The auto-regressive language models (e.g., GPT3 [BMR+20]) trained on human-written text can produce natural text as humans do. In this homework, you will implement and use various decoding algorithms, generate text using the pre-trained large language models (LLMs) on different generation tasks, evaluate the output text, and justify the limitations of current decoding methods. The lead TA for this assignment is Junhan Wu and Bin Hu (wu001412@umn.edu and hu000562@umn.edu). Please communicate with the lead TA via Slack, email, or during office hours. This homework is team-based. Your team should work together on both the implementation of the decoding algorithms and the evaluation of the generated texts.

This assignment assumes that you have covered most of the search algorithms and evaluation metrics in text generation on Language Models: Search and Decoding (Feb 18) and Language Models: Evaluations and Applications (Mar 4). Please read the reading materials and lecture notes if you missed class.

In this homework, you don't actually need to implement anything from scratch; instead, you will make a complete pipeline of text generation research including task selection, decoding, automatic evaluation, human evaluation as a team, and analysis of output text. Please follow the steps below, report outputs from the **Tasks** of each step, and submit the spreadsheet, codebase, and report.

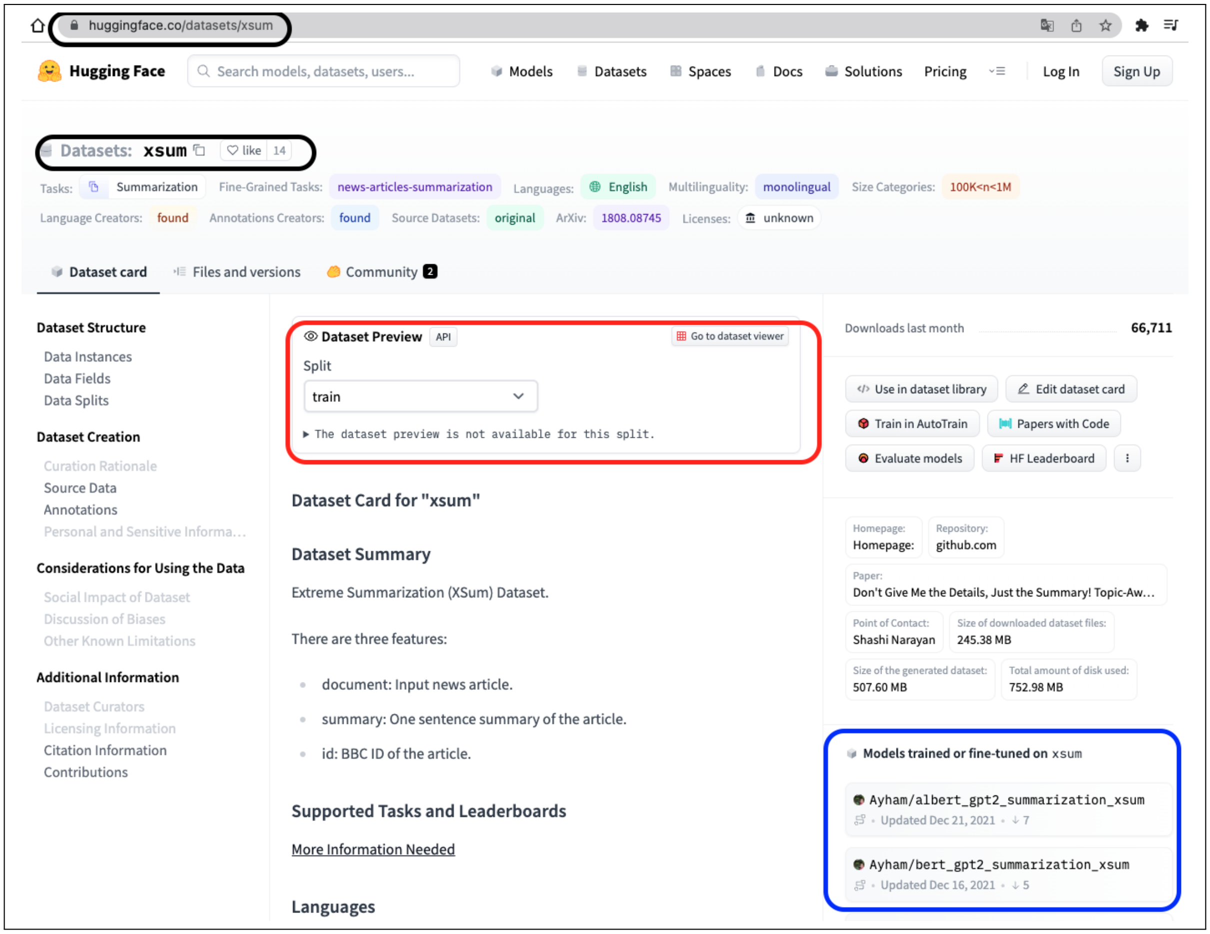
## Step 1: Trying out different decoding algorithms using HuggingFace

```
from transformers import AutoTokenizer, AutoModelForCausalLM

tokenizer = AutoTokenizer.from_pretrained("gpt2")
model = AutoModelForCausalLM.from_pretrained("gpt2")

prompt = "Today I believe we can finally"
input_ids = tokenizer(prompt, return_tensors="pt").input_ids

/* generate up to 30 tokens */
outputs = model.generate(input_ids, do_sample=False, max_length=30)
tokenizer.batch_decode(outputs, skip_special_tokens=True)

/* step 1 */
outputs1 = model.YourDecodingAlgorithmToImplement1(input_ids)
outputs2 = model.YourDecodingAlgorithmToImplement2(input_ids)
..

```

You can first go to (HuggingFace API on text generation) and run an example script to generate text. For instance in the example above, once you load pre-trained autoregressive language models like GPT2 [RWC+19], the HuggingFace library allows you to select a variety of decoding algorithms.

**Task 1** You should report the outputs from four different decoding algorithms covered in the class: *greedy search*, *beam search*, *top-k sampling*, and *top-p sampling*. You don't actually need to implement these algorithms by yourself. Instead, I encourage you to use pre-implemented decoding functions in HuggingFace.

For a prompt like "Today, I believe we can finally," you should report **four output text from the four different decoding algorithms with the specific parameters** you used (e.g., beam size, n-best, k, p). For this step, make up five prompts yourself – you can use any random prompts you



Tasks: Summarization Fine-Grained Tasks: news-articles-summarization Languages: English Multilinguality: monolingual Size Categories: 100K<n<1M

Language Creators: found Annotations Creators: found Source Datasets: original ArXiv: 1808.08745 Licenses: unknown

Split: train

▸ The dataset preview is not available for this split.

Dataset Card for "xsum"

Dataset Summary

Extreme Summarization (XSum) Dataset.

There are three features:

- document: Input news article.
- summary: One sentence summary of the article.
- id: BBC ID of the article.

Supported Tasks and Leaderboards

More Information Needed

Languages

Downloads last month 66,711

Homepage: Homepage:

Repository: github.com

Paper: Don't Give Me the Details, Just the Summary! Topic-Aw...

Point of Contact: Shashi Narayan

Size of downloaded dataset files: 245.38 MB

Size of the generated dataset: 507.60 MB

Total amount of disk used: 752.98 MB

Models trained or fine-tuned on xsum

Ayham/albert_gpt2_summarization_xsum
Updated Dec 21, 2021 • ↓ 7

Ayham/bert_gpt2_summarization_xsum
Updated Dec 16, 2021 • ↓ 5

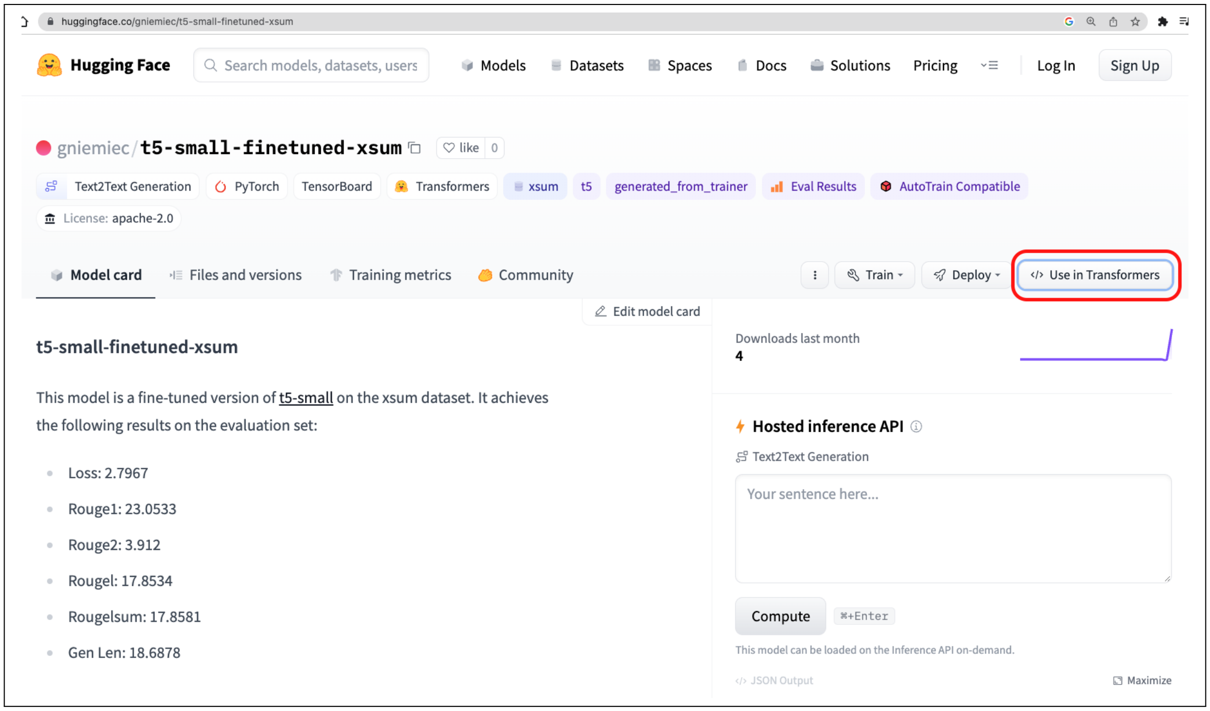
Figure 1: HuggingFace Dataset Interface: https://huggingface.co/datasets?task_categories=task_categories:summarization

want. You must also calculate the **perplexity** or the **likelihood of each output sequence** by (log-)summing over every generated token logit. Please refer to this tutorial for the perplexity calculation on generated tokens.

To report results, you must make a **spreadsheet**. In the first tab of your spreadsheet, have a row for each prompt. In each row, we expect additional four columns of outputs from decoding algorithms and two additional columns, one for parameters and the other for perplexity/likelihood. Concretely, the first tab of spreadsheet should be N-by-7, where N is the number of prompts (5) and columns are prompts, four outputs, hyper-parameters, and perplexity (or log-likelihood). You will fill in the other tabs of the spreadsheet later in the assignment.

## Step 2: Decoding for downstream generation tasks

Perplexity is an intrinsic method to evaluate your language model. Now, we evaluate the language model with an extrinsic evaluation. First, select a **specific task** for evaluating decoding algorithms where the task provides reference text. For instance, you can choose a dataset called XSUM [NCL18] from the summarization task in the HuggingFace dataset repository, as depicted in Figure 1. You can see some example instances from Dataset Preview and download the dataset easily from a few lines of



t5-small-finetuned-xsum

This model is a fine-tuned version of t5-small on the xsum dataset. It achieves the following results on the evaluation set:

- Loss: 2.7967
- Rouge1: 23.0533
- Rouge2: 3.912
- Rougel: 17.8534
- Rougelsum: 17.8581
- Gen Len: 18.6878

Downloads last month
4

Hosted inference API

Text2Text Generation

Your sentence here...

This model can be loaded on the Inference API on-demand.

Figure 2: Loading the pre-trained T5 model fine-tuned on XSUM dataset

code:

```
from datasets import load_dataset
dataset = load_dataset("xsum")
```

Various tasks are available, such as machine translation, abstraction summarization, dialogue generation, paraphrasing, and style transfer, where the input and output text (reference text) are provided. Please check available tasks and fine-tuned models in HuggingFace Tasks.

Once you choose a specific task and dataset for your text generation, you then need to get actual outputs from the generation model. This homework does not require you to train your own generation models from scratch on the target dataset. Instead, on the dataset page, you can find the existing fine-tuned models (blue box in Figure 1).[1] For instance, you can load the small T5 model already fine-tuned on XSUM dataset https://huggingface.co/gniemiec/t5-small-finetuned-xsum, as shown in Figure 2. On the top right, click the USE IN TRANSFORMERS button to access lines of code for loading the model into HuggingFace.

**Task 2** On the test set (or development set if there is no test set given) of the dataset you choose, you can simply generate the output summary or responses using the default decoding functions in HuggingFace. In this step, you have to write your own script to load the fine-tuned model and decode output text given input text from the test samples. Below is an example script to load the model and decode a batch of test input:

[1] If the dataset page does not include the model list, you can search the dataset name in the model cards.

```
from transformers import AutoTokenizer, AutoModelForSeq2SeqLM

tokenizer = AutoTokenizer.from_pretrained("gniemiec/t5-small-finetuned-xsum")

model = AutoModelForSeq2SeqLM.from_pretrained("gniemiec/t5-small-finetuned-xsum")

/* generate your own summary using different decoding algorithms */
outputs1 = model.YourDecodingAlgorithmToImplement1(input_ids)
outputs2 = model.YourDecodingAlgorithmToImplement2(input_ids)
..
tokenizer.batch_decode(outputs1, skip_special_tokens=True)
..
```

Specifically, you will use the four decoding algorithms implemented in Step #1 and generate output texts on the test set of your target task. If your test set is more than 50 samples, please only use the *first 50 samples* in the following evaluation.

In the second tab of your **spreadsheet**, make a row for a text sample in the test set. Make four columns of outputs from the decoding algorithms, with one column of reference text provided in the test set. In other words, the second tab of your spreadsheet should be N-by-6, where N is the number of the test set (maximum 50) and columns are input text, four outputs, and reference text.

## Step 3: Automatic and Human Evaluation

Lastly, you evaluate quality of your generated text by choosing the right evaluation metric for your task. Since this is not an open-ended generation task, you can use reference-based evaluation metrics to determine how similar your generated outputs are to the reference text.

```

/* generate your own summary using different decoding algorithms */
outputs1 = model.YourDecodingAlgorithmToImplement1(input_ids)
outputs2 = model.YourDecodingAlgorithmToImplement2(input_ids)
..
token_outputs1 = tokenizer.batch_decode(outputs1, skip_special_tokens=True)
..
```

**Task 3.1** There are two categories of automatic evaluation: content overlap-based metrics (e.g., BLEU [PRWZ02], ROUGE [LH03]) and model-based metrics (e.g., Word Mover's distance [KSKW15], BERT score [ZKW+20]). You should choose **at least one** content-overlap metric **and** at least one model-based metric, and **measure these metric scores of your decoded outputs in Step #2 with respect to the reference text**. Please consider which automatic metrics would be appropriate for your task and provide a justification in the report. By reading the original papers of the dataset or task you are using, you can find which evaluation metrics are used on which tasks. Again, it is not necessary to implement these metrics from scratch; instead, you can find pre-implemented evaluation metrics at Huggingface's evaluate-metric. For instance, below is an example usage of Huggingface's evaluate function for BLEU metric:

```

>>> predictions = ["hello there general kenobi", "foo bar foobar"]
>>> references = [
...     ["hello there general kenobi", "hello there !"],
...     ["foo bar foobar"]
... ]
>>> bleu = evaluate.load("bleu")
>>> results = bleu.compute(predictions=predictions, references=references)
>>> print(results)
{"bleu": 1.0, "precisions": [1.0, 1.0, 1.0, 1.0], "brevity_penalty": 1.0,
"length_ratio": 1.1666666666666667, "translation_length": 7,
"reference_length": 6}
```

As you decode your outputs, you need to report **the metric score of each sample** in a new column in the spreadsheet made in Step #2. The report should include **the averaged metric scores across all samples** (e.g., 50 test samples) and a comparison of the decoding algorithms that work.

**Task 3.2** You may notice that automatic evaluation does not always accurately measure your task's performance. In this task, you will **devise two or three aspects of human evaluation related to your target task**; please check out what types of aspects (e.g., fluency, coherence, formality, typicality) could be used in the human evaluation of generated text in the lecture on Language Model Evaluation. Include a justification for these choices in your report. After this, each person in your team will **manually annotate scores of each aspect with a Likert scale (1-5)** and rate the level of agreement between the human evaluation scores of all of the team members.

This step aims to identify the gap between automatic evaluation metrics and human evaluations and show their difference in your report. Because human evaluation is time-consuming and costly, you can **only select the first 20 samples** from your test set.

To avoid any biases from the predicted outputs, you should make a third tab in your spreadsheet with a row for each of the first 20 test samples. Since you are not an expert judge, or your judgment could be subjective, each team member in your team should annotate each sample. Each team member should have a additional column for each of their annotations (for example, *factuality_john*, *factuality_jane*, *factuality_joe*). You will aggregate the scores across team members by majority voting or averaging. For example, if your team members' Likert scores on factuality are 4, 3, and 5, your average score is 4. Your spreadsheet should include the first 20 test samples and all annotations. Report **the averaged automatic and human evaluation scores for the first 20 sentences** and **describe how they differ in practice in your report**.

Since humans are inconsistent and subjective, we next need to evaluate how consistent annotators were with one another. You can use the nltk's nltk.metrics library to calculate the inter-annotator agreement (IAA) scores such as Krippendorff's alpha.[2] Below is an example code for the calculation of Krippendorff's alpha to measure the inter-annotator agreement.

[2] The detailed agreement measurement on human annotations will be covered on an upcoming lecture on Dataset, Annotation, and Evaluation.

```
from nltk import agreement
rater1 = [1,1,1]
rater2 = [1,1,0]
rater3 = [0,1,1]

taskdata=[[0,str(i),str(rater1[i])] for i in range(0,len(rater1))]+ \
         [[1,str(i),str(rater2[I])] for i in range(0,len(rater2))]+ \
         [[2,str(i),str(rater3[i])] for i in range(0,len(rater3))]
ratingtask = agreement.AnnotationTask(data=taskdata)
print("alpha " +str(ratingtask.alpha()))
```

Please report the agreement score in your report and explain how you think of it.

## Deliverables

Please upload your code, spreadsheet, and report to Canvas by Mar 27 , 11:59pm.

**Code:** You should submit a **zipped file** containing the decoding algorithms with evaluation scripts or a link to your GitHub repository.

**Report and Spreadsheet:** Submit a maximum six pages PDF report and spreadsheet (e.g., CVS, Excel files, Google Spreadsheet) of your decoded outputs with evaluation scores from both automatic and human measurements in Step #2 and #3. The page limit of homework doesn't include references and an appendix with additional information. For report, you must use this LaTex template (link).

**Formatting convention:** All your files submitted should follow this naming convention: **CSCI5541-S25-HW4-{Team Name}.{zip,pdf,csv}**.

## Rubric (25 points + 4 bonus points)

- **Task 1 : Implementation of Decoding Algorithms (12 points)**
  - All 4 decoding algorithms implemented, outputs in spreadsheet (+2 x 4 algorithms = +8)
  - Parameters of the algorithms included in spreadsheet (+1)
  - Prompt is consistent across all algorithms (+1)
  - Perplexity/Likelihood of each output is calculated and in spreadsheet (+2)
- **Task 2: Decoding for extrinsic evaluation (2 points)**
  - Nx6 spreadsheet correctly generated with inputs, four outputs, and reference text (+1)
  - No mistakes in results or code (+1)
- **Task 3.1 Automatic Evaluation (4 points)**
  - At least one overlap-based metric is implemented and justification included (+1)
  - At least one model-based metric is implemented and justification included (+1)
  - Metrics are calculated between reference text and decoded outputs (+1)
  - Average metric score across all samples is reported (+1)
- **Task 3.2 Human Evaluation (5 points)**
  - At least 2-3 aspects of human evaluation for the target task devised (+1)
  - Reasoning given behind choice of aspects (+1)
  - Majority/Average voting is implemented (+1)
  - Difference between human and automatic evaluation is highlighted in report (+1)
  - Inter-annotator agreement is calculated (+1)

- **Report (2 points)**
  - Report contains full information about models and dataset chosen, the requested spreadsheets and associated metric results, a comparison of decoding algorithms, and justification of design decisions. (+2)
  - Partial report submitted (i.e., some pieces of the report are missing) (+1)
- **Bonus Point (Max: +4 points)**
  - Trying out other advanced decoding algorithms implemented in HuggingFace (+1)
  - Multiple evaluation metrics (2 of each category(content overlap and model-metric) are implemented) (+1)
  - Any other interesting analyses performed (+2)

# References

[BMR+20] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners, 2020.

[KSKW15] Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. From word embeddings to document distances. In Francis Bach and David Blei, editors, Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, pages 957–966, Lille, France, 07–09 Jul 2015. PMLR.

[LH03] Chin-Yew Lin and Eduard Hovy. Automatic evaluation of summaries using n-gram co-occurrence statistics. In Proceedings of the 2003 Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics, pages 150–157, 2003.

[NCL18] Shashi Narayan, Shay B. Cohen, and Mirella Lapata. Don't give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. ArXiv, abs/1808.08745, 2018.

[PRWZ02] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics.

[RWC+19] Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019.

[ZKW+20] Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. Bertscore: Evaluating text generation with bert, 2020.