%) than natural (4.7\%). Our analysis of causes for error suggest avenues for future research:

1. Incorporating real world knowledge: Lack of real world knowledge causes errors in identifying quantities and valid comparisons. Errors include inability to map abbreviations to correct units (eq: “m” to “meters”), to detect part-whole coreference (eg: “seats” can be used to refer to “buses”), or correct-
Algorithm 1: PredictEntailmentLabel($P, H, C, E$)

**Input:** Premise quantities $P$, Hypothesis quantities $H$, Compatible pairs $C$, Equations $E$

**Output:** Entailment label $l \in \{e, c, n\}$

1. if $C = \emptyset$ then return $n$
2. $J \leftarrow \emptyset$
3. $L \leftarrow []$
4. for $q_h \in H$ do
   5. $J_h \leftarrow \{q_p \mid q_p \in P, (q_p, q_h) \in C\}$
   6. $J \leftarrow J \cup \{(q_h, J_h)\}$
   7. $L \leftarrow L + [false]$
8. for $(q_h, J_h) \in J$ do
   9. if $J_h = \emptyset$ then return $n$
   10. for $q_p \in J_h$ do
      11. $s \leftarrow \text{MaxSimilarityClass}(q_p, q_h)$
      12. if $s = e$ then
         13. if $\text{ValueMatch}(q_p, q_h)$ then
            14. $L[q_h] = true$
      15. if $\text{ValueMatch}(q_p, q_h)$ then
            16. $L[q_h] = false$
      17. if $s = c$ then
         18. if $\text{ValueMatch}(q_p, q_h)$ then
            19. $L[q_h] = c$
20. for $q_h \in H$ do
21. $E_q \leftarrow \{e_i \in E \mid \text{hyp}(e_i) = q_h\}$
22. if $E_q \neq \emptyset$ then
      23. $L[q_h] = true$
24. if $c \in L$ then return $c$
25. if $\text{count}(L, true) = \text{len}(L)$ then return $e$
26. return $n$

1. **Inferring underspecified quantities:**
   - Quantity attributes can be implicitly specified, requiring inference to generate a complete representation. Consider “A mortar attack killed four people and injured 80”. A system must infer that the quantity “80” refers to people. On RTE-Quant, 20% of such cases stem from zero anaphora, a hard problem even in coreference resolution.

2. **Arithmetic comparison limitations:**
   - These examples require composition between incompatible quantities. For example, consider (“There were 3 birds and 6 nests”, “There were 3 more nests than birds”). To correctly label this pair “3 birds” and “6 nests” must be composed.

3. **Integrating verbal reasoning:**
   - No model integrates complex verbal and quantitative reasoning. For example, consider the pair (“Two people were injured in the attack”, “Two people perpetrated the attack”). Quantities “two people” and “two people” are unit-compatible, but must not be compared. Numbers and language are intricately interleaved and developing a reasoner capable of handling this complex interplay is challenging.

6. **Conclusion**

In this work, we present EQUATE, an evaluation framework to estimate the ability of models to reason quantitatively in textual entailment. We observe that existing neural approaches rely on the verbal reasoning aspect of the task to succeed rather than reasoning about quantities. We also present Q-REAS , a baseline that symbolically reasons about quantities and while it achieves some success at numerical reasoning, it lacks sophisticated verbal reasoning capabilities, indicating the complexity of inference. We believe that a promising avenue to explore is combining the strengths of neural models and specialized reasoners in hybrid architectures to be more effective, though it remains unclear how this can be achieved. In the future, we hope our insights, and the EQUATE evaluation framework, lead to the development of models that can more precisely reason about quantities in natural language.

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Supplementary Material

Baseline implementation performances on MultiNLI-Dev Matched. All reimplementation closely match performance reported in the original publications.

| Model              | MultiNLI Dev |
|--------------------|--------------|
| Hyp Only           | 53.18%       |
| ALIGN              | 45.0%        |
| CBOW               | 63.5%        |
| BiLSTM             | 70.2%        |
| Chen               | 73.7%        |
| NB                 | 74.2%        |
| InferSent          | 70.3%        |
| ESIM               | 76.2%        |
| OpenAI! Transformer| 81.35%       |