

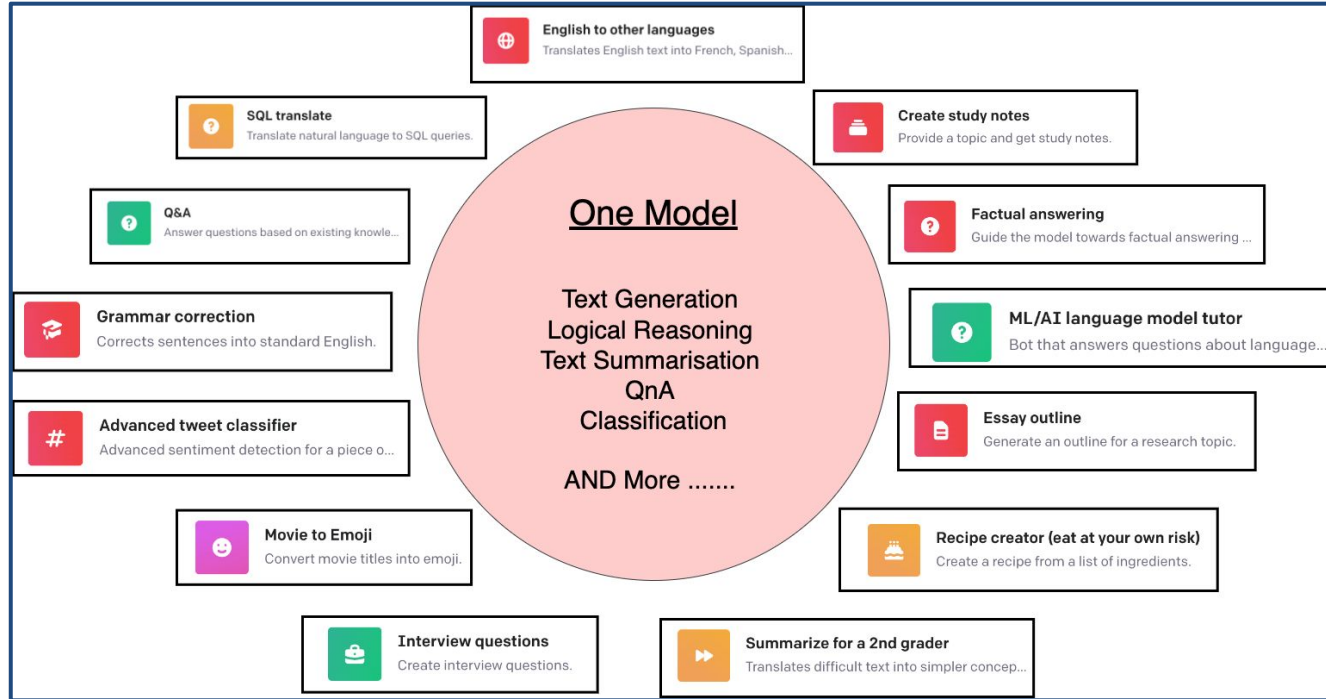


CSCI-B 659 Advanced Natural Language Processing

# Language Models are Few-Shot Learners

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# One ring to rule them all



SECTION 1

# Let's Play!

# Examples

- Render HTML output

<https://twitter.com/i/status/1282676454690451457>

- Render HTML Layout
- Arpita's Cooking Recipe

- Arpita's Cooking Recipe

Give recipe that includes following ingredients:  
spaghetti, basil, olive oil

Basil Spaghetti with Olive Oil

Ingredients:

- 1 pound spaghetti
- 1/2 cup olive oil
- 1/4 cup chopped basil
- 1/4 cup grated Parmesan cheese
- 1/4 teaspoon salt
- 1/4 teaspoon black pepper

Directions:

1. Cook spaghetti according to package instructions.
2. In a large bowl, combine cooked spaghetti, olive oil, basil, Parmesan cheese, salt, and black pepper.



# Examples

## Hardik's Dilemma:

I missed an important person in the email. What should I do?



If you realize that you have missed an important person in the email after you have already sent it, you can send a follow-up email to that person apologizing for forgetting to include them in the original email and then include the original email as an attachment.

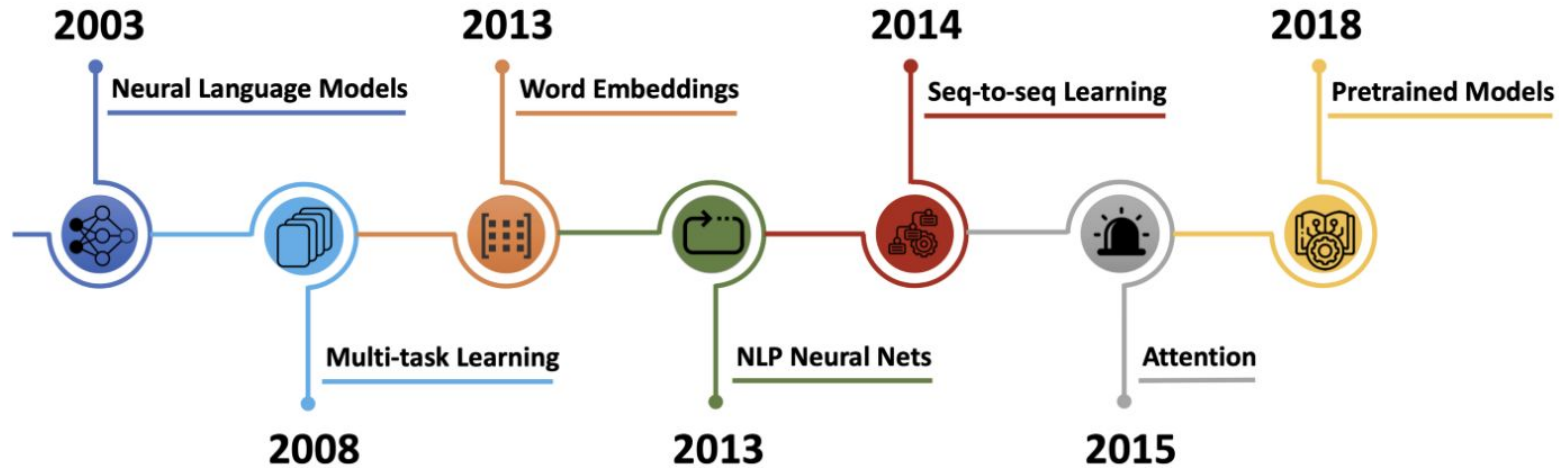
## Activity : Names Meaning Prediction



SECTION 2

# Why GPT3?

# Language Model Evolution



The big stages of NLP in the deep learning era.



# GPT3 v/s the rest

- State of the art architectures are task agnostic but require task-specific data
  - Need Labeled examples – Time intensive hand labeling
  - Difficult to get large supervised train set
  - Repeated for every task
  - Lack of fluidity and scalability
- GPT3 eliminates all of this - few shot learning
- No fine tuning
- Little human supervision





SECTION 3

# What's GPT3?

# Some Basics - Language Models

- ▶ What - Statistical and probabilistic techniques determine the probability of a given sequence of words
- ▶ Where - Linguistic Applications - Speech Recognition, OCR (Optical Character Recognition), code generation, and many more
- ▶ Example - Unigrams, Bigrams, Bidirectional Encoder Representation, Transformers Models.



# Zero-shot

- Requires no examples
- Little Human Intervention
- Models depends on historical trained concepts and data
- Example:



The diagram shows a light blue rounded rectangle containing two lines of text. The first line is '1 Translate English to French:' and the second line is '2 cheese =>'. To the right of the rectangle, there are two arrows pointing to the lines. The first arrow points to the first line and is labeled 'task description'. The second arrow points to the second line and is labeled 'prompt'.

```
1 Translate English to French: ← task description
2 cheese => ..... ← prompt
```



# One Shot

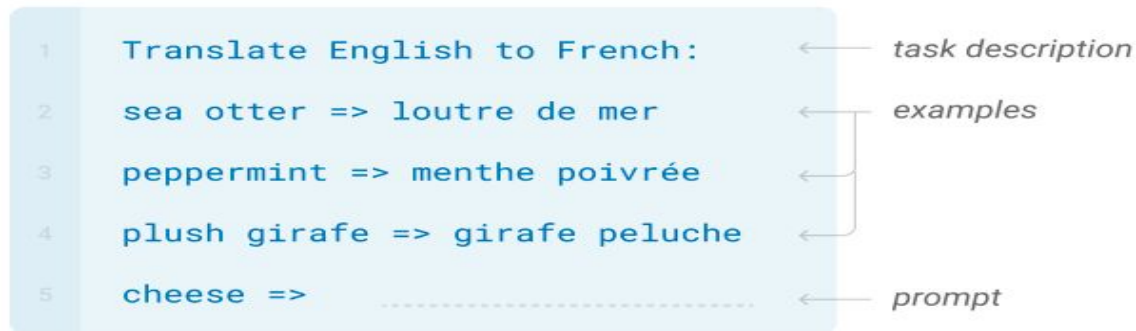
- Exactly as the name suggest
- Single example per task description
- Example:

1	<code>Translate English to French:</code>	← <i>task description</i>
2	<code>sea otter =&gt; loutre de mer</code>	← <i>example</i>
3	<code>cheese =&gt; .....</code>	← <i>prompt</i>



# Few Shots

- Provide few examples for the task description to predict the output
- 10 - 100 examples can fit the context window
- Reduction in the need for task-specific data
- Example:



SECTION 4

# GPT3 Architecture

# GPT3

- Generative Pre-trained Transformer 3
- Released in June 2020, claimed to largest one in terms of params and storage
- Autoregressive Language Model
- Meta Learning, In-context Learning
- Uses Deep Learning for Natural Language Tasks (like text classification, machine translation, Q&A)
- Human like Text Output
- Performs tasks using all, Zero Shot, One Shot and Few Shots.



# What's 3 doing in GPT3?

	GPT-1	GPT-2	GPT-3
Parameters	117 Million	1.5 Billion	175 Billion
Decoder Layers	12	48	96
Context Token Size	512	1024	2048
Hidden Layer	768	1600	12288
Batch Size	64	512	3.2M



**GPT-2**  
**1.5B Parameters**

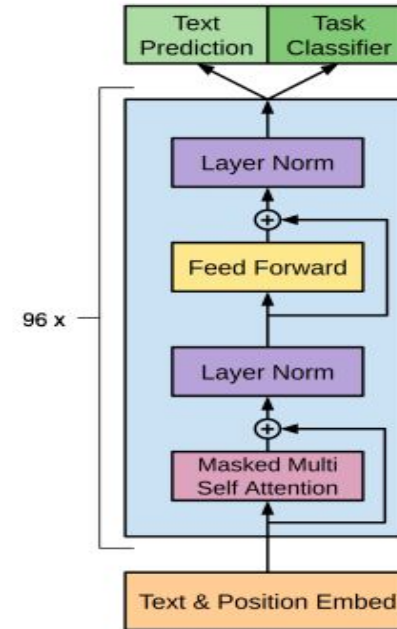
**GPT-3**  
**175B Parameters**



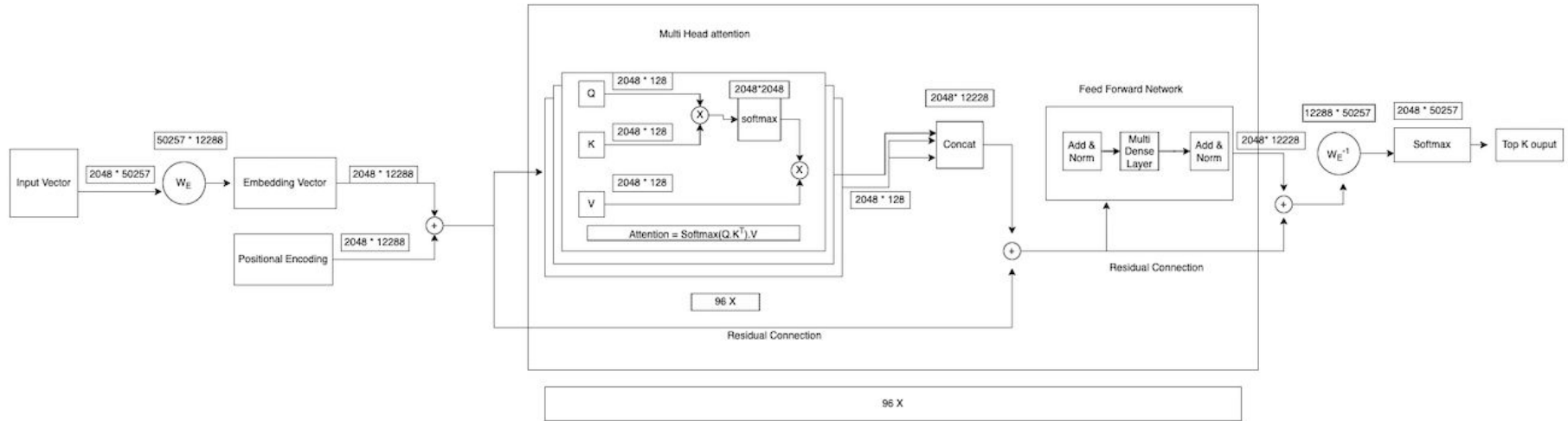
# Architecture

GPT 3 Model consists of following layers

- Input Embeddings
- Positional Embeddings
- MultiHead Attention
- Normalisation
- Feed Forward Layers
- Softmax



# GPT3 Model Architecture



# GPT3 Model

- GPT3 model was trained on vocabulary of 50257 words
- The input sequence is actually fixed to 2048 words.
- If the input is less than 2048 words, it will pad with 0's.
- The output sequence is also fixed to 2048 words.
- GPT3 uses the embedding dimensions of 12288 dimensions.
- Embedding dimensions are nothing but the features of the input like “softness”, “color”, “past tense”, “numerical” etc..



SECTION 5

# Approach

# Data

1. Common Crawl Dataset
2. Downloaded from 41 shards of monthly covering from 2016-19
3. 45TB of plain text before filtering, 570GB after that
4. 400 billion byte-paired encoded tokens



# Data Preprocessing

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

- Filtered based on similarity to range of high-quality corpora
- Fuzzy de-duplication at document level to prevent redundancy
- Sampling and Augmentation - Addition of other datasets – increased diversity
- Higher quality datasets sampled more frequently



# Training

- Large models might go out of memory - Parallelism in matrix multiplication
- Used Gradient Noise Scale to determine batch size
- V100 GPU's - high bandwidth cluster by Microsoft
- Adam with cosine decay for Learning Rate

Model Name	$n_{\text{params}}$	$n_{\text{layers}}$	$d_{\text{model}}$	$n_{\text{heads}}$	$d_{\text{head}}$	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	$6.0 \times 10^{-4}$
GPT-3 Medium	350M	24	1024	16	64	0.5M	$3.0 \times 10^{-4}$
GPT-3 Large	760M	24	1536	16	96	0.5M	$2.5 \times 10^{-4}$
GPT-3 XL	1.3B	24	2048	24	128	1M	$2.0 \times 10^{-4}$
GPT-3 2.7B	2.7B	32	2560	32	80	1M	$1.6 \times 10^{-4}$
GPT-3 6.7B	6.7B	32	4096	32	128	2M	$1.2 \times 10^{-4}$
GPT-3 13B	13.0B	40	5140	40	128	2M	$1.0 \times 10^{-4}$
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	$0.6 \times 10^{-4}$



# Evaluation

- Randomly draw K samples from training as conditioning for few-shots
  - Maximum size of k depends on matrix window (2048)
  - Typically fits 0 to 100 examples
- Evaluation is Task specific
- For example, for MCQ's, K samples of context + completion with 1 of context only. Then compare LM likelihood of each completion
- Another eg, for free-form completion tasks, beam search is used with score using F1 similarity score, BLEU, or exact match based on data
- Evaluated 8 models - 175B GPT3 + 7 smaller models





# Results

- Results of various datasets grouped into 9 task-specific categories
- Examples:
  - Language Models
  - Translation
  - Reading Comprehension



# Results - Language Translation

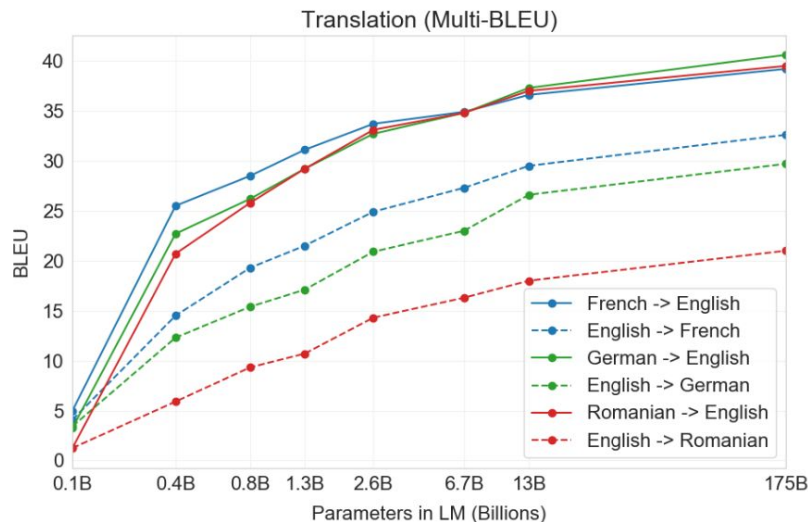
- GPT-3 Few shot gives similar average performance with SOTA while translating to English
- Significant improvement from unsupervised models while translating to English
- Better BLEU score accuracy with increase in number of shots

Setting	En→Fr	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	<b>45.6<sup>a</sup></b>	35.0 <sup>b</sup>	<b>41.2<sup>c</sup></b>	40.2 <sup>d</sup>	<b>38.5<sup>e</sup></b>	<b>39.9<sup>e</sup></b>
XLM [LC19]	33.4	33.3	26.4	34.3	33.3	31.8
MASS [STQ <sup>+</sup> 19]	<u>37.5</u>	34.9	28.3	35.2	<u>35.2</u>	33.1
mBART [LGG <sup>+</sup> 20]	-	-	<u>29.8</u>	34.0	35.0	30.5
GPT-3 Zero-Shot	25.2	21.2	24.6	27.2	14.1	19.9
GPT-3 One-Shot	28.3	33.7	26.2	30.4	20.6	38.6
GPT-3 Few-Shot	32.6	<u>39.2</u>	29.7	<u>40.6</u>	21.0	<u>39.5</u>



# Results - Language Translation

- Improvement in BLEU score across different model capacity for all translation tasks



SECTION 6

# Nothing's Perfect

# Limitations

- Text Synthesis - Loses coherence, predictions contradict themselves
- Limited Input and Output Size
- Underperforms in case of bidirectional use cases
  - Eg: Fill in the blanks, Reading comprehension
- Pre-training limitations with scaling
  - Weights tokens equally, lack of world context
- Is it really adaptive?
- Bias from data, non-interpretable
- And yes, it's expensive, large, inconvenient....



# Future Work

- Improve pre-training, sample efficiency
- How exactly few shots learning works?
- Distillation to sized specific tasks

**GPT4 expected to come by end of this year!**



# Broader Impacts

- Misinformation, spam, phishing, legal abuse, social engineering pretexting
  - GPT3 can generate text indistinguishable from human-written ones.
- Enabling Threat actors
- Bias in Data
  - Generates prejudiced content, (Gender, Race, Religion)
  - May result in demeaning portrayal
- Energy usage



# Fun Facts

In one study, GPT-3 was able to generate “news articles” almost indistinguishable from human-made pieces. Judges barely achieved above-chance accuracy (52%) at correctly classifying GPT-3 texts.

GPT-3 has an artist’s soul! Arram Sabeti told GPT-3 to write a poem about Elon Musk by Dr. Seuss and a rap song about Harry Potter by Lil Wayne.

GPT3 can also generate PowerPoint presentations!  
(Though this presentation is solely prepared by us, hope you believe it :))





# Questions?

- Ask GPT3!



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SECTION 7

# Practical

# Task 1

- Study the Impact of GPT3 Parameters on Classification Accuracy
  - Few shot learning
  - Twitter Sentiment Classification
  - Plot Accuracy Scores vs Parameters
- Parameters
  - Engine Type
  - Temperature
  - Token Length



# Task 2

- Given the abstract of a research paper, generate it's title
  - Feeding examples to GPT-3
  - Zero/Few Shots
  - BLEU Score
  - Plot
  - Learnings
- Dataset

Title and Abstract of Research Papers

	title	abstract
0	On the Cohomological Derivation of Yang-Mills Theory in the Antifield Formalism	We present a brief review of the cohomological solutions of self-coupling interac
1	Regularity of solutions of the isoperimetric problem that are close to a smooth manifold	In this work we consider a question in the calculus of variations motivated by rie
2	Asymptotic theory of least squares estimators for nearly unstable processes under strong dependence	This paper considers the effect of least squares procedures for nearly unstable l
5	Weight Reduction for Mod $l$ Bianchi Modular Forms	Let $K$ be an imaginary quadratic field with class number one and ring of integers
6	Nonequilibrium phase transition in a spreading process on a timeline	We consider a nonequilibrium process on a timeline with discrete sites which ev



# Task 3

- By this task we will learn how GPT3 perform better than any SOTA models by comparing the performance of GPT3 with any fine-tuning Language Model.
- For our ease, let's take the reference of our last practical Seq\_to\_Seq translation use case.
- Let's solve the problem using the Bahdinou\_Attention fine-tuning model and solve the same using the GPT3 and compare the metrics and results.



# Things to Explore

- Openai Playground - <https://beta.openai.com/playground>
- GPT3 Github Repo - <https://github.com/elyase/awesome-gpt3>



# References

- GPT3 Paper - <https://arxiv.org/pdf/2005.14165.pdf>
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- [https://dugas.ch/artificial\\_curiosity/GPT\\_architecture.html](https://dugas.ch/artificial_curiosity/GPT_architecture.html)
- <https://towardsdatascience.com/gpt-3-a-complete-overview-190232eb25fd>
- <https://medium.com/walmartglobaltech/the-journey-of-open-ai-gpt-models-32d95b7b7fb2>





**THANK YOU**