Carnegie Mellon University

Setting Expectations

Large Language Models: Methods and Applications

Daphne Ippolito and Chenyan Xiong

Setting expectations – final exam

- The semester ends on December 6. Final exam week is December 9-13.
- We’ll know the final exam date once SCS announces it.
- CMU students are expected to be on campus through the final exam week.
- Barring medical issues, there will be no accommodations for missing the final exam.

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Setting expectations – Piazza

- TAs are expected to work weekdays only.
- We aim for a Piazza response time of 1-2 business days.
- If you don't get a response within 2 business days, you may reach out by email to escalate.

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Setting expectations – coming to class

- We are going to be releasing class recordings ~1 week after class happens.
- Get the most out of your experience by coming in-person to class.
- When you all participate in class:
  - we can adjust our lectures on the fly to better teach you.
  - we learn what to emphasize in future lectures.
- Your in-class participation makes the class better!

QUIZ

Learning Objectives

Large Language Models: Methods and Applications

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What I’ve told you so far:

Language models are trained with the objective of predicting the next word in a sequence given the previous words (and possibly some other conditioning signal).

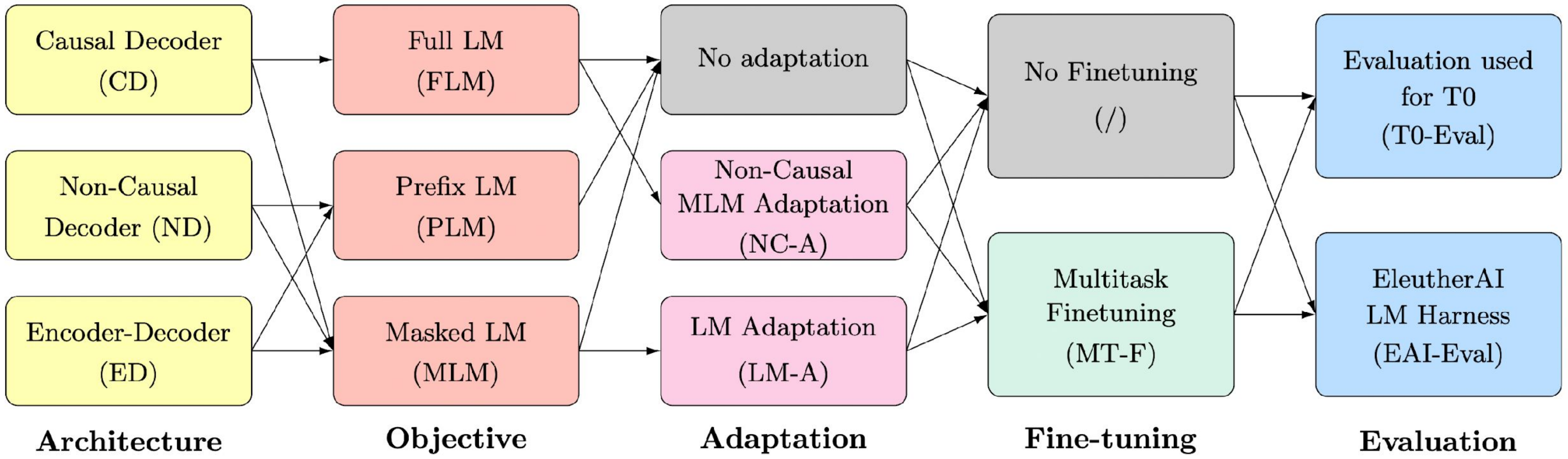
Possible objectives for pre-training an encoder-decoder model:

- Predict a suffix given a prefix.
  - Input: ***I took my dog, Fido, to the***
  - Target**:** ***park for his walk.***
- Masked language modeling
  - Input: ***I took <x> to <y> his walk.***
  - Target: ***<x> my dog, Fido, <y> the park for***

Possible objectives for pre-training a decoder-only model:

- Predict a suffix given a prefix.
    - Input: ***I took my dog, Fido, to the***
    - Target: ***park for his walk.***
- Masked language modeling
    - Input: ***I took <x> to <y> his walk.***
    - Target: ***<x> my dog, Fido, <y> the park for***
- Full language modeling: predict next token given previous tokens
    - Target: ***I took my dog, Fido, to the park for his walk.***

It is also possible to mix and match different training objectives.



Wang et al. "What Language Model Architecture and Pretraining Objective Work Best for Zero-Shot Generalization?"

Turning Text into Pretraining Data

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Preprocessing

Data **preprocessing** is the pipeline to turn raw data (in whatever format it has been give to you) into data that is ready to be ingested by the neural network.

Ideal scenario: start off with fairly clean text

- When this might happen
  - Wikipedia, Books, datasets meant for classic NLP applications
  - High-resource languages: English, French, etc.
- A perfect world situation: Texts are clean and well-formatted
  - (Unlikely to achieve in real-world systems)

Preprocessing Clean Texts

Since the text is already cleaned, all we need to do is convert it into batches of training data.

The Steelers enjoy a large, widespread fanbase nicknamed Steeler Nation. They currently play their home games at Acrisure Stadium.

Raw Clean Text

Tokenization →

'_The', '_Steel', 'ers', '_enjoy', '_a', '_large', ',', '_wide', 'spre', 'ad', '_fan', 'base', '_nick', 'na', 'med', '_Steel', 'er', '_Nation', '.', '_They', '_currently', '_play', '_their', '_home', '_games', '_at', '_A', 'cris', 'ure', '_Stadium', '.'

Tokenized

Batching →

[580, 109027, 1313, 25224, 9, 21333, 3, 38133, 21328, 711, 1206, 37381, 128910, 75, 4805, 109027, 55, 82580, 4, 0]
[10659, 82423, 11300, 2362, 5367, 27527, 98, 61, 58531, 3407, 88259, 4,0,0,0,0,0,0,0,0]

Tensor

Tokenizing Text

A **tokenizer** takes text and turns it into a sequence of discrete **tokens.**

A **vocabulary** is the list of all available tokens.

Let's tokenize: "A hippopotamus ate my homework."

Vocab Type	Example	Ex. length
character-level	['A', ' ', 'h', 'i', 'p', 'p', 'o', 'p', 'o', 't', 'a', 'm', 'u', 's', ' ', 'a', 't', 'e', ' ', 'm', 'y', ' ', 'h', 'o', 'm', 'e', 'w', 'o', 'r', 'k', '.']	31
subword-level	['A', 'hip', '##pop', '##ota', '##mus', 'ate', 'my', 'homework', '.']	9
word-level	['A', 'hippopotamus', 'ate', 'my', 'homework', '.']	5

Word-level Tokenization

Method: rule-based---split text by spaces, punctuation, and other hand-written rules.

Challenges:

- Open vocabulary problem
    - Many words may never appear in training data. They become [UNK].
    - This is more several in some languages, e.g. languages that concatenate words.
- Typo'ed words also get tokenized to _UNK

Subword Tokenization

Method: words get split into multiple tokens.

Advantages:

- Vocabulary is built dynamically
    - Frequent words get assigned their own token
    - Rare words are split into sub-words.

Subword Tokenization: Byte Pair Encoding (BPE)

Main Idea:

- Construct subword vocabulary by learning to merge characters
- Inspiration comes from compression algorithms

Training Steps:

1. Initialize your vocabulary with every character as a token.
    - E.g., in English, alphabet + numbers + punctuation
2. Merge the most frequent token pair in your corpus.
    - Vocabulary size +1
3. Re-tokenize the corpus with the merged subword pair
    - That is, merge all appearances of the pair, and replace with the new token.
4. Repeat step 2-3 until the target vocabulary size is reached.

Subword Tokenization: Byte Pair Encoding (BPE)

An efficient learning implementation of BPE

1. Take your corpus and split it into words (e.g. using a rule-based tokenizer)
2. Construct a word dictionary with frequency counts

   ("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)

3. Start from uni-character vocabulary, merge pairs by frequency, till reached target vocabulary size

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Iteration	Current Vocab	Tokenization of Words
1	*["b", "g", "h", "n", "p", "s", "u"]*	*("h" <u>"u" "g"</u>, 10), ("p" <u>"u" "g"</u>, 5), ("p" "u" "n", 12), ("b" "u" "n", 4), ("h" <u>"u" "g"</u> "s", 5)*

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2	["b", "g", "h", "n", "p", "s", "u", "ug"]	("h" "ug", 10), ("p" "ug", 5), ("p" "u" "n", 12), ("b" "u" "n", 4), ("h" "ug" "s", 5)

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3	["b", "g", "h", "n", "p", "s", "u", "ug" "un"]	("h" "ug", 10), ("p" "ug", 5), ("p" "un" , 12), ("b" "un", 4), ("h" "ug" "s", 5)
4	["b", "g", "h", "n", "p", "s", "u", "ug" "un", "hug"]	("hug", 10), ("p" "ug", 5), ("p" "un", 12), ("b" "un", 4), ("hug" "s", 5)

Subword Tokenization: Pros

Controlled vocabulary size

- A pre-defined hyperparameter as a design choice

Learned vocabulary, best compromise between character-level and word-level tokenization.

- Frequent words kept whole
- Tail words split to sub-words
    - More observations on sub-words
    - Utilization of morphology information

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Units are well-suited to neural methods

- Trivial for Transformers to figure out common combinations
- Neural representations smooth rare combinations

Subword Tokenization: Further Quandries

When treating characters as your basic units, unknown (sub)tokens can still exist.

- Example: If your basic units are [A-Za-z], Chinese characters can't be tokenized.
- Solution: Byte-level BPE that uses raw bytes (e.g., Unicode bytes) as the basic character set.

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Algorithm requires an initial word-level tokenization. This can be tricky.

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Step of finding most frequent pairs has a naive runtime of $O(n^2)$
- Why: For each possible combination of two tokens, count number of occurrences.
- Solution: Various algorithmic and implementation improvements, such as caching occurrence counts.

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Tokenized

Batching →

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What is batch size?

- Number of examples
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- Number of documents
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Batching Data

How can we batch the following?

"Pittsburgh, Pennsylvania"	➡	[47, 1468, 26320, 11, 20355]
"Fido the dog likes eating rabbit-flavored ice cream	➡	[37, 5362, 279, 5679, 13452, 12459, 39824, 12556, 76486, 10054, 12932, 13]
"It is raining outside"	➡	[2181, 374, 84353, 4994]

Let's assume a batch-size of 8.

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OPTION 1: Each document gets placed into its own batch.

Batch_0 = [47, 1468, 26320, 11, 20355, 0, 0, 0]
Batch_1 = [37, 5362, 279, 5679, 13452, 12459, 39824, 12556]
Batch_3 = [2181, 374 , 84353, 4994, 0, 0, 0, 0]

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Let's assume a batch-size of 8.

OPTION 2: Documents get patched into batches.

Batch_0 = [47, 1468, 26320, 11, 20355, 0, 37, 5362]
Batch_1 = [279, 5679, 13452, 12459, 39824, 12556, 76486, 10054]
Batch_3 = [12932, 13, 0, 2181, 374 , 84353, 4994, 0, 55]

What is batch size?

- Number of examples
  - Makes sense in computer vision when examples are all the same shape.
  - Doesn't make sure for language models.
- Number of sentences/paragraphs
  - This would require parsing the text.
  - Same issues with variable length.
- Number of documents
  - We could do one document per batch, but padding is inefficient.
- Number of tokens
  - This is what people tend to mean when they refer to batches during pre-training.
  - Common batch sizes:
    - LLaMA-1: 4 million tokens
    - T5: 65,536 tokens
    - Olmo: 4.19 M tokens
    - GPT-3 175B: 3.2M tokens

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There are lots of complexities around batch size and multi-GPU parallelism I'm glossing over.

Scaling up Pretraining Data

Large Language Models: Methods and Applications

Daphne Ippolito and Chenyan Xiong

What are the goals of pre-training?

The goals of **pre-training** are to get the language model to:

- learn the structure of natural language
- learn humans' understanding of the world (as encoded in the training data).

- Goal:

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The goals of **pre-training** are to get the language model to:

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- learn humans’ understanding of the world (as encoded in the training data).

Ideal data for pre-training:

- Data that is high-quality, clean, and diverse.
- Books, Wikipedia, news, scientific papers, etc.

Pre-training data reality

More data is almost always better.

Table 11: $\text{RoBERTa}_{\text{Large}}$ Pretrained with Different Data Setups[10].

Pretrain Setups	Data Size	Batch Size	Steps	MNLI-m (ACC)	SQuAD 1.1 (F1)
Wiki + Books	16GB	8K	100K	89.0	93.6
+Additional Data	160GB	8K	100K	89.3	94.0
+Pretrain More Steps	160GB	8K	300K	90.0	94.4
+Even More Steps	160GB	8K	500K	90.2	94.6

- Same model, same pretraining steps, more data helps
- With more data more pretraining steps also help
- Empirical gains more than many "fancier" improvements

Li, et al. "RoBERTa: A robustly optimized BeRT pretraining approach." arXiv preprint arXiv:1907.11692. 2019.

Pre-training Data Reality

High quality data eventually runs out.

In practice, the web is the most viable option for data collection.

- In the digital era, this is the go-to place for general domain human knowledge.
- It is massive and unlikely to grow slower than computing resources*
- Publicly available*

*. More on how true these points are later in the class.

Pre-training Data Reality

Web data is plentiful, but can be challenging to work with.

- Copyright and usage constraints can get extremely complicated
- Data is noisy, dirty, and biased
- Data is contaminated with auto-generated text
    - Not just from LLM usage, but also tons of templated text.

The Web Data Pipeline

1. Content is posted to the web.

2. Webcrawlers identify and download a portion of this content.

3. The data is filtered and cleaned.

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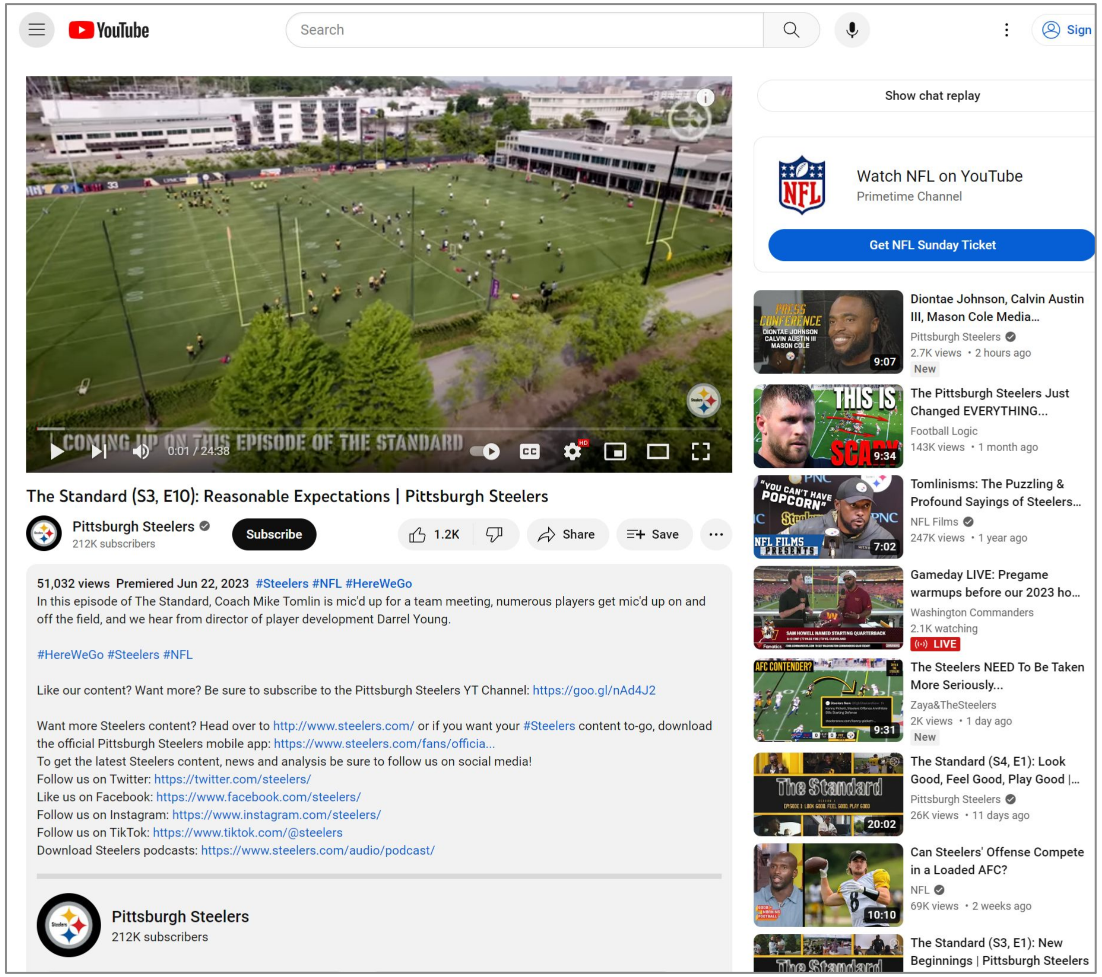
1. Content is posted to the internet.

Challenges

- Biases in what's available:
  - Recency bias
  - Demographic biases
  - Language biases
- Web is much more dynamic than static HTML pages
  - CSS, JavaScript, interactivity, etc.
  - Responsive design
  - Many HTML pages involves 20+ secondary URLs, iframes, etc.
- What counts as content?
  - Ads, recommendation, navigation, etc.
  - Multimedia: images, videos, tables, etc.
  - Spam



Goal:

1. Content is posted to the internet.

Content extraction from webpages is a well-studied problem in industry.

- Can be very engineering and resource heavy to do well.
- Existing toolkits is a strategic advantage of some proprietary LLMs

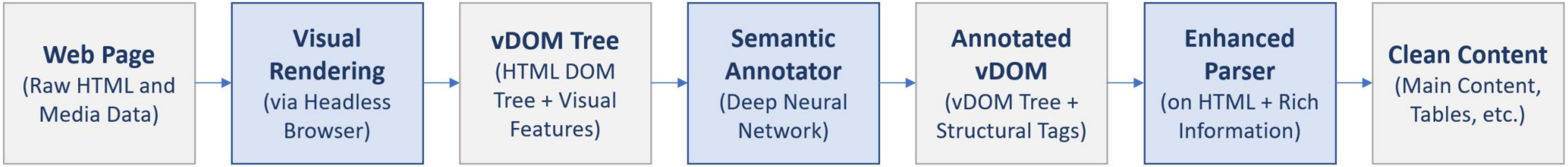


Figure 8: A Content Extraction Pipeline from Bing Used for ClueWeb22

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2. Webcrawlers identify and download a portion of this content.

General Idea

1. Start with a set of seed websites
2. Explore outward by following all hyperlinks on the webpage.
3. Systematically download each webpage and extract the raw text.

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General Idea

1. Start with a set of seed websites
2. Explore outward by following all hyperlinks on the webpage.
3. Systematically download each webpage and extract the raw text.

Challenges

- How to harvest a large number of seed URLs efficiently
- How to select “high quality” URLs and skip over “bad” URLs
  - Some cases are clear cut: spammy, unsafe, etc.
  - Some are hard to detect or up to debate: certain biases.
- How to keep the crawl up-to-date
  - Given a fixed compute budget each month, is it better to crawl new webpages, or recrawl old ones that might’ve changed?

The Web Data Pipeline

1. Content is posted to the web.

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3. The data is filtered and cleaned.

Remove noisy, spammy, templated, and and fragmented texts

- These portions lack the content needed to meet pretraining goals.

Select higher quality texts from a massive candidate pool

- Given a limited pretraining compute budget, we'd like pretrain on better texts

Avoid toxic and biased content

- NSFW content
- Texts with strong biases

3. The data is filtered and cleaned.

Methods to identify high-quality content:

- Rule-based heuristics for quality
  - You'll be implementing a bunch of these in the homework
- Proximity to known high-quality indicators
  - E.g. a website that was highly upvoted on Reddit, or a website that was included as a reference on Wikipedia
- Classifiers
  - Trained quality and toxicity classifiers are common.
  - E.g. train a classifier with Wikipeida as the positive examples and random web pages as the negative examples

3. The data is filtered and cleaned.

Example: Rule-based filtering in C4 (pre-training dataset for T5 model)

1. Start from Common Crawl's official extracted texts from HTML
2. Only keep text lines ended with a terminal punctuation mark
3. Discard pages with fewer than 5 sentences
4. Only keep lines with at least 3 words
5. Remove any line with the word "Javascript"
6. Remove any page
    1. with any words in a toxic word dictionary
    2. with the phrase "lorem ipsum"
    3. With "{"
7. De-dup at three-sentence span level

3. The data is filtered and cleaned.

Challenges

- At what granularity should filtering be performed?
  - Word-level, sentence-level, paragraph-level, document level?
- What constitutes “high quality” or “non-toxic”?
- Are our filters/classifiers multilingual? Even within English, do they treat all groups equally?
- It is very expensive to ablate pre-training dataset decisions.

A Couple Dataset Case Studies

Large Language Models: Methods and Applications

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Case Study: WebText

WebText: The pretraining corpus of GPT-2

- Harvested all outbound links from Reddit
  - These are all URLs that were manually mentioned by humans
- Only kept links that received >= 3 “Karma”
- Deduplicated URLs
  - Total 45 million URLs deduped to 8 million web pages

Case Study: WebText

Web exploration method

How to harvest URLs:

- From Reddit mentions

Definition of good URLs:

- Other Reddit users like it

- Pros
  - Easy to harvest a relatively large set of URLs from a common resource
  - Human votes on the URLs
- Cons
  - Since then, Reddit has forbid the use of its data for pretraining LLMs
  - Limited scale
  - Reddit is not the cleanest part of the internet

Case Study: CommonCrawl

Common Crawl: commoncrawl.org

- Non-profit organization provides **open** access to large scale web crawls
- Petabytes of web pages available
- Monthly crawls and dumps
  - Re-crawled web pages and fresh dumps (bi)monthly
  - Recent dumps are ~3 billion pages
  - Date back to past 10 years
    - "220 billion web pages (HTML) captured 2008 – 2021"

Case Study: CommonCrawl

Web exploration approach

- Start from a set of seed URLs: popular, high-quality, and trustworthy websites
  - Gov, Edu, etc.
  - Top web domains
- Traverse the web to obtain a candidate set of URLs
  - Around 500 billion links discovered per month crawl
  - About 25+ billion unique ones
- Prioritizes a subset (~3 billion) of URLs to crawl and include in the dump
  - Does this to make the best use of crawling budget.

Case Study: CommonCrawl

Which URLs to crawl?

- 2008-2012: CC's in-house Page Rank
- 2012-2015: Added ranking and metadata of 22 billion pages donated from web search engine blekko
- 2016-2018: Occasional seed URL donations, ~400 million URLs
- 2016: Alexa and Common Search Rankings
- 2017-Now: CC's in-house web graph based rankings (page rank and centrality)
    - Importance score calculated based on past three-month dumps
    - Steer the crawler for next three month
    - Capped # of URLs per domain

Case Study: CommonCrawl

Pros

- The one and the only public web crawl at this scale
  - Still far away from commercial search engines, but the closest we have
- 10 years of crawl dumps have enabled various data subsamples
- Accumulation of low resource languages
  - One can combine low resources languages from years of dumps to pair with English texts from one month

Cons

Each crawl is ~3billion documents, still limited coverage of the massive web

- Crawls every month restart from the seed URLs
  - Crawls never grow above ~3B documents
- URL distributions skewed by crawling prioritization, per domain URL cap, and physical location of the crawling machines (and people)

Questions?