

ReaLLM ASIC

Make Your Own Lightweight LLMs

Outline of the Tutorial

- Intro
 - LLMs and Applications
 - Recap of LLM architecture
- Hands-on Al From Scratch:
 - Building and training a custom lightweight LLM
 - Data preparation and preprocessing
 - Model training options and optimization
- Checkpoints and Finetuning

LLM Capabilities and Datasets

LLM Training - "Next Token Prediction"

LLMs do not require us to label the correct data, it simply trains on datasets.

To improve, it corrects itself to get better at prediction of the next element, for example:

- Music
 - Prediction of the next note
- Translation
 - Prediction of next word
- Mathematics
 - Prediction of next number

Translation Dataset

以下の英語を日本語に翻訳してください Do you deliver on Sundays? 日曜日に配達していますか。

Midi Dataset

```
64,50,47,44
64,52,49,45
64,52,49,45
64,54,4B,47
64,54,4B,47
64,56,50,49
64,56,50,49
62,58,52,4B
```

Math Dataset

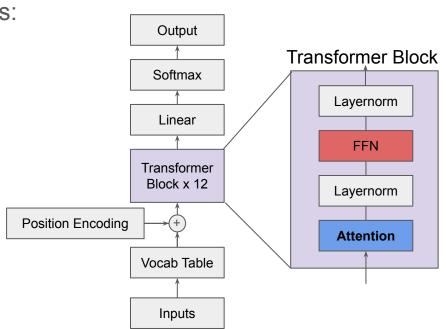
question: There are 10 6-ounces of glasses that are only 4/5 full of water. How many ounces of water are needed to fill to the brim all those 10 glasses? answer: 12

LLM Applications And Datasets

LLM Transformer Architecture

One architecture, limited only by datasets:

- Translation
- Poetry
- Music
- Robotics Motion
- Cooking Recipes
- Editing and Writing Reports



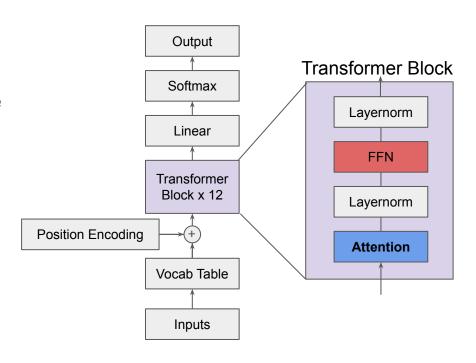
Settings When Training LLMs

Major Hyperparameters

- "Height" Number of Layers
 - Deep Networks -> Abstract Knowledge
 - Linearly increases size of network

- "Width" Dimensions per Token
 - Better Per Token Understanding
 - Non-linear increase in size

LLM Transformer Architecture



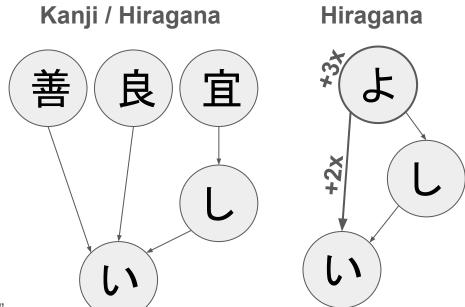
Tokenization Settings

Tokens need to gain "Experience Points":

 Higher frequency of a token in the dataset then the easier it is an LLM to learn about it.

Language Example:

- Preprocessing Kanji -> Hiragana:
 - Each Hiragana is a Token
 - Faster training (smaller model)
 - Faster accumulation of "experience points"

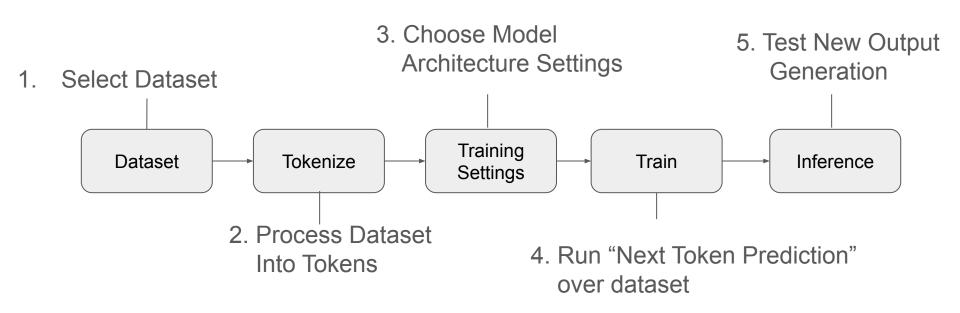


Datasets

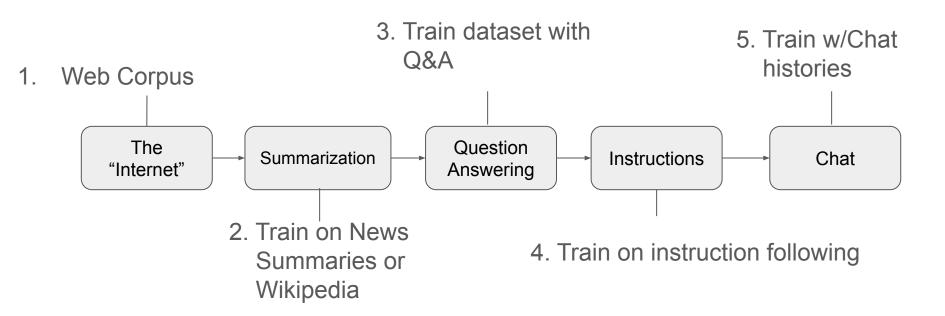
We are limited only by the datasets we can train on.

- Music
 - We'll work with JS Bach
 - Tokenization: CSV with Base 12 to represent Octaves
- Language
 - Japanese <-> English Translation Pairs
 - Tokenization: Hiragana, Katakana, English and Punctuation.
- Generation
 - Shakespeare
 - Tokenization: Letters

Standard LLM Training Recipe



Curriculums - Dataset Training Order



Kanji to Hiragana Preprocessors

- Hiragana is essentially phonetic
- Kanji -> Hiragana Processors Exist
 - https://github.com/passaglia/yomikata
 - https://github.com/morikatron/yakinori
- -> Phonetic sub-char approach

はた [hata]	Flag
よる [yoru]	Night
て [te]	Hand
みち [michi]	Road



```
from yomikata.dbert import dBert reader = dBert() reader.furigana('そして、畳の表は、すでに幾年前に換えられたのか分らなかった。') # => そして、畳の{表/おもて}は、すでに幾年前に換えられたのか分らなかった。
```

Pre-process Into Individual Numbers, Letters, Hiragana, Katakana

Language Translation Pairs

次の文を英語に翻訳してください。 最初の月面着陸は1969年7月20日のアポロ計画によって達成された the first lunar landing was achieved by the Apollo program on July 20, 1969

Preprocess Kanji -> Hiragana

nanogpt 23:2<mark>0) p hiragana_converter.py japanese_eigo_kanji_hiragana_katakana.txt</mark> hiragana.txt | 4151774/27894727 [01:58<11:21, 34817.19lines/s

Obtain ~210 Vocab Size Set

nanogpt 7:48》p prepare.py -t hiragana_no_kanji.txt --method char

Length of dataset in characters: 497,603,358
All unique characters:
!"#\$%&'()*+,-.0123456789:;?@ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz
、。々〈〉《》「」『』【】〒〓〔〕~゛、ゝぁぁぃぃぅうぇえぉおかがきぎくぐけげこごさざしじすずせぜそぞただちぢっつづてでとどなにぬねのはばぱひびぴふぶぷへべぺほぼぽまみむめもゃやゅゆょよらりるれろゎわゐゑをんゔゕゖ゚゛゜ゝゞ゠ヷヸヹ・ーヿヒムレ。「」、
Vocab size: 210
train has 447,843,022 tokens
val has 49,760,336 tokens

Long Tail Stats Before and After Kanji -> Hiragana

 Initially many characters appeared a small number of times

Key Stats:

Before:

7700 vocab

■ Median = 9

- After Sub-Char:
 - 210 vocab
 - Median = 219,297

Before

```
Mean Usage: 109751.39
Median Usage: 9
Mode Usage: 2

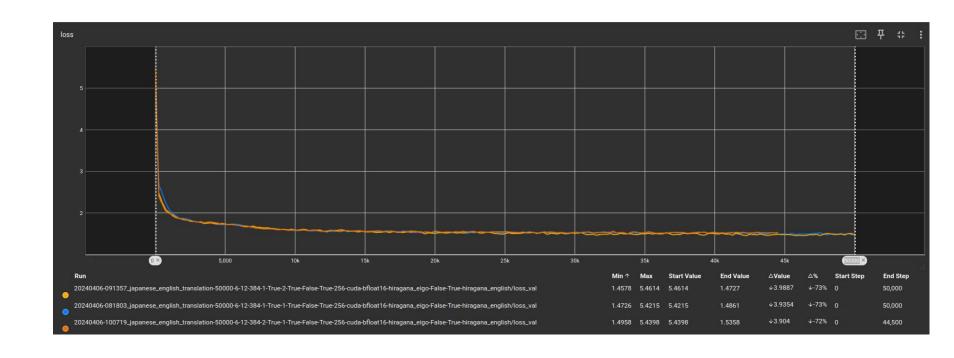
Counts of characters appearing from 1 to 100 times:
1 times: 472
2 times: 960
3 times: 197
4 times: 497
5 times: 116
6 times: 307
7 times: 91
8 times: 227
9 times: 73
10 times: 164
11 times: 70
12 times: 125
```

```
Mean Usage: 2369539.80
Median Usage: 219297.0
Mode Usage: 2

Counts of characters appearing from 1 to 100 times: 1 times: 3
2 times: 4
3 times: 1
4 times: 3
6 times: 2
11 times: 1
22 times: 1
43 times: 1
53 times: 1
59 times: 1
66 times: 1
```

After

~1 Hour of Training Later... Will it Translate?



Spelling, Punctuation and Word Re-Ordering Demonstrated

Learned many phrase translations

 Observed to do re-ordering of out of distribution entities

 Above expectations for 1 hour training on 11M params つぎのにっぽんごをえいごにほんやくしてください。 ほんとにですか? really, excuse me?

つぎのにっぽんごをえいごにほんやくしてください。 machineていうのいみはなにですか what do we mean by the machine?

つぎのにっぽんごをえいごにほんやくしてください。 "Transformer"ていうのいみはなにですか what is the transformer?

Colab

Workshop Colab

- Workshop colab
 - based on the popular NanoGPT framework

https://colab.research.google.com/drive/1wf JB4k5KPUgsb0SlbyKtbjlXzBs4sMyl?usp=s haring#scrollTo=tUDCG38Ylpor

 We'll migrate to the Colab for the remainder of the workshop.

Run GPU Training !python3 data/shakespeare char/prepare.py → length of dataset in characters: 1,115,394 all the unique characters: !\$&',-.3:;?ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopgrstuvwxyz vocab size: 65 train has 1,003,854 tokens val has 111,540 tokens !python3 train.py --device="cuda" --dtype="float16" --max iters= → 2024-05-13 06:59:01.957995: E external/local xla/xla/stream exec 2024-05-13 06:59:01.958075: E external/local xla/xla/stream exec 2024-05-13 06:59:02.106433: E external/local xla/xla/stream exec 2024-05-13 06:59:02.395367: I tensorflow/core/platform/cpu featu To enable the following instructions: AVX2 FMA, in other operations 2024-05-13 06:59:04.921801: W tensorflow/compiler/tf2tensorrt/ut seed: 1337 seed offset: 0 number of parameters: 2.98M num decayed parameter tensors: 16, with 3,072,384 parameters num non-decayed parameter tensors: 13, with 4,992 parameters using fused AdamW: True step 0: train loss 4.2075, val loss 4.2067 iter 0: loss 4.2097, time 14979.17 ms, mfu -100.00% iter 10: loss 3.3180, time 130.96 ms, mfu 1.00% iter 20: loss 3.2074, time 132.72 ms, mfu 1.00% iter 30: loss 2.9536, time 131.67 ms, mfu 1.00% iter 40: loss 2.7902, time 132.85 ms, mfu 1.00% iter 50: loss 2.6889, time 132.28 ms, mfu 1.00% iter 60: loss 2.6815, time 132.55 ms, mfu 1.00%