Textbooks Are All You Need

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Introduction

- Variant of Scaling Law
  - higher **quality** of the dataset -> better result (Eldan and Li, 2023)
- This work aims to show that high quality data can:
  - improve the SOTA of large language models
  - reduces the dataset size and training compute.
- **Contribution:**
  - Trained a tiny and competitive LLM for Python code generation by data filtering techniques.
  - Outperform other coder LLM that are trained on larger dataset with more parameters.

Data Filtering

- **Data Sources:** Deduplicated Python files in The Stack and the StackOverflow ~35B tokens, ~35M code examples)
- Annotate the quality of ~100K samples via asking GPT-4 (Prompt: "determine the educational value of a code snippet.")
  - Minimizes human-annotation efforts
- Train a random forest classifier to filter out low-quality data.
- Result: a 6B high-quality dataset "The Stack"
- Significant reduction in size.

Educational values deemed by the filter

High educational value

```
import torch
import torch.nn.functional as F

def normalize(x, axis=-1):
    """Performs L2-Norm."""
    num = x
    denom = torch.norm(x, 2, axis, keepdim=True)
    .expand_as(x) + 1e-12
    return num / denom

def euclidean_dist(x, y):
    """Computes Euclidean distance."""
    m, n = x.size(0), y.size(0)
    xx = torch.pow(x, 2).sum(1, keepdim=True).
    expand(m, n)
    yy = torch.pow(x, 2).sum(1, keepdim=True).
    expand(m, m).t()
    dist = xx + yy - 2 * torch.matmul(x, y.t())
    dist = dist.clamp(min=1e-12).sqrt()
    return dist

def cosine_dist(x, y):
    """Computes Cosine Distance."""
    x = F.normalize(x, dim=1)
    y = F.normalize(y, dim=1)
    dist = 2 - 2 * torch.mm(x, y.t())
    return dist
```

Low educational value

```
import re
import typing
...

class Default(object):
    def __init__(self, vim: Nvim) -> None:
        self._vim = vim
        self._denite: typing.Optional[SyncParent]
    = None
        self._selected_candidates: typing.List[int
    ] = []
        self._candidates: Candidates = []
        self._cursor = 0
        self._entire_len = 0
        self._result: typing.List[typing.Any] = []
        self._context: UserContext = {}
        self._bufnr = -1
        self._winid = -1
        self._winrestcmd = ''
        self._initialized = False
        self._winheight = 0
        self._winwidth = 0
        self._winminheight = -1
        self._is_multi = False
        self._is_async = False
        self._matched_pattern = ''
        ...
```

Data Generation

- **Method:** Prompt GPT-3.5 to write code snippet.
- **Challenge:** ensuring that the generated dataset is diverse and non-repetitive.
  - Trick: inject randomness into the prompt regarding by providing constraints on vocabulary, topics and target audience of the generated textbook.
- This creates a ~1B dataset called "CodeTextbook".

```
To begin, let us define singular and nonsingular matrices. A matrix is said to be singular if its
determinant is zero. On the other hand, a matrix is said to be nonsingular if its determinant is not
 zero. Now, let's explore these concepts through examples.

Example 1: Consider the matrix A = np.array([[1, 2], [2, 4]]). We can check if this matrix is
singular or nonsingular using the determinant function. We can define a Python function, `
is_singular(A)`, which  returns true if the determinant of A is zero, and false otherwise.

import numpy as np
def is_singular(A):
    det = np.linalg.det(A)
    if det == 0:
        return True
    else:
        return False

A = np.array([[1, 2], [2, 4]])
print(is_singular(A)) # True
```

Data Generation for alignment

- A small synthetic exercises dataset CodeExercise (~180M tokens).
  - Each exercise is a docstring of a function that needs to be completed to
  - Align the model to perform function completion in the fine-tuning stage.
  - This dataset was generated by GPT-3.5, where the main means of eliciting diversity is by constraining the function names.

```python
def valid_guessing_letters(word: str, guesses: List[str]) -> List[str]:
    """
    Returns a list of valid guessing letters, which are letters that have not been guessed yet and
    are present in the word.
    Parameters:
    word (str): The word to guess.
    guesses (List[str]): A list of letters that have already been guessed.
    Returns:
    List[str]: A list of valid guessing letters.
    """
    valid_letters = []
    for letter in word:
        if letter not in guesses and letter not in valid_letters:
            valid_letters.append(letter)
    return valid_letters
```

Model Architecture

- **Model Overview:**
  - Decoder-only Transformer with 1.3B parameters.
  - FlashAttention for efficient multi-head attention.
- Parameters:
  - Batch size: 1024 for pretraining, 256 for finetuning.
- Hardware: 8 A100 GPUs
  - <4 days for pretraining
  - 7 hours for finetuning.

phi-1 and Its Variants

- **phi-1-base:** Pretrained on “The Stack” + “CodeTextbook” dataset for 8 passes.
- **phi-1:** Also finetuned on “CodeExercises”.
- Achieved 50.6% pass@1 accuracy on HumanEval, 55.5% on MBPP.
  - HumanEval: 164 programs with 8 tests for each.
  - MBPP (Mostly Basic Python Programming: 1000 programs, 3 tests for each.
  - pass@1: check whether its initial code generation is correct.
- **phi-1-small:** 350M-parameter variant.
- **Emergent Properties:** Finetuning improves logical reasoning and library usage.
- Demonstrates scaling laws for performance improvements with quality data.

Results: Code Benchmark Evaluation

Date	Model	Model size (Parameters)	Dataset size (Tokens)	HumanEval (Pass@1)	MBPP (Pass@1)
2021 Jul	Codex-300M [CTJ+21]	300M	100B	13.2%	-
2021 Jul	Codex-12B [CTJ+21]	12B	100B	28.8%	-
2022 Mar	CodeGen-Mono-350M [NPH+23]	350M	577B	12.8%	-
2022 Mar	CodeGen-Mono-16.1B [NPH+23]	16.1B	577B	29.3%	35.3%
2022 Apr	PaLM-Coder [CND+22]	540B	780B	35.9%	47.0%
2022 Sep	CodeGeeX [ZXZ+23]	13B	850B	22.9%	24.4%
2022 Nov	GPT-3.5 [Ope23]	175B	N.A.	47%	-
2022 Dec	SantaCoder [ALK+23]	1.1B	236B	14.0%	35.0%
2023 Mar	GPT-4 [Ope23]	N.A.	N.A.	67%	-
2023 Apr	Replit [Rep23]	2.7B	525B	21.9%	-
2023 Apr	Replit-Finetuned [Rep23]	2.7B	525B	30.5%	-
2023 May	CodeGen2-1B [NHX+23]	1B	N.A.	10.3%	-
2023 May	CodeGen2-7B [NHX+23]	7B	N.A.	19.1%	-
2023 May	StarCoder [LAZ+23]	15.5B	1T	33.6%	52.7%
2023 May	StarCoder-Prompted [LAZ+23]	15.5B	1T	40.8%	49.5%
2023 May	PaLM 2-S [ADF+23]	N.A.	N.A.	37.6%	50.0%
2023 May	CodeT5+ [WLG+23]	2B	52B	24.2%	-
2023 May	CodeT5+ [WLG+23]	16B	52B	30.9%	-
2023 May	InstructCodeT5+ [WLG+23]	16B	52B	35.0%	-
2023 Jun	WizardCoder [LXZ+23]	16B	1T	57.3%	51.8%
2023 Jun	**phi-1**	1.3B	7B	50.6%	55.5%

Their Model

Observe:
- ~ 1 OOM less data than CodeT5 models, twice as good
- ~ 2 OOM less data than Code Gen, almost twice as good
- Only competitive models are WizardCoder and GPT-4, which have vastly larger models and data

Results: Similarity Pruning

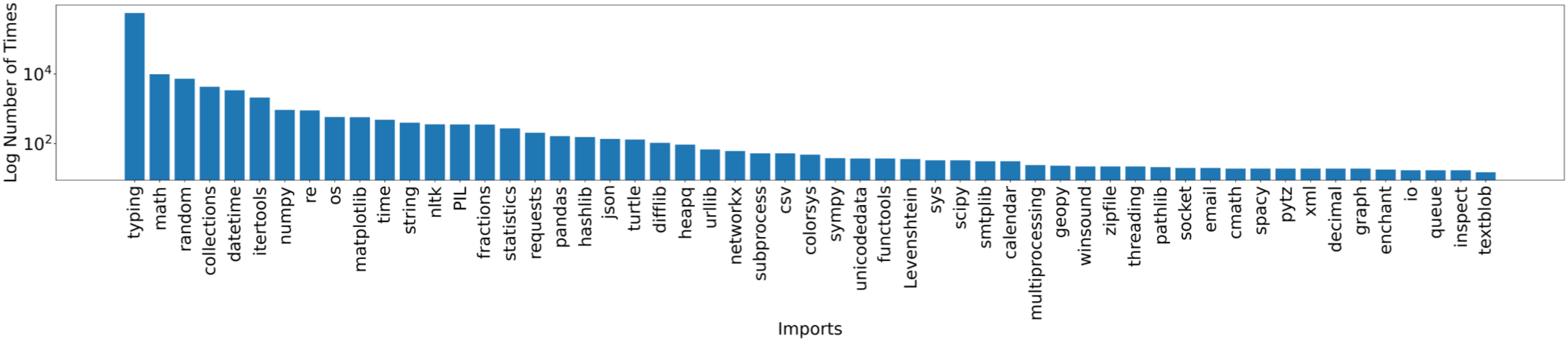
Removing More Data

τ		Problem Count	**phi-1**	**phi-1 retrained on pruned data**	StarCoder-Prompted [LAZ+23]
0.95	similar	71	81.7%	74.6%	57.7%
	non-similar	93	26.9%	32.3%	29.0%
	total	164	50.6%	50.6%	41.5%
0.9	similar	93	63.4%	51.6%	48.4%
	non-similar	71	33.8%	36.6%	32.4%
	total	164	50.6%	45.1%	41.5%
0.85	similar	106	62.3%	52.8%	47.2%
	non-similar	58	29.3%	34.5%	31.0%
	total	164	50.6%	46.3%	41.5%
0.8	similar	116	59.5%	52.6%	45.7%
	non-similar	48	29.2%	27.1%	31.2%
	total	164	50.6%	45.1%	41.5%

Results: Emergence Properties

1] General understanding improves

2] Use of libraries **not in the fine-tuning dataset** increases and improves



Critical Response

ICLR 24 Reviews: https://openreview.net/forum?id=Fq8tKtjACC

Main critiques:

1] Data leakage possible in main CodeTextbook (even though not present in fine-tuning CodeExercices) dataset

2] Limited eval

3] Ambiguity in the data generation process (i.e., how do they ensure data diversity?) apparently motivated by propriety

References

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