



Reading Report 7

Language Models are Unsupervised Multitask Learners



Introduction

Traditional Approach:

NLP tasks like question answering and translation use supervised learning on large, annotated datasets

WebText & Zero-Shot Shift:

GPT-2, trained on millions of web pages (WebText), performs NLP tasks without explicit supervision

Key Result:

Achieves 55 F1 on CoQA without using 127k training examples, surpassing 3 of 4 baselines

Model Capacity Matters:

Larger models like GPT-2 (1.5B parameters) improve performance across tasks in a log-linear fashion



Towards Generalized ML

From Narrow Experts to Zero-Shot

Current ML Systems:

Perform well on narrow tasks but struggle with generalization and data shifts

Challenges:

Erratic performance in tasks like captioning and image classification due to single-task training

Multitask Learning:

Benchmarks like GLUE show promise, but multitask training is still nascent

Zero-Shot Potential:

Pre-trained language models can perform tasks without fine-tuning, showing promise for generalized ML



Core Approach of Language Modeling

Language Modeling:

Framed as unsupervised distribution estimation over sequences of symbols

Conditional Probabilities:

Factorize joint probabilities into conditional probabilities for tractable sampling, e.g., $p(x) = \prod p(sn|s1,...,sn-1)$

Self-Attention & Transformer:

Modern architectures like the Transformer improve conditional probability computation

Task Learning:

General models learn tasks as p(output|input, task), leveraging language to specify tasks, inputs, and outputs

Multitask Learning:

Language models can infer and perform multiple tasks without explicit supervision



Experimental Setup

Training:

Four Language Models (LMs) were trained, including GPT, BERT, and GPT-2, with varying sizes and learning rates optimized for best perplexity on WebText

Language Modeling:

GPT-2 excelled at zero-shot transfer across domains, improving perplexity and achieving state-of-the-art results on 7 of 8 datasets

CBT & LAMBADA:

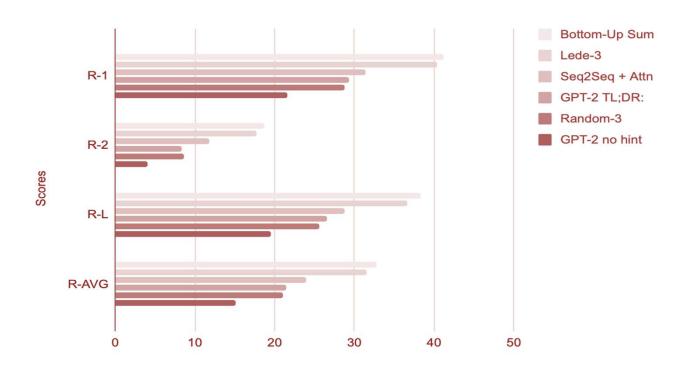
Significant performance boosts were seen in Children's Book Test (93.3% on nouns) and LAMBADA dataset (accuracy from 19% to 52.66%), highlighting GPT-2's ability to handle long-term dependencies

Challenges:

While GPT-2 outperformed in many areas, it struggled with datasets like the One Billion Word Benchmark due to heavy preprocessing



Performance Comparision





Generalization v/s Memorization

Aspect	Generalization	Memorization
Definition	Performs well on unseen data	Relies on recalling training data
Dataset Overlap	Low overlap (1-6%)	High overlap (e.g., 13.2% in 1BW)
Impact	Reflects true model capabilities	Inflates reported performance
Example	CoQA (0.5-1.0 F1 gain due to overlap)	GPT-2 shows some memorization, but still underfits WebText
Best Practice	De-duplicate training and test splits	Avoid excessive overlap in datasets



Discussion and Conclusion

- Unsupervised Task Learning:
 Shows potential for models to perform tasks without supervision
- Zero-Shot Performance:
 GPT-2 competes in reading comprehension but underperforms in summarization
- Capacity Matters:
 Performance improves with model capacity; many tasks still fail to exceed random guessing
- Fine-Tuning Exploration: Further investigation needed on benchmarks like decaNLP and GLUE
- Overall Insight:

Large, diverse datasets enable models like GPT-2 to excel across various tasks with minimal supervision



Quiz Question

- Question: How do larger language models, trained on vast amounts of data, typically perform in comparison to their smaller counterparts?
- A) Smaller models consistently outperform larger ones in all scenarios.
- B) The performance of larger models significantly enhances as both the model size and the dataset size increase.
- C) Increasing the training data does not provide any benefits for larger models.
- D) The performance of larger models is entirely determined by the underlying architecture, not by size or data.
- Answer:
 - The Correct Answer is Option B