

Exploring the Numerical Reasoning Capabilities of Language Models: A Comprehensive Analysis on Tabular Data

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Abstract

Numbers are crucial for various real-world domains such as finance, economics, and science. Thus, understanding and reasoning with numbers are essential skills for language models to solve different tasks. While different numerical benchmarks have been introduced in recent years, they are limited to specific numerical aspects mostly. In this paper, we propose a hierarchical taxonomy for numerical reasoning skills with more than ten reasoning types across four levels: representation, number sense, manipulation, and complex reasoning. We conduct a comprehensive evaluation of state-of-the-art models to identify reasoning challenges specific to them. Henceforth, we develop a diverse set of numerical probes employing a semi-automated approach. We focus on the tabular Natural Language Inference (TNLI) task as a case study and measure models’ performance shifts. Our results show that no model consistently excels across all numerical reasoning types. Among the probed models, FlanT5 (few-/zero-shot) and GPT-3.5 (few-shot) demonstrate strong overall numerical reasoning skills compared to other models. Label-flipping probes indicate that models often exploit dataset artifacts to predict the correct labels.¹

1 Introduction

Numerical data is ubiquitous in the real-world. Many applications in domains such as finance, economics and science require understanding and reasoning with numbers. In recent years, benchmarks were introduced to study language models’ numeracy skills (Zhang et al., 2020; Wallace et al., 2019; Dua et al., 2019). However, these datasets mostly concentrate on few, specific numerical reasoning types (e.g. scales (Zhang et al., 2020)).

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¹Data and code are available at https://github.com/mubasharaak/numerical_reasoning.

Hulk	
Directed by	Ang Lee
Release date	June 20, 2003
Running time	138 minutes
Budget	\$137 million
Box office	\$245.4 million

H1: Hulk was released on 20th June, 2003. (<i>E</i>)
Date: Hulk was released on 20-06-2003. (<i>E</i>)
Date Flip: Hulk was released on 12-08-2009. (<i>C</i>)
H2: The movie has a length of 138 minutes. (<i>E</i>)
Appr: The movie has a length of about 150 minutes. (<i>C</i>)
H3: The movie can be watched in about two hours. (<i>E</i>)
Num: The movie can be watched in about 2 hours. (<i>E</i>)
Num Flip: The movie can be watched in 1 hours. (<i>C</i>)
Arith: Hulk brought in \$108.4 million profit. (<i>E</i>)
Arith Flip: Hulk brought in \$120.9 million profit. (<i>C</i>)

Table 1: Base hypotheses (H1, H2, H3) and (**flipped**) probes for heterogeneous numbers (i.e. **date**), **approximation**, **numeracy**, and **arithmetic**. Labelled as **Entail** or **Contradict**.

Moreover, evaluating models on numerical benchmarks, it often remains unclear why models struggle with the tasks. For example, the issues can arise from models struggling to recognize numerical representations in text, failing to compute arithmetic operations, or predicting incorrect outputs due to a lack of numerical commonsense knowledge. We aim to explore these questions in greater detail in this study. Limitations of language models’ numerical abilities, as discussed in prior research, include tokenization and representation of numbers in text (Thawani et al., 2021b), hallucination (Ji et al., 2023; Chen et al., 2023; Ye et al., 2023), and generalizability/robustness issues (Razeghi et al., 2022; Geva et al., 2020; Xu et al., 2022).

Successful numerical reasoning requires a combination of skillsets: understanding representation of numbers (Thawani et al., 2021a,b) and their meaning in a given context (Loukas et al., 2022), applying operations (Geva et al., 2020; Patel et al., 2021), and integrating factual and commonsense numerical knowledge to solve numerical

problems (Lin et al., 2020; Park et al., 2022). For example, classifying the hypotheses “The movie can be watched in about 2 (or ‘two’) hours.” from Table 1 requires understanding that both “2” and “two” depict the same numerical value, converting “2 hours” to another unit (i.e. 120 minutes), and applying approximation to map “120 minutes” to “138 minutes” in the table.

In this paper, we evaluate state-of-the-art models on various numerical reasoning types. To assess which reasoning types are challenging for specific models, we create a diverse and large set of numerical probes and measure shifts in models’ performance. We organize all probed reasoning types in a hierarchical taxonomy. Inspired by how humans understand and reason with numbers, as well as previous numerical benchmarks, we include eleven reasoning types across four level: *representation*, *number sense*, *manipulation*, and *complex reasoning* (Figure 1). We apply a semi-automated approaches for probe creation. We select tabular NLI (TNLI) as a case study task, given three criteria: (i) numerical data (numbers, percentages, dates, etc.) is prevalent in tables; (ii) tables are common in real-world data sources such as in scientific publications, database systems and financial documents; (iii) tables as structured data facilitate automated perturbations to create large-scale probing sets. See Table 1 for some examples of probes created from hypotheses (H1, H2, H3) and the given table.

Our experiments conclude that large language models (LLMs) like FlanT5 and GPT3.5 perform better than other models on various numerical reasoning tasks. Both table-based and numerical models struggled to understand data with flipped labels and negative values. Moreover, we observe that some models’ performance improves significantly for counterfactual probes (e.g. NT5 and TAPAS) and label-flipping probes (e.g. FlanT5 zero-shot), which indicates that models might exploit dataset artifacts and are biased towards one label. These findings emphasize the importance of further systematically investigating numerical reasoning capabilities across various NLP models. Our **contributions** are as follows:

- We introduce a taxonomy for numerical reasoning skills, including representation/number sense/manipulation skills and complex reasoning with numbers.
- We propose a semi-automated approach to

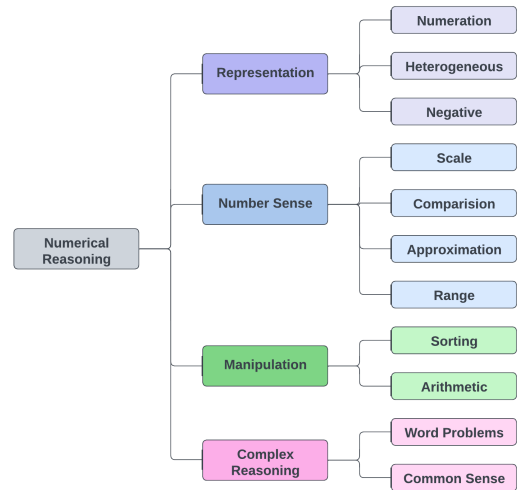


Figure 1: Overview of numerical reasoning types.

create large-scale, numerical probe sets using table NLI datasets.

- We evaluate three different categories of language models (LMs) on our numerical probe sets: (i) numerical LMs; (ii) LMs for tabular data; and (iii) zero-/few-shot LMs.

2 A Taxonomy for Numerical Reasoning

This section introduces a hierarchical taxonomy for numerical reasoning, inspired by previous works on numeracy in NLP (Thawani et al., 2021b; Xu et al., 2022) and psychology (Barrouillet and Fayol, 1998a; Whyte and Bull, 2008; Bofferding, 2019). We group numerical reasoning skills given their complexity level in four categories: $R1 - R4$.

2.1 Number Representation ($R1$)

This category includes skills for understanding the *form* of numerical data. Similar to the notion of form in language (Bender and Koller, 2020), this is the realization of numbers in text; the way they are represented and expressed.

Numeration. Numeration studies language model’s understanding of representation systems common for numbers in English: the Arabic (“2”) and English (“two”) numeration systems. Specifically, we probe if LMs can link between distinct symbols used for the same number. For example in Figure 1, H3 contains “two” as a word, which can be also represented through “2”.

Heterogeneous Number Types. Formatted numbers (e.g. dates, times, and fractions) are frequently used to convey additional information associated with a numerical value. Numbers are formatted in a specific way given their context and purpose,

such as expressing times and dates using full-stop (“.”), using the “%” symbol to indicate fractions, and different currency symbols for money (i.e. “\$” or “€”), e.g. H1 and “Arith” in Figure 1.

Negative Numbers. Early on in their development, children develop some mental model for negative numbers (see experiments with first-graders in [Bofferding \(2019\)](#)). Using negative numbers requires understanding the notation of negatives (i.e. “-” followed by a number). This also includes distinguishing between minus in subtractions ($1 - 3$), dates (12-12-2022), counts (i.e. from one to three) and in negative number (-2).

2.2 Number Sense (R2)

Number sense includes reasoning skills for conceptualizing number quantities and understanding their meaning in a given context.

Scale. In everyday communication, numbers commonly occur with measurement scales, e.g. weights, distances, or heights. Understanding numbers in context of scales is a basis for various applications, e.g. question answering (e.g. “*We are driving 80 km/h, is this within the speed limit?*”), commonsense (e.g. “*Cats weight between four and five kilograms.*”) ([Lin et al., 2020](#)), and temporal reasoning (e.g. “*She left the office thirty minutes ago.*”) ([Zhou et al., 2020](#); [Zhang et al., 2020](#)).

Comparison. Comparing numbers allows understanding numerical relationships. It involves identifying which numbers are greater than, less than, or equal to others. For example, given the table in Figure 1, understanding “*The running time of Hulk is longer than 120 minutes.*” requires comparison.

Range. The question “*Was the budget of the movie between \$130 and \$245.4?*” about the table in Figure 1 requires understanding number ranges. Already at an age between two and three years, children develop numerical abilities to understand sequences of numbers and start reciting numbers in an appropriate order ([Fuson, 2012](#); [Laski and Siegler, 2007](#)). Models’ that understand the notation of ranges, can correctly answer the question by knowing that 137 is in the range $130 - 245.4$.

Approximation. Humans commonly approximate number values in everyday life ([Odic and Starr, 2018](#); [Bonny and Lourenco, 2013](#)). H3 in Figure 1 requires approximation among other skills to map “about two hours” to “138 minutes” in the

table. As a reasoning skill, it allows to make quick estimations and metric unit conversations, and understand the approximate values of numbers without calculating them explicitly.

2.3 Manipulation (R3)

Manipulation reasoning types are used to apply basic operations on numbers such as addition. Successful manipulation of numbers requires understanding their *representations* and meaning in the given context (i.e. *number sense*).

Sorting. The sentence “*Out of all Ang Lee’s directed movies, ‘Hulk’ was the one with the second highest box office income.*” requires sorting all movies according to their box office income in order to select the one with the second highest income. Sorting objects according to some criteria is a basic milestone for developing cognitive skills. By age two, children already begin to understand the concept of sorting.

Simple arithmetic. Arithmetic reasoning is the ability of manipulating numbers with basic operations (addition, subtraction, multiplication, division). While adults commonly retrieve results of simple calculations from memory, children use different operations ([Barrouillet and Fayol, 1998b](#)).

2.4 Complex Reasoning (R4)

This category builds on all previous reasoning categories ($R1 - R3$) to solve numerical word problems (NWP). NWP are expressed through natural language and require multistep reasoning. Extracting information from the problem description and applying numerical/mathematical reasoning using the retrieved information and world/commonsense knowledge is required ([Upadhyay and Chang, 2017](#); [Amini et al., 2019](#); [Huang et al., 2016](#)).

3 Numerical Probing Framework

This section provides an overview of the probing framework. We use tabular Natural Language Inference (TNLI) for automated probe creation.

3.1 Preliminaries

Tables for numerical probing. Tables align well with our objectives given three key criteria: (i) numerical data is common in tables; (ii) tables are frequent in real-world data sources; (iii) tables, due to their structured formats, facilitate automated perturbations for probe creation. Tables’

semi-structured format, the alignments available between table cells and column/row headers, and the frequency of numbers, make them well suitable for creating numerical probes automatically.

Table NLI. Given a natural language sentence as hypothesis and a tabular premise, the aim of TNLI is to classify if the hypothesis *entails* or *contradicts* the table (Gupta et al., 2020). We use the table NLI datasets *TabFact* (Chen et al., 2020) and *InfoTabs* (Gupta et al., 2020), as well as recast the table QA datasets TAT-QA (Zhu et al., 2021) and *TabMWP* (Lu et al., 2023) to NLI (i.e. *TATQA-NLI*, *TabMWP-NLI*). TAT-QA includes metadata, i.e. annotations of cells and operations per correct answer. This information is not available for any TNLI dataset and is crucial to create probes for specific reasoning types, e.g. *arithmetic reasoning*. Table 2 provides an overview of the TNLI datasets.

Preprocessing. For each of numerical reasoning type, we first identify base TNLI hypotheses and/or tables in the datasets that can be used for automated probe creation. Hereby, we defined a list of reference tokens specific for each reasoning type and to filter relevant dataset samples. For example, we used units of measurements such as “hour”, “meter”, or “kilogram” filter hypotheses for *scale* probes (see §4 for more details). To recast the TAT-QA dataset, we follow the simple yet effective, rule-based approach proposed by Demszky et al. (2018) for QA to NLI conversion.

3.2 Probes through Structural Perturbation

Overall, we our framework includes three types of probes, created through hypotheses perturbation and counterfactual tables.

1. Hypothesis label-preserving probes We create label-preserving probes changing the base hypothesis such that its meaning is not changed and the initial label is preserved. They are used to evaluate model’s ability to reason and predict the correct label given semantically-equivalent changes.

2. Hypothesis label-flipping probes To generate label-flipping probes, we modify the base hypothesis such that its meaning alters and the label of the probe flips, e.g. from entailment to contradiction. We aim to overcome potential dataset artefacts that might be exploited for label prediction instead of performing numerical reasoning.

These changes are specific to the reasoning types. For example, to flip labels for *scale* probes, we

Dataset	Hypotheses	Tables	Num cells	Probes
TabFact	118,275	16,573	59.00%	214,440
InfoTabs	23,738	2,540	53.6%	19,779
TATQA-NLI	4,947	2,156	59.7%	15,139
ToTTo	1,000	892	45.7%	1,000
TabMWP	283	283	38.3%	238

Table 2: TNLI probing datasets; *num cells* refers to the average ratio of numerical cells in tables.

substitute measurement units for a particular scale (e.g. “kilograms”) by another unit (e.g. “meters”) or introduce errors in conversion of units (e.g. 3 kilometers replaced by 3,000 meters).

3. Table Probes through Counterfactual Table Editing We also probe with counterfactual tables to evaluate if models rely on spurious patterns in the premise table for label prediction. We filter the counterfactual datasets by Jena et al. (2022) consisting of *{hypothesis; original table; counterfactual table}* for numerical hypotheses.

4 Probing with TNLI Datasets

This section discussed probes in detail and how we created them for each reasoning type from §3.²

Numeration. To study models’ understanding of string (“two”) and numerical (e.g. “2”) number representations, we create two types of numeration probes. One converting number representations from strings to numeric, while the second category applies the conversion vice versa. We filter hypotheses with numbers written as strings (“two”) and substitute them by their numeric counterpart (e.g. “2”). The label-preserving probes are semantically equivalent to the base hypotheses and the label (e.g. *entailment*) is not changed. Label-flipping probes replace the converted number x by a random number in the range of $[x - x * 0.5; x + x * 0.5]$. For example, the numeration flipping probe of H1 (Table 3) replaces 112 by one hundred and forty-four and flips the label from *entailment* to *contradiction*.

Heterogeneous number types. We created heterogeneous probes for the following categories frequent in the TNLI datasets: date formats, ordinals, percentage, currencies, and scientific notation. To filter base hypotheses, we applied a simple, rule-based approach specific to each category (i.e. dates formats, percentage, ordinals, etc.). To create label-preserving probes we applied representation-level changes which did not change the semantic meaning. For H3, we substituted 3rd June, 1986 by another English date format 03-06-1986. To flip the

²Find details on probe statistics in Appendix B.

Rafael Nadal	
Plays	Left-handed
Born	3 June 1986 (age 37)
Height	1.85 m
Turned pro	2001
Prize money	US\$116,111,561 (3rd all-time leader in earnings)

<i>Base Hypothesis H₁</i>	Born in 1986, Nadal is age 37 currently.
<i>Numeration Probe H₁</i>	Born in nineteen eighty six, Nadal is age thirty seven currently.
<i>Num Flip Probe H₁</i>	Born in nineteen ninety two, Nadal is age forty one currently.
<i>Range Probe H₁</i>	Born in 1986, Nadal is age between 31-43 currently.
<i>Base Hypothesis H₂</i>	The player’s birth date is on 3rd June, 1986.
<i>Heterog Probe H₂</i>	The player’s birth date is on 03-06-1986.
<i>Heterog Flip Probe H₂</i>	The player’s birth date is on 15-01-1999.
<i>Base Hypothesis H₃</i>	With \$116,111,561 prize money, he is the 3rd highest earning all-time player.
<i>Heterog Probe H₃</i>	With \$116.111561e – 6 prize money, he is the third highest earning all-time player.
<i>Approx Probe H₃</i>	With about \$116, 000, 000 prize money, he is the 3rd highest earning all-time player.
<i>Base Hypothesis H₄</i>	Rafael Nadal has a height of 1.85 meters.
<i>Scale Probe H₄</i>	Rafael Nadal has a height of 185 centimeters.
<i>Scale Flip Probe H₄</i>	Rafael Nadal has a height of 5.2 ft.
<i>Base Hypothesis H₅</i>	After the year 2000, the player Nadal turned pro.
<i>Comparison Probe H₅</i>	After the year 1995, the player Nadal turned pro.
<i>Comparison Flip Probe H₅</i>	Before the year 1990, the player Nadal turned pro.

Table 3: Exemplary hypotheses and non-/flipping probes for evaluated reasoning types

label, we replaced the date in the adjusted format by a random date, i.e. 15-01-1999. We replaced percentage signs by the token “percentages” and vice versa. Similarly, ordinals written as words (*first*) were exchanged by numerical representations (1st) and the other way around. For hypotheses with large numbers (e.g. “\$116,111,561” in H3), we introduced scientific notations (\$116.111561e – 6).

Negative numbers. To create negative probes, we replaced negative numbers $-n$ (e.g. -3) by string equivalents (e.g. *minus 3*; *negative 3*) and evaluated changes in model performances on these semantically same sentence pairs. For label-flipping probes, we converted negative numbers into the positive counterpart n . For example, converting “The company’s monthly closing resulted in -5 million USD.” to “The company’s monthly closing resulted in 5 million USD.” flips the label.

Scale. We created two types of scale probes: (i) *conversion*; (ii) *mapping*. Conversion convert numbers within a measurement scale. For H4 in Table 3, we converted the number and measurement unit (1.85 meters) to the next smaller unit within the same scale (185 centimeters) for the label-preserving probe. For label-flip, we introduced an error in the converted number, i.e. converting 1.85 meters. to 5.2 ft instead of 6.07 ft.

Mapping probes replace the number and measurement unit by an equivalent (e.g. 1.85m by 1.85 meters) for label-preserving probes and a random measurement unit e.g. 1.85m to 1.85 kilograms) to flip the base hypotheses.

Comparison. We first created a list of signal word-pairs by prompting GPT3.5. The list includes pairs such as {“bigger”：“smaller”}, {“taller”：“shorter”}, and {“faster”：“slower”}. Using these pairs and their synonyms, we filtered base hypotheses and created three types of comparison probes. First, changing the signal word with its opposite counterpart to flip labels (see H5 in Table 3 flipping “after” to “before”). Second, altering the number such that the comparison and label do not change: replacing “after 2000” by “after 1995” (H5). Finally, we combine both prior approaches to create label-flipping probes, e.g. “Before the year 1990, the player Nadal turned pro.”s

Approximation. We first extract a number n from our base hypothesis and given the value of n , we decide the magnitude of rounding to apply. While smaller numbers are rounded to tens, larger number are rounded to hundreds, thousands or larger decimal points. For example, we created the probe “With about \$116, 000, 000 prize money, he is the 3rd highest earning all-time player”

by rounding n equal \$116,111,561 to “about \$116,000,000” (H3 in Table 3).

Range. To create range probes, we substitute number n in the base hypothesis by an appropriate range, e.g. 37 by “between 31-43” (H1). We define the radius of the range and its boundaries automatically given the value of n . For example, given $n < 10$, we randomly sample a radius between 1 – 5. For $n = 7$ and a sampled radius of 2, the range will be [5 – 9]. We select decimal boundaries if n is a decimal number.

Sorting. We utilized table columns as number sequences to create sorting probes. We generated a list of position indicators in number sequences (e.g. “top”, “second”, “3rd”, “biggest”, “lowest”). These words were used to filter base hypotheses. To create label-flipping probes, we changed the position of the sequence to another one. For instance, we modified “in the first quarter of 2018” to “in the third quarter of 2018” by selecting the value from the third row instead of the first.

Simple arithmetic. Using on TATQA-NLI its metadata indicating the involved numbers and operations for numerical reasoning, we created arithmetic probes. We extracted probes involving addition, subtraction, multiplication, and division. Additionally, we generated label-flipping probes by replacing the operation output (e.g. result of subtraction) in the hypothesis with a different number. In Table 1, the “Arith” probe involves calculating the difference between the *budget* and *box office* values to determine the correctness of 108.4. The flipped arithmetic probe produces a close but incorrect subtraction output, 120.9.

Numerical word problems. We converted TabMWP questions and answers into declarative hypotheses. TabMWP is a dataset of free-text math word problems that involve reasoning with tabular data. For label-flipping probes, we substituted numbers in the hypotheses with random numbers from the same column.

Counterfactual Table NLI Probes. We filtered the counterfactual ToTTo (Parikh et al., 2020) dataset by Jena et al. (2022) for numerical hypothesis. To create counterfactual tables, they swap two or more table cells to modify the tables such that the label of the respective hypothesis changes from entailment to contradiction and vice versa.

5 Experiments and Analysis

Next, we provide an overview of all models that were evaluated on the probes from §4. We also discuss the obtained results and insights.

5.1 Probed Models

We use state-of-the-art models which are diverse in terms of architecture, size, and training setup, grouped into three categories:

(C1) **Numerical LMs.** This category includes LMs adapted for numerical reasoning. *LUNA* (Han et al., 2022) is a recent transformer-based model with an adapted tokenization approach for numbers. The model encodes numbers as single tokens (e.g. 3, 201) instead of splitting them down into subwords or binned tokens. *NT5* (Yang et al., 2021) is a variation of the T5 model. It has been modified for numerical reasoning through additional pretraining objectives and fine-tuning using numerical datasets. *PASTA* (Gu et al., 2022) is based on DeBERTa and is pretrained with objectives that use table-based numeric operations.

(C2) **LMs for tabular reasoning.** *TAPAS* (Herzig et al., 2020) extends the BERT encoder with table-specific embeddings. We used a TAPAS model trained with intermediate pretraining on synthetic and counterfactual data (Eisenschlos et al., 2020). We also probe TAPEX (Liu et al., 2022), which uses BART (Lewis et al., 2020) as its base model and pretrains the model to mimic a neural SQL executor over tables. Similarly, ReasTAP (Zhao et al., 2022) is a BART-based model pretrained on synthetically generated data requiring seven table reasoning skills, including a numerical task, temporal reasoning, and conjunction. Previous works have also shown the success of the *BERT models on tabular NLI tasks (Herzig et al., 2020; Yin et al., 2020; Shankarampeta et al., 2022; Akhtar et al., 2022). Tables are either linearized or processed into sentences or structured formats. The transformed tables are then used as input to the models. We used a DeBERTa model (He et al., 2021) trained on multiple NLI datasets for this setting.

(C3) **Large LMs.** For few-/zero-shot evaluation, we selected FlanT5 (Shen et al., 2023), GPT3.5, and PaLM 2 (Chowdhery et al., 2022) and probed them in both a few-shot and zero-shot setting.

Model	Table Specific			Numerical Specific				Large LMs					
	TAPAS	DeBERTa	TAPEX	NT5	LUNA	PASTA	ReasTAP	FlanT5		GPT3.5		PaLM	
Reasoning								few	zero	few	zero	few	zero
Representation													
Numeration	-0.32	-1.82	-7.84	-4.18	-5.22	-7.7	-7.18	1.28	-8.84	-0.47	5.65	-1.35	-3.07
Heterogeneous	-4.03	-2.36	-5.94	-3	-10.09	-7.76	-3.18	0.34	-5.49	6.8	6.65	0.44	-2.22
Negative	-46.11	-13.77	0.56	-94.48	-75.55	-10.68	2.65	19.21	42.3	8.24	2.3	-2.17	1.14
Label Flipped													
Numeration	-38.87	4.09	-43.3	-48.53	-71.35	-25.85	-37.21	-78.37	33.38	-37.78	44.71	-37.29	-46.45
Heterogeneous	-9.57	8.53	-32.25	-1.97	-43.48	-23.59	-16.21	-53.44	86.6	-27.97	27.79	-20.65	-25.31
Negative	-64.81	-41.56	-97.01	-17.87	76.85	-70.58	-96.46	-83.92	173.14	-63.64	2.2	-80.43	-78.41
Number Sense													
Scale	0.03	-6.25	-12.91	1.21	-11.43	-1.56	-4.6	-9.45	-7.05	2.46	-0.52	-3.71	-17.58
Comparison	-21.8	-18.18	-12.58	-29.19	-30	-35.11	-40.02	29.38	140.82	-9.39	9.13	-16.91	-20.08
Approximation	-5.61	-6.65	-18.9	-9.55	-7.67	-27.44	-7.81	-9.66	-12.94	0.03	12.08	-10.44	-12.03
Range	-18.89	-33.77	-1.96	-20.43	-86.77	-84.66	4.97	22.44	178.13	0.5	-1.07	14.37	4.41
Label Flipped													
Scale	-23.73	-64.58	-30.41	-39.08	-68.44	-51.66	-16.54	-69.56	93.77	-39.08	39.98	-17.85	-27.4
Comparison	57.67	-19.36	-4.83	-29.62	-0.28	-19.1	-15.65	-8.47	-40.75	-20.81	14.67	-17.96	-16.09
Manipulation													
Sorting	-34.8	28.66	-91	-22.6	54.31	-4.9	-83.96	-86.67	25	-57.39	-5.62	-32.45	-39.59
Arithmetic	-58.62	-24.96	-95.53	-27.1	7.07	-49.06	-88.87	-71.53	265.07	-60.34	4.87	-67.67	-64.98
Complex Reasoning													
Complex	63.37	6.93	-80.18	-3.22	41.41	-50.84	116.17	-89.77	-40	-60.22	-4.35	-73.4	-75.9
Counterfactual	44.5	55.54	-12.29	159.3	0.98	-6.09	-10.12	61.5	12.23	40.63	5.26	30.57	48.56

Table 4: Probing results given as accuracy difference (in %) between base hypotheses and probes.

5.2 Training and Evaluation

To fine-tune models, we used the base hypotheses of the training datasets (e.g. InfoTabs) and evaluated models only on probes created with their testsets. The few-shot models were prompted with 2-shot extrapolation. We evaluated all models in a 3-step process: (1) evaluation of base hypotheses H ; (2) evaluation of probes P , created using H ; (3) calculating changes in model performance by comparing accuracy of P to H . As our TNLI task is a binary classification task, we used accuracy for evaluation.

5.3 Results and Discussion

Table 4 gives an overview of all probing results. If available, we separately list scores for flipped probes, e.g. *numeration* and *numeration flipped*.

(Q1) Does any model excel in all numerical reasoning types? While there is not one best-performing model across all reasoning types and different models struggle with different types, FlanT5 and GPT3.5 show overall good performance in a zero-shot setting. While GPT3.5 (few-shot) performance drops by -60.22% for complex reasoning probes, the model’s average accuracy change is around -16.7% for other types. This can be related to (1) models pretraining data, and (2) training on chain-of-thought reasoning tasks (Wei et al., 2022). GPT3.5 was trained on more than 300 TB data Common Crawl, allowing the model to memorize much more numerical data than other probed models. In comparison, DeBERTa was

trained on only 78GB of data (He et al., 2021). Interestingly, both NT5 and FlanT5 use T5 as their base model. FlanT5 was instruction-fine-tuned and outperforms NT5 many probing categories.

(Q2) What factors can contribute to high performance variations across certain reasoning types? Large performance variations mainly occur due to inconsistent numerical reasoning of models across tasks. For example, we observe that some models struggle with more basic reasoning (e.g., FlanT5 zero on numeration) while performing very well on more complex types. This behavior might have different reasons. One potential reason is memorization. Previous works (Petroni et al., 2019; Carlini et al., 2021; Ishihara, 2023) show that large pretrained language models store knowledge in their parameters, which they tend to retrieve instead of reasoning over the provided input (Gupta et al., 2022a). Hence, models can memorize common arithmetic operations they encounter during training and perform well on certain downstream tasks. For example, flipping numbers as words (“two”) to numerals (“2”) might allow models to retrieve knowledge which they didn’t consider for the initial hypothesis. Another reason for high-performance drops can be the hallucination of models. While models initially perform well on hypotheses, adjusting the numbers can hinder models from relying on spurious patterns.

(Q3) How do models perform on different types of numerical reasoning? Representation. In

Table 4, comparing numeration probes, we find for all models a performance drop of between $[0; -10]$ percentages for numeration probes, except FlanT5 (few). This drop strongly increases for almost all models evaluated numeration flipped probes. For example, FlanT5 (few) shows a performance drop of -78.37% . FlanT5 (few) also performs well on heterogeneous probes, followed by DeBERTa (-2.4%) and NT5 (-3%). Whereas LUNA performance drops significantly for heterogeneous probes (flipped and non-flipped). TAPAS, NT5, and LUNA show significant performance drops (between -38.87% and -71.35%) on negative number probes. This could be because the models exploit correlations between the “-” sign and labels for predicting base hypotheses. Interestingly, few- and zero-shot models like FlanT5 and GPT3.5 show improvements on negative number probes. This may be because the models understand probed versions of negative numbers (e.g. “minus 22”) as a negative number but not the initial representation (e.g. “-22”).

Number sense. Comparing models based on number sense probes, we observe different patterns for fine-tuned models and few-/zero-shot models. Fine-tuned models struggle especially with comparison probes, with a -26.7% average performance drop. Scale probes show a -42.1% decrease on flipping probes, while approximation (flipping) probes report a -12.0% decrease in model performance. In contrast, FlanT5 perform better on comparison and range probes, sometimes surpassing predictions on the base hypotheses. All models demonstrate lower performance on approximation probes compared to the base hypotheses, with PASTA performance dropping by -27.44% .

Manipulation and Complex Reasoning. Fine-tuned models exhibit an average accuracy drop of -57% on arithmetic probes, except for LUNA with a slight performance increase. The performance of PaLM (zero) and FlanT5 (few) drops by -67.67% and -71.53% , respectively. All models’ performance drops on sorting probes (avg. -27%), except for DeBERTa, LUNA, and FlanT5 (zero). Unlike most other reasoning types, fine-tuned models outperform few-/zero-shot models on complex reasoning probes. ReasTAP achieves the highest accuracy, followed by TAPAS and LUNA. FlanT5, TAPEX, and PaLM have the largest performance drops on complex reasoning probes.

(Q4) Do models perform similarly for flipped and non-flipped probes? We observe higher performance drops for label-flipping probes compared to non-flipping probes across models. Models that struggle with flipping probes but perform well on their non-flipping counterparts indicate a reliance on spurious patterns for label prediction. The performance of TAPAS, TAPEX, PASTA, ReasTAP, FlanT5 (few), and PaLM drops significantly for the representation reasoning category comparing non-flipping and flipping probes. For example, TAPAS performance drops by -2.28% on numeration probes, but show a drop of -45.98% on numeration flipping probes. Similarly, DeBERTa performs well on scale probes (-6.25%) compared to the flipping version (-64.58%). PaLM performance on numeration, heterogeneous, and negative probes drops by approximately -35% , -20% , and -80% on flipping counterparts. DeBERTa exhibits robust performance on number flipping probes for sorting and FlanT5 on negative numbers, as well as arithmetic probes.

(Q5) Are numerical and table-specific models better for numerical reasoning than LLMs? Numerical models. Our experiments do not indicate any superiority of numerical models over others. LUNA, a transformer model that uses a specific tokenization method for numbers, performs similarly to other models on many reasoning types. The only reasoning type where LUNA outperforms is comparison flipping probes, with a small improvement of 0.28% . PASTA is a DeBERTa-based model trained on numerical data and pretraining objectives. However, compared to DeBERTa, it only performs better on negative number and scale probes.

6 Related Work

Numeracy Taxonomies in NLP. Prior works have introduced surveys and taxonomies to organise numeracy in NLP research. Thawani et al. (2021b) categorise NLP work on numeracy into seven subtasks along the dimensions granularity (i.e. exact and approximate numbers) and unit (i.e. abstract and grounded numbers). Xu et al. (2022) focus on the robustness of QA systems in handling numerical data and organize their numeracy probing tasks in two broad categories: (i) numerical parsing, and (ii) semantic parsing. The DROP benchmark (Dua et al., 2019) is a QA dataset that requires discrete operations (e.g. subtraction, count,

sort) to answer questions over text. While [Thawani et al. \(2021b\)](#) concentrate on number representations in NLP systems, our work includes three further numerical reasoning categories. [Xu et al. \(2022\)](#) focus on the robustness of NLP models in handling numerical data. Our probing study on the other side pivots towards the reasoning capabilities of models when dealing with numerical and tabular data. Different to prior work, our study gives a broad and in-depth evaluation of ten different models from three different categories (numerical, tabular, large pretrained LMs) on more than ten different reasoning types (representation, number sense, manipulation, and complex reasoning).

Language Model / Numerical Skills. Various studies have evaluated LMs’ numerical skills in recent years. Earlier works probed word embeddings for numeration (e.g. 4=four) ([Naik et al., 2019](#)), comparison (e.g. $3 < 4$) ([Wallace et al., 2019](#)), scale ([Zhang et al., 2020](#)), and superlatives ([Wallace et al., 2019](#)). More recent works evaluate LMs on out-of-distribution numbers ([Kim et al., 2021](#)), numeration/magnitude/sorting/superlatives ([Pal and Baral, 2021](#)), and arithmetic ([Muffo et al., 2022](#)). Our work builds upon these previous evaluation studies and extends them with further numerical probing categories, e.g. heterogeneous numbers.

Numerically-tuned Language Models. Various numerical LMs have been developed in recent times. [Geva et al. \(2020\)](#) and [Liang et al. \(2022\)](#) inject numerical skills into BERT through numerical pretraining objectives. PASTA ([Gu et al., 2022](#)) and NT5 ([Yang et al., 2021](#)), which are based on DeBERTa and T5 respectively, fall into the same category of models. Another line of work adjusts LMs’ architectures for numerical reasoning through numerical tokenization ([Han et al., 2022](#)) or additional, numerical embeddings ([Jin et al., 2021](#)).

Systematic Probes for Tables. Tables have been utilized previously used to create probes for table grounding ([Gupta et al., 2022b](#)) or recasting non-NLI datasets (e.g. question-answering) to NLI ([Jena et al., 2022](#)). Unlike unstructured text data, tables have a natural structure that allows creating controlled experiments more easily ([Gupta et al., 2022a](#)). We drew inspiration from prior tabular probing approaches and extended them for automating probing of numerical tabular data. [Jena et al. \(2022\)](#) introduce a generic approach to adjust

table QA datasets and generate NLI data. For data recasting, they follow a systemic approach similar to ours. However, the focus is on transforming QA datasets, emphasizing the end-result (i.e. the NLI data) through data augmentation. They do not evaluate the presence of numerical data in their tables or consider numerical reasoning in the model evaluation phrase.

Comparison to Prior Work. All the above mentioned prior works on numerical reasoning have provided motivation for our research. However, their evaluations have focused on a narrow range of reasoning types and models. Most study only concentrated on one specific model such as T5 ([Pal and Baral, 2021](#)), GPT3 ([Muffo et al., 2022](#)), or BERT ([Park et al., 2022](#)). In contrast, our framework provides a comprehensive evaluation of numerical reasoning skills. We cover a wide spectrum of complexity levels, ranging from representation to complex reasoning. Moreover, we assess a variety of models with diverse architectures, sizes, and training settings for numerical reasoning.

7 Conclusion

This paper presents a framework for probing language models’ numerical reasoning skills. We organise skills in a taxonomy and generate large-scale sets of probes covering more than ten numerical reasoning types. Using table NLI as a case study, we evaluate the numerical reasoning abilities of ten models. These models belong to the categories numerical LMs, tabular LMs, and few-/zero-shot LLMs. We discuss reasoning types that prove challenging for the probed models and explore promising directions for future research.

Future Directions. For certain (numerical) tasks, tool-augmented LMs equipped with capabilities such as calculators or code execution have been proven valuable ([Mialon et al., 2023](#)). However, certain tasks require implicit numerical reasoning which might not necessarily involve direct calculations based on numbers. For instance, classifying sentences that incorporate numbers in varied settings, like time indications ([Feng et al., 2023](#)), currencies or conversations ([Macina et al., 2023](#)). Such tasks demand a numerical interpretation beyond mere arithmetic computations. Moreover, calling external tools using LMs requires basic numerical comprehension to invoke an external tool correctly ([Chen et al., 2022](#)).

Limitations

This work proposes a taxonomy and framework to probe numerical reasoning skills in LMs. It involves the creation of large-scale probing sets using an automated approach. However, the evaluation of this approach is currently limited to the task of table NLI. For future research, it is interesting to extend this to include additional tasks and datasets. This extension serves two purposes: first, it allows evaluating a more diverse range of datasets. Second, it enables including challenges specific to other tasks.

In this paper, the evaluation of most reasoning types primarily involves structural changes at the hypotheses level. While we include counterfactual table probes, they are limited to one dataset and perturbations method only. Further research is needed to study models' performance on numerical data in the premise data. Therefore, we need table-based probes for all reasoning types of the proposed taxonomy.

Ethics Statement

In this paper, we study the numerical reasoning skills of different LMs. However, to deploy these systems in real-world applications, further studies and evaluations specific to the intended use cases are required. In order to support future research, we plan to release all the scripts and resources used for probe creation and model evaluation. This will facilitate and encourage further research in this field.

References

- Mubashara Akhtar, Oana Cocarascu, and Elena Simperl. 2022. [PubHealthTab: A public health table-based dataset for evidence-based fact checking](#). In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 1–16, Seattle, United States. Association for Computational Linguistics.
- Aida Amini, Saadia Gabriel, Shanchuan Lin, Rik Koncel-Kedziorski, Yejin Choi, and Hannaneh Hajishirzi. 2019. [MathQA: Towards interpretable math word problem solving with operation-based formalisms](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2357–2367, Minneapolis, Minnesota. Association for Computational Linguistics.
- Pierre Barrouillet and Michel Fayol. 1998a. [From algorithmic computing to direct retrieval: Evidence from number and alphabetic arithmetic in children and adults](#). *Memory & Cognition*, 26(2):355–368.
- Pierre Barrouillet and Michel Fayol. 1998b. From algorithmic computing to direct retrieval: Evidence from number and alphabetic arithmetic in children and adults. *Memory & Cognition*, 26:355–368.
- Emily M. Bender and Alexander Koller. 2020. [Climbing towards NLU: On meaning, form, and understanding in the age of data](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5185–5198, Online. Association for Computational Linguistics.
- Laura Bofferding. 2019. *Understanding Negative Numbers*, pages 251–277. Springer International Publishing, Cham.
- Justin W. Bonny and Stella F. Lourenco. 2013. [The approximate number system and its relation to early math achievement: Evidence from the preschool years](#). *Journal of Experimental Child Psychology*, 114(3):375–388.
- Nicholas Carlini, Florian Tramèr, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom B. Brown, Dawn Song, Úlfar Erlingsson, Alina Oprea, and Colin Raffel. 2021. [Extracting training data from large language models](#). In *30th USENIX Security Symposium, USENIX Security 2021, August 11-13, 2021*, pages 2633–2650. USENIX Association.
- Anthony Chen, Panupong Pasupat, Sameer Singh, Hongrae Lee, and Kelvin Guu. 2023. [PURR: efficiently editing language model hallucinations by denoising language model corruptions](#). *CoRR*, abs/2305.14908.
- Wenhu Chen, Xueguang Ma, Xinyi Wang, and William W. Cohen. 2022. [Program of thoughts prompting: Disentangling computation from reasoning for numerical reasoning tasks](#). *CoRR*, abs/2211.12588.
- Wenhu Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyou Zhou, and William Yang Wang. 2020. [Tabfact: A large-scale dataset for table-based fact verification](#). In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny

- Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayanan Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. [Palm: Scaling language modeling with pathways](#). *CoRR*, abs/2204.02311.
- Dorottya Demszky, Kelvin Guu, and Percy Liang. 2018. [Transforming question answering datasets into natural language inference datasets](#). *CoRR*, abs/1809.02922.
- Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. [DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2368–2378, Minneapolis, Minnesota. Association for Computational Linguistics.
- Julian Eisenschlos, Syrine Krichene, and Thomas Müller. 2020. [Understanding tables with intermediate pre-training](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 281–296, Online. Association for Computational Linguistics.
- Yu Feng, Ben Zhou, Haoyu Wang, Helen Jin, and Dan Roth. 2023. [Generic temporal reasoning with differential analysis and explanation](#). In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 12013–12029, Toronto, Canada. Association for Computational Linguistics.
- Karen C Fuson. 2012. *Children’s counting and concepts of number*. Springer Science & Business Media.
- Mor Geva, Ankit Gupta, and Jonathan Berant. 2020. [Injecting numerical reasoning skills into language models](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 946–958, Online. Association for Computational Linguistics.
- Zihui Gu, Ju Fan, Nan Tang, Preslav Nakov, Xiaoman Zhao, and Xiaoyong Du. 2022. [PASTA: Table-operations aware fact verification via sentence-table cloze pre-training](#). In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 4971–4983, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Vivek Gupta, Riyaz A. Bhat, Atreya Ghosal, Manish Shrivastava, Maneesh Singh, and Vivek Srikumar. 2022a. [Is my model using the right evidence? systematic probes for examining evidence-based tabular reasoning](#). *Transactions of the Association for Computational Linguistics*, 10:659–679.
- Vivek Gupta, Maitrey Mehta, Pegah Nokhiz, and Vivek Srikumar. 2020. [INFOTABS: Inference on tables as semi-structured data](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2309–2324, Online. Association for Computational Linguistics.
- Vivek Gupta, Shuo Zhang, Alakananda Vempala, Yujie He, Temma Choji, and Vivek Srikumar. 2022b. [Right for the right reason: Evidence extraction for trustworthy tabular reasoning](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3268–3283, Dublin, Ireland. Association for Computational Linguistics.
- Hongwei Han, Jialiang Xu, Mengyu Zhou, Yijia Shao, Shi Han, and Dongmei Zhang. 2022. [LUNA: language understanding with number augmentations on transformers via number plugins and pre-training](#). *CoRR*, abs/2212.02691.
- Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2021. [Deberta: decoding-enhanced bert with disentangled attention](#). In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net.
- Jonathan Herzig, Pawel Krzysztof Nowak, Thomas Müller, Francesco Piccinno, and Julian Eisenschlos. 2020. [TaPas: Weakly supervised table parsing via pre-training](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4320–4333, Online. Association for Computational Linguistics.
- Danqing Huang, Shuming Shi, Chin-Yew Lin, Jian Yin, and Wei-Ying Ma. 2016. [How well do computers solve math word problems? large-scale dataset construction and evaluation](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 887–896, Berlin, Germany. Association for Computational Linguistics.
- Shotaro Ishihara. 2023. [Training data extraction from pre-trained language models: A survey](#). *CoRR*, abs/2305.16157.
- Aashna Jena, Vivek Gupta, Manish Shrivastava, and Julian Eisenschlos. 2022. [Leveraging data recasting to enhance tabular reasoning](#). In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 4483–4496, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Yejin Bang, Andrea Madotto, and Pascale Fung. 2023. [Survey of hallucination in natural language generation](#). *ACM Comput. Surv.*, 55(12):248:1–248:38.

- Zhihua Jin, Xin Jiang, Xingbo Wang, Qun Liu, Yong Wang, Xiaozhe Ren, and Huamin Qu. 2021. [Numgpt: Improving numeracy ability of generative pre-trained models](#). *CoRR*, abs/2109.03137.
- Jeonghwan Kim, Giwon Hong, Kyung-min Kim, Junmo Kang, and Sung-Hyon Myaeng. 2021. [Have you seen that number? investigating extrapolation in question answering models](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7031–7037, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Elida V. Laski and Robert S. Siegler. 2007. [Is 27 a big number? correlational and causal connections among numerical categorization, number line estimation, and numerical magnitude comparison](#). *Child Development*, 78(6):1723–1743.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. [BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.
- Zhenwen Liang, Jipeng Zhang, Lei Wang, Wei Qin, Yunshi Lan, Jie Shao, and Xiangliang Zhang. 2022. [MWP-BERT: Numeracy-augmented pre-training for math word problem solving](#). In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 997–1009, Seattle, United States. Association for Computational Linguistics.
- Bill Yuchen Lin, Seyeon Lee, Rahul Khanna, and Xiang Ren. 2020. [Birds have four legs?! NumerSense: Probing Numerical Commonsense Knowledge of Pre-Trained Language Models](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6862–6868, Online. Association for Computational Linguistics.
- Qian Liu, Bei Chen, Jiaqi Guo, Morteza Ziyadi, Zeqi Lin, Weizhu Chen, and Jian-Guang Lou. 2022. [TAPEX: table pre-training via learning a neural SQL executor](#). In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.
- Lefteris Loukas, Manos Fergadiotis, Ilias Chalkidis, Eirini Spyropoulou, Prodromos Malakasiotis, Ion Androusoyopoulos, and Georgios Paliouras. 2022. [FiNER: Financial numeric entity recognition for XBRL tagging](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 4419–4431, Dublin, Ireland. Association for Computational Linguistics.
- Pan Lu, Liang Qiu, Kai-Wei Chang, Ying Nian Wu, Song-Chun Zhu, Tanmay Rajpurohit, Peter Clark, and Ashwin Kalyan. 2023. [Dynamic prompt learning via policy gradient for semi-structured mathematical reasoning](#). In *International Conference on Learning Representations (ICLR)*.
- Jakub Macina, Nico Daheim, Sankalan Pal Chowdhury, Tanmay Sinha, Manu Kapur, Iryna Gurevych, and Mrinmaya Sachan. 2023. [Mathdial: A dialogue tutoring dataset with rich pedagogical properties grounded in math reasoning problems](#). *CoRR*, abs/2305.14536.
- Grégoire Mialon, Roberto Dessì, Maria Lomeli, Christoforos Nalmpantis, Ramakanth Pasunuru, Roberta Raileanu, Baptiste Rozière, Timo Schick, Jane Dwivedi-Yu, Asli Celikyilmaz, Edouard Grave, Yann LeCun, and Thomas Scialom. 2023. [Augmented language models: a survey](#). *CoRR*, abs/2302.07842.
- Matteo Muffo, Aldo Cocco, and Enrico Bertino. 2022. [Evaluating transformer language models on arithmetic operations using number decomposition](#). In *Proceedings of the Thirteenth Language Resources and Evaluation Conference, LREC 2022, Marseille, France, 20-25 June 2022*, pages 291–297. European Language Resources Association.
- Aakanksha Naik, Abhilasha Ravichander, Carolyn Rose, and Eduard Hovy. 2019. [Exploring numeracy in word embeddings](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3374–3380, Florence, Italy. Association for Computational Linguistics.
- Darko Odic and Ariel Starr. 2018. [An introduction to the approximate number system](#). *Child Development Perspectives*, 12(4):223–229.
- Kuntal Kumar Pal and Chitta Baral. 2021. [Investigating numeracy learning ability of a text-to-text transfer model](#). In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 3095–3101, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Ankur Parikh, Xuezhi Wang, Sebastian Gehrmann, Manaal Faruqui, Bhuwan Dhingra, Diyi Yang, and Dipanjan Das. 2020. [ToTTo: A controlled table-to-text generation dataset](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1173–1186, Online. Association for Computational Linguistics.
- Sungjin Park, Seungwoo Ryu, and Edward Choi. 2022. [Do language models understand measurements?](#) In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 1782–1792, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Arkil Patel, Satwik Bhattamishra, and Navin Goyal. 2021. [Are NLP models really able to solve simple math word problems?](#) In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2080–2094, Online. Association for Computational Linguistics.

- Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. 2019. [Language models as knowledge bases?](#) In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2463–2473, Hong Kong, China. Association for Computational Linguistics.
- Yasaman Razeghi, Robert L Logan IV, Matt Gardner, and Sameer Singh. 2022. [Impact of pretraining term frequencies on few-shot numerical reasoning.](#) In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 840–854, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Abhilash Shankarampeta, Vivek Gupta, and Shuo Zhang. 2022. [Enhancing tabular reasoning with pattern exploiting training.](#) In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 706–726, Online only. Association for Computational Linguistics.
- Sheng Shen, Le Hou, Yanqi Zhou, Nan Du, Shayne Longpre, Jason Wei, Hyung Won Chung, Barret Zoph, William Fedus, Xinyun Chen, Tu Vu, Yuexin Wu, Wuyang Chen, Albert Webson, Yunxuan Li, Vincent Zhao, Hongkun Yu, Kurt Keutzer, Trevor Darrell, and Denny Zhou. 2023. [Flan-moe: Scaling instruction-finetuned language models with sparse mixture of experts.](#) *CoRR*, abs/2305.14705.
- Avijit Thawani, Jay Pujara, and Filip Ilievski. 2021a. [Numeracy enhances the literacy of language models.](#) In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6960–6967, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Avijit Thawani, Jay Pujara, Filip Ilievski, and Pedro Szekely. 2021b. [Representing numbers in NLP: a survey and a vision.](#) In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 644–656, Online. Association for Computational Linguistics.
- Shyam Upadhyay and Ming-Wei Chang. 2017. [Annotating derivations: A new evaluation strategy and dataset for algebra word problems.](#) In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 494–504, Valencia, Spain. Association for Computational Linguistics.
- Eric Wallace, Yizhong Wang, Sujian Li, Sameer Singh, and Matt Gardner. 2019. [Do NLP models know numbers? probing numeracy in embeddings.](#) In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5307–5315, Hong Kong, China. Association for Computational Linguistics.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, brian ichter, Fei Xia, Ed H. Chi, Quoc V Le, and Denny Zhou. 2022. [Chain of thought prompting elicits reasoning in large language models.](#) In *Advances in Neural Information Processing Systems*.
- Jemma Catherine Whyte and Rebecca Bull. 2008. [Number games, magnitude representation, and basic number skills in preschoolers.](#) *Developmental Psychology*, 44(2):588–596.
- Jialiang Xu, Mengyu Zhou, Xinyi He, Shi Han, and Dongmei Zhang. 2022. [Towards robust numerical question answering: Diagnosing numerical capabilities of NLP systems.](#) In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 7950–7966, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Peng-Jian Yang, Ying-Ting Chen, Yuechan Chen, and Daniel Cer. 2021. [Nt5?! training T5 to perform numerical reasoning.](#) *CoRR*, abs/2104.07307.
- Yunhu Ye, Binyuan Hui, Min Yang, Binhua Li, Fei Huang, and Yongbin Li. 2023. [Large language models are versatile decomposers: Decompose evidence and questions for table-based reasoning.](#) *CoRR*, abs/2301.13808.
- Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. 2020. [TaBERT: Pretraining for joint understanding of textual and tabular data.](#) In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8413–8426, Online. Association for Computational Linguistics.
- Xikun Zhang, Deepak Ramachandran, Ian Tenney, Yanai Elazar, and Dan Roth. 2020. [Do language embeddings capture scales?](#) In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4889–4896, Online. Association for Computational Linguistics.
- Yilun Zhao, Linyong Nan, Zhenting Qi, Rui Zhang, and Dragomir Radev. 2022. [ReasTAP: Injecting table reasoning skills during pre-training via synthetic reasoning examples.](#) In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9006–9018, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Ben Zhou, Qiang Ning, Daniel Khashabi, and Dan Roth. 2020. [Temporal common sense acquisition with minimal supervision.](#) In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7579–7589, Online. Association for Computational Linguistics.

Fengbin Zhu, Wenqiang Lei, Youcheng Huang, Chao Wang, Shuo Zhang, Jiancheng Lv, Fuli Feng, and Tat-Seng Chua. 2021. [TAT-QA: A question answering benchmark on a hybrid of tabular and textual content in finance](#). In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3277–3287, Online. Association for Computational Linguistics.

improved significantly, which leads to the conclusion that models are biased toward one label.

Overall no language model excels in all the numerical reasoning tasks. Surprisingly, models perform relatively well in complex tasks like Numerical Word Problems but struggle at simple reasoning tasks like numeration and comparison.

A Insights

Main Insights. We investigated the language models and found that LLMs like FlanT5 and GPT3.5 perform better than other models on various numerical reasoning tasks. When the labels are switched around and when dealing with negative values, we found that both table-based and numerical models had difficulty comprehending the data. In contrast, DeBERTa performs relatively well compared to models like LUNA and PASTA, which are tuned for improved numerical reasoning skills.

B Probe Statistics

Reasoning Type	Count
Word Problems	238
Sorting	379
Counterfactual	1,000
Currency	1,014
Negative	3,316
Range	4,208
Scientific notation	6,274
Arithmetic	8,082
Ordinal	10,569
Percentage	16,851
Date	18,642
Approximation	20,440
Comparison	30,763
Numeration	166,319
Total	288,095
Flipped probes	77,687

Table 5: Breakdown of probes per reasoning type.

Table 2 gives an overview of probes per dataset. Most probes (i.e. 214, 440) are created from TabFact hypotheses as this is also the biggest dataset available, followed by InfoTabs (19, 779). Table 5 provides a breakdown of probes per reasoning type. In total, we have 286, 857 probes, of which 76, 404 are label-flipping probes.

In the ideal scenario with counterfactual tables, the models’ performance should be similar to the performance on the original tables. However, we observed that TAPAS and DeBERTa’s performance

Model	Table Specific			Numerical Specific				Large LMs					
	TAPAS	DeBERTa	TAPEX	NT5	LUNA	PASTA	ReasTAP	FlanT5		GPT3.5		PaLM	
Reasoning								few	zero	few	zero	few	zero
Representation													
Numeration	19.02	61.69	74.83	64.19	63.57	85.43	75.35	64.59	67.58	77.6	61.83	76.38	70.76
Heterogeneous	79.25	56.61	81.17	66.85	70.71	89.11	76.49	70.17	71.04	78.82	61.26	76.75	69.85
Negative	59.38	69.81	97.01	51.77	24.66	70.44	81.04	70.8	20.37	85	87	92	88
Label Flipped													
Numeration	23	61.92	75.79	71.98	76.34	86.96	73.64	88.93	66.93	90.57	54.11	85.97	87.91
Heterogeneous	67.66	53.12	82.96	62.94	77.57	83.75	68.37	87.48	51.55	89.18	65.32	86.55	79.14
Negative	59.38	69.81	97.01	51.77	24.66	70.44	72.53	70.8	20.37	88	85	92	88
Number Sense													
Scale	74.11	67.29	78.32	63.05	72.24	77.82	31.1	61.25	69.59	79.17	69	78.04	71.15
Comparison	68.43	68.7	54.12	66.85	69.19	84.75	58.46	37.77	23.87	83.31	50.58	77.43	63.78
Approximation	75.49	64.65	71.64	63.3	67.09	86.08	58.66	62.28	78.09	75.13	59.62	76.88	75.35
Range	70.84	57.53	94.99	58.14	48.86	73.25	87.77	80.2	20.09	90	85.5	80	81.41
Label Flipped													
Scale	72.33	76.74	71.78	65.17	78.8	87	95.92	85.71	59.6	92.62	60.71	79.58	80.21
Comparison	53.55	70.75	38.29	68.64	69.76	85.74	42.69	86.12	49.66	96.05	37.34	82	54.86
Manipulation													
Sorting	68.71	49.98	94.65	69.83	51.11	69.87	83.33	75.44	61.4	91.44	77	68.94	70.5
Arithmetic	71.15	58.01	95.92	58.83	73.6	73.6	88.97	78.92	22.42	89.5	85.5	83.5	81.5
Complex Reasoning													
Complex	54.6	52.65	82.69	52.94	39.22	81.93	95.92	91.69	69.03	93	56.1	94	91.3
Counterfactual	59.71	43.23	88.7	80.98	81.3	83.52	86.9	35.46	62.5	58.18	69.09	55.38	53.85

Table 6: Results on original sets (average accuracy).

Model	Table Specific			Numerical Specific				Large LMs					
	TAPAS	DeBERTa	TAPEX	NT5	LUNA	PASTA	ReasTAP	FlanT5		GPT3.5		PaLM	
Reasoning								few	zero	few	zero	few	zero
Representation													
Numeration	18.4	59.24	68.34	60.5	59.44	79.64	69.36	64.5	63.01	77.19	64.3	75.38	74
Heterogeneous	72.76	54.52	75.75	62.19	63.73	80.59	74.32	68.92	67.52	77.36	65.78	75.5	70.22
Negative	32	60.2	97.55	2.86	6.03	62.92	76.19	84.4	28.98	92	89	90	89
Label Flipped													
Numeration	10.13	43.68	39.41	33.89	29.82	53.3	41.05	17.34	70.04	56.83	73.37	52.54	45.91
Heterogeneous	63.1	42.45	49.44	57.08	47.97	68.75	56.58	40.57	80.34	62.16	78.83	70.12	62.18
Negative	20.9	40.8	2.9	42.52	43.61	20.72	41.28	11.38	55.63	32	86.87	18	19
Number Sense													
Scale	71.68	49.43	68.38	60.39	62.21	73.63	67.23	53.12	62	80.46	66	75.15	59.39
Comparison	42.78	54.91	45.32	45.94	54.79	60.04	40.73	48.84	55.33	73.74	58.69	64.97	51.71
Approximation	62.94	58.65	56.01	56.75	61.56	61.55	51.26	56.23	67.65	74.96	66.1	69.25	66.4
Range	57.73	38.09	93.13	46.28	6.46	11.24	92.12	98.2	55.87	90.47	84.5	91.5	85
Label Flipped													
Scale	39.26	44.24	38.91	44.55	28.63	43.12	98.46	23.69	77.67	56.31	66.94	60.93	52.57
Comparison	62.59	57.28	37.15	46.9	66.75	69.72	34.74	66.43	50.29	75.22	54.6	69.43	44.98
Manipulation													
Sorting	44.8	63.75	8.47	53.89	77.79	64.54	13.29	10.03	76.75	38.75	72.81	46.38	42.31
Arithmetic	71.15	43.52	4.28	42.89	37.5	37.5	9.88	22.45	81.08	35.5	89.5	27	28.5
Complex Reasoning													
Complex	89.22	56.3	16.39	51.24	55.46	40.28	3.4	9.38	41.42	37	72.78	25	22
Counterfactual	86.21	67.24	77.8	31.23	82.1	78.43	78.1	57.27	70.14	81.82	72.73	72.31	80

Table 7: Results on probed sets (average accuracy).