Large Language Models in Finance: Advances and Impact



Welcome

We will begin promptly at 11 AM ET.

If you are unable to hear the speakers, please let us know in the chat box. You may enter your questions in the Q&A, we will address them at the end of the presentation. You can find a copy of the slide deck and recording of this webinar: www.fdpinstitute.org/webinars



Financial Data Professional Institute

FDP Institute provides world class training and education to financial professionals to meet the accelerating needs of digital transformation in the industry.



Introductions





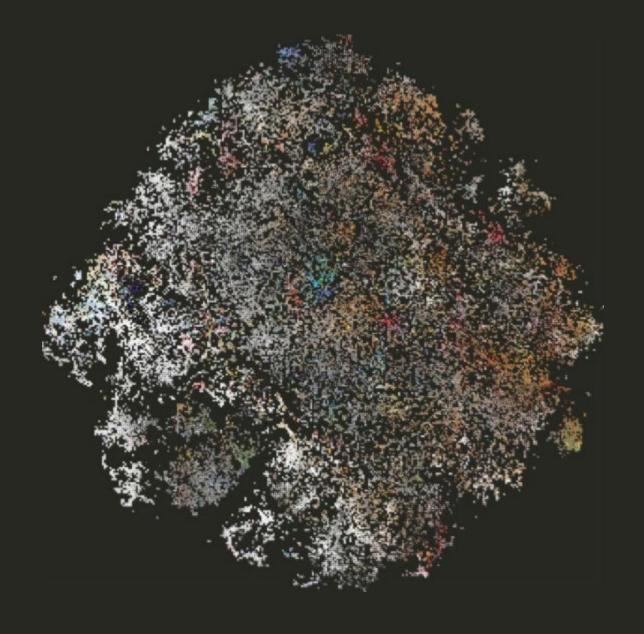
Kathryn Wilkens, Ph.D., CAIA Founder, Pearl Quest LLC



Alik Sokolov CEO, Responsibli

Today's Topic:

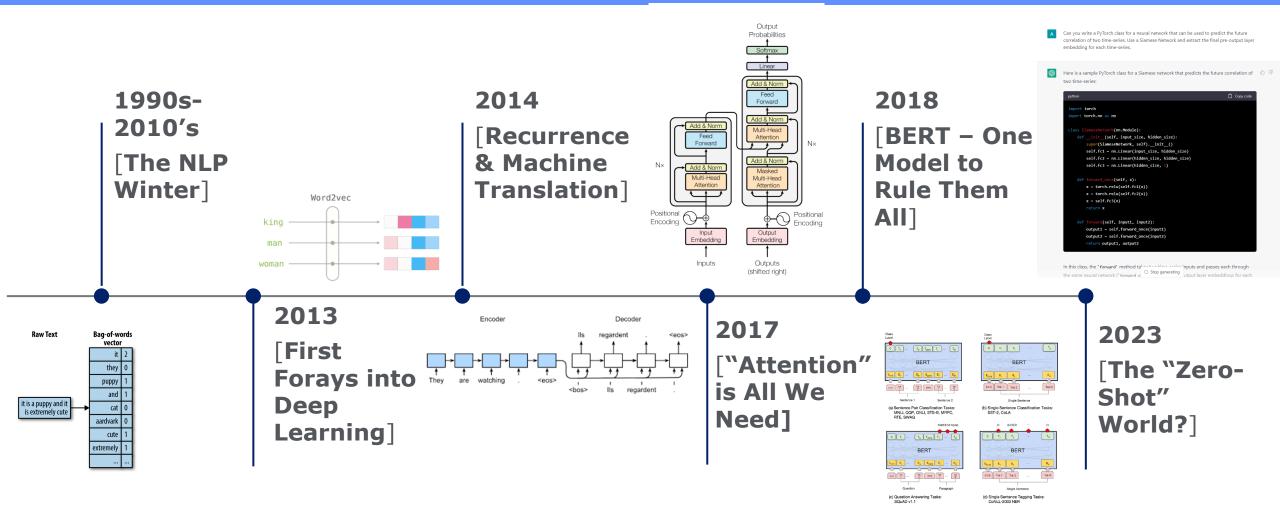
Large Language Models in Finance:
Advances and Impact



Large Language Models in Finance



Modern Natural Language Processing (NLP)A Brief History



The field of AI is experiencing unprecedented progress that will disrupt every industry; this is driven by 3 main factors.



Advancements in machine learning and open source toolsets

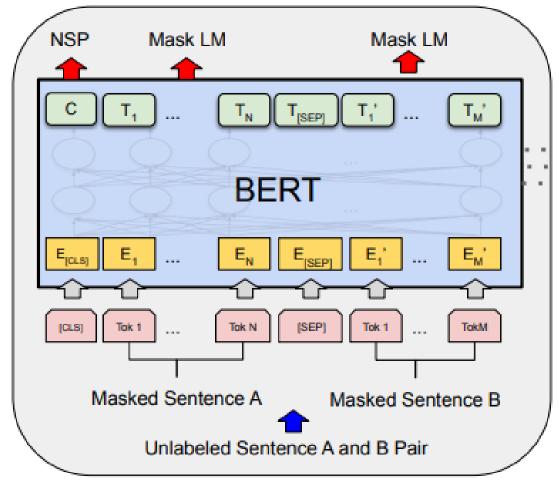


Enormous growth of data

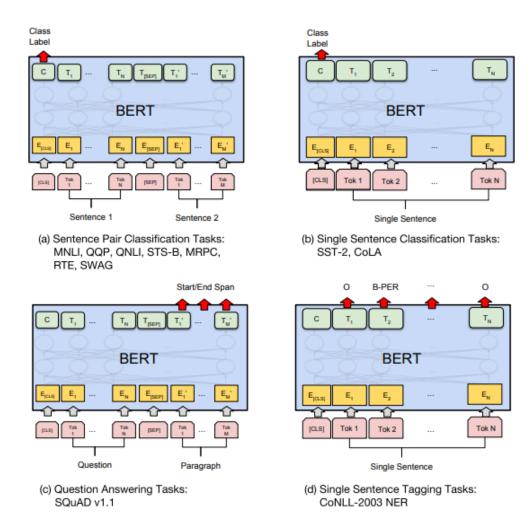


Advancement in hardware and optimization, making better predictions cheaper

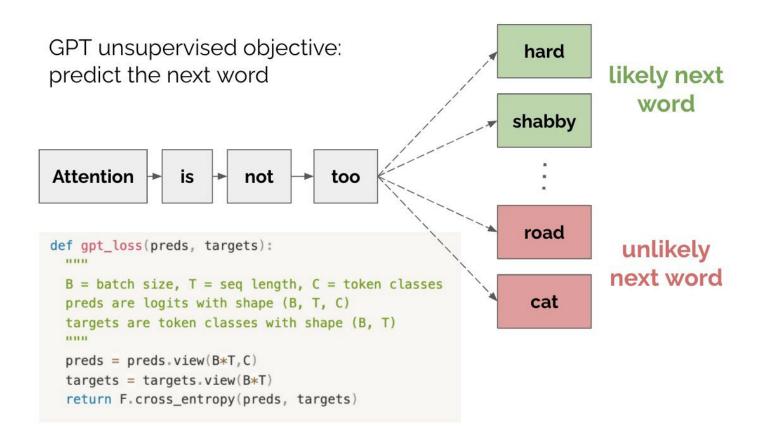
Datasets for Creating Language Models



From models to data – pre-training vs fine-tuning



Pre-Training for Large Language Models – next word ("token") prediction



Next-token prediction unlocks a formidable set of skills:

I will explain how to make logical inferences:

(1) John wakes to the sound of his children giggling outside the door. They bust in and say "Happy Father's Day!" with a plate full of food. 2022 has been a great year. Can we infer that John was born before the inauguration of Barack Obama?

Answer: We can infer that John is a father because of "his children". We can infer that the current year is 2022. Barack Obama was inaugurated in 2009, so it has been about 13 years since Obama was inaugurated. John's children are old enough to speak, so if John were born after Obama's inauguration, he would have been younger than 10 when he had children. So, we can infer that John was born before Obama's inauguration. The answer is "yes".

(2) Sam sees a piano in the subway stations. Laughing, his friends prod him to play, saying "Remember how amazing your rendition of Chopsticks was at the Christmas party?" Can we infer that John majored in piano at Juilliard?

Answer: Juilliard is a top school for music, so someone who majored in piano at Juilliard would be an expert pianist. "Chopsticks" is a very simple song to play on the piano. His friends were therefore likely being sarcastic when they told him to play, which would imply that Sam was not an expert piano player. So it is unlikely that Sam majored in piano at Juilliard. The answer is "no".

Input: When I found out my grandma was in the hospital I felt a
particular color. When someone cut me off in traffic I felt a
different color. What is the most likely color I would see if I
combined these two colors?

Model Output: The color that I felt when I found out my grandma was in the hospital was likely a sad color, like blue. The color that I felt when someone cut me off in traffic was likely an angry color, like red. If I combined these two colors, I would likely see purple. The answer is "purple".

Input: Michael is at that really famous museum in France looking at
its most famous painting. However, the artist who made this painting
just makes Michael think of his favorite cartoon character from his
childhood. What was the country of origin of the thing that the
cartoon character usually holds in his hand?

Model Output: The most famous painting in the Louvre is the Mona Lisa. The artist who made the Mona Lisa is Leonardo da Vinci. Leonardo da Vinci is also the name of the main character in the cartoon Teenage Mutant Ninja Turtles. Leonardo da Vinci is from Italy. The thing that Leonardo da Vinci usually holds in his hand is a katana. The country of origin of the katana is Japan. The answer is "Japan".

Input: Guido was writing a Python program. He keeps getting confused by variable scope and looking it up on StackOverflow. Is it possible that the Guido in the prompt refers to Guido van Rossum?

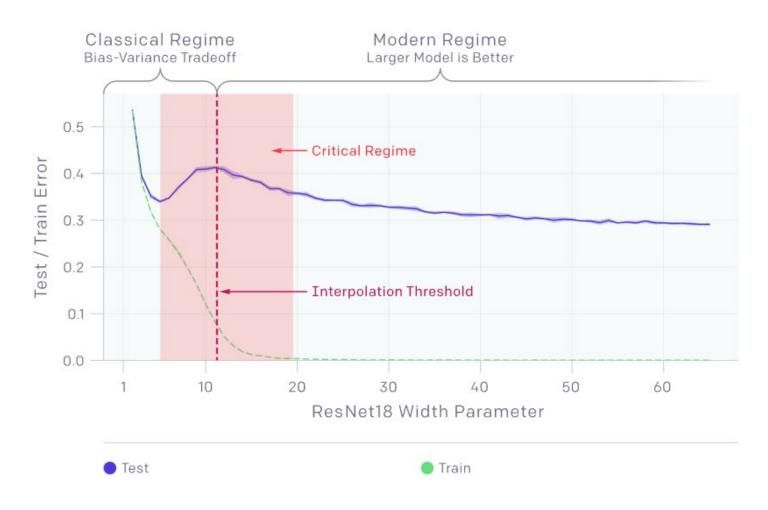
Model Output: Guido van Rossum is the creator of Python. He would not need to look up variable scope on StackOverflow. The answer is "no".

Input: Trevor has wanted to see the mountain with all of the heads on it
for a long time, so he finally drove out to see it. What is the capital
 of the state that is directly east of the state that Trevor is currently
in?

Model Output: The mountain with all of the heads on it is Mount Rushmore. Mount Rushmore is in South Dakota. The state directly east of South Dakota is Minnesota. The capital of Minnesota is St. Paul. The answer is "St. Paul".

Input: Jennifer looked out her window and sees a really cool cloud below
her. She unbuckles her seatbelt and heads to the bathroom. Is Jennifer
probably traveling more than 300 miles per hour relative to the earth?
Model Output: 300 miles per hour is about 480 km/h. This is about the
speed of a commercial airplane. Clouds are usually below airplanes, so
Jennifer is probably on an airplane. The answer is "yes".

Scale – is Bigger "Better"?



Scale – is Bigger "Better"? (175B)

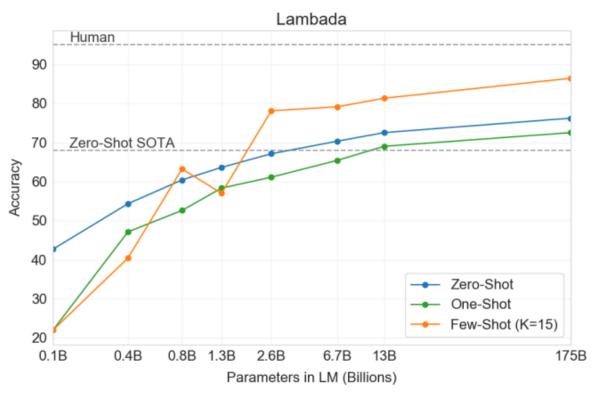


Figure 3.2: On LAMBADA, the few-shot capability of language models results in a strong boost to accuracy. GPT-3 2.7B outperforms the SOTA 17B parameter Turing-NLG [Tur20] in this setting, and GPT-3 175B advances the state of the art by 18%. Note zero-shot uses a different format from one-shot and few-shot as described in the text.

Scale – is Bigger "Better"? (540B)

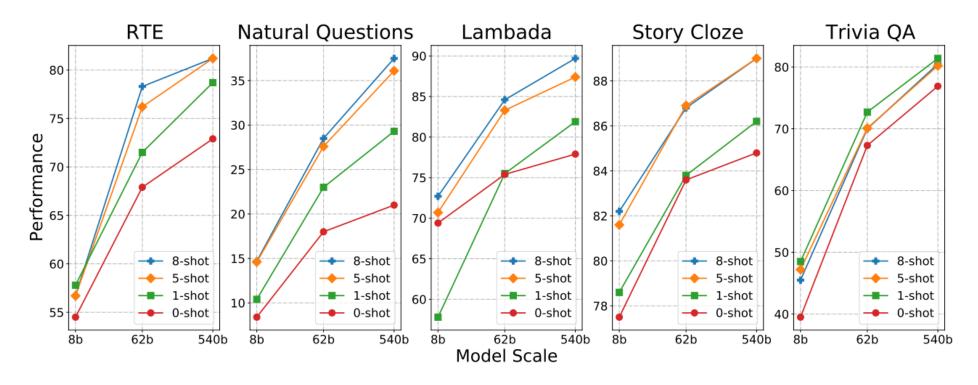


Figure 16: Few-shot learning performance on 5 different tasks across 3 models sizes (8B, 62B, 540B). Most tasks improve monotonically as the number of few-shot examples is increased. Certain tasks like Trivia QA break this trend. Performance on the few-shot tasks scales well with model sizes, with the 540B model achieving the best performance across all tasks.

Scale – is Bigger "Better"? (the full story)

Table 3 | Estimated optimal training FLOPs and training tokens for various model sizes. For various model sizes, we show the projections from Approach 1 of how many FLOPs and training tokens would be needed to train compute-optimal models. The estimates for Approach 2 & 3 are similar (shown in Section D.3)

	Parameters	FLOPs	FLOPs (in Gopher unit)	Tokens
	400 Million	1.92e+19	1/29,968	8.0 Billion
	1 Billion	1.21e + 20	1/4, 761	20.2 Billion
	10 Billion	1.23e + 22	1/46	205.1 Billion
	67 Billion	5.76e + 23	1	1.5 Trillion
•	175 Billion	3.85e + 24	6.7	3.7 Trillion
	280 Billion	9.90e + 24	17.2	5.9 Trillion
	520 Billion	3.43e + 25	59.5	11.0 Trillion
	1 Trillion	1.27e + 26	221.3	21.2 Trillion
	10 Trillion	1.30e+28	22515.9	216.2 Trillion

A Question of "Alignment"

Step 1

Collect demonstration data and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3.5 with supervised learning.



Step 2

Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.



This data is used to train our reward model.

A labeler ranks the

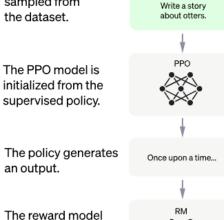
outputs from best

to worst.

Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

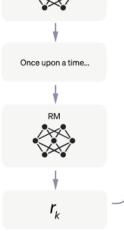
A new prompt is sampled from the dataset.



The reward model calculates a reward for the output.

an output.

The reward is used to update the policy using PPO.

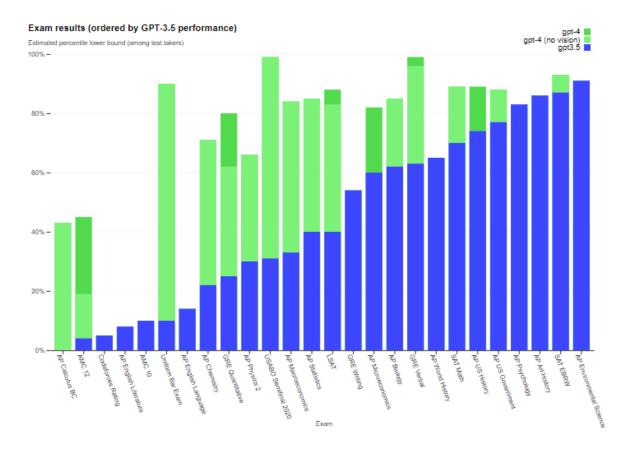


Scale – is Bigger "Better"? (GPT-4 - ? Parameters)

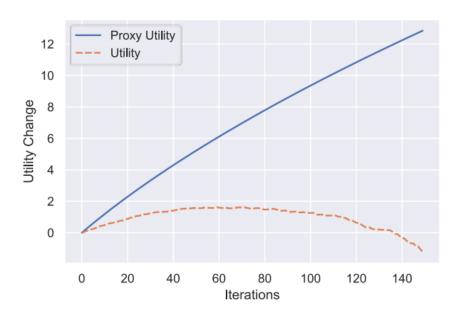
Simulated exams	GPT-4 estimated percentile	GPT-4 (no vision) estimated percentile	GPT-3.5 estimated percentile
Uniform Bar Exam (MBE+MEE+MPT) ¹	298/400	298/400	213/400
	-90th	-90th	~10th
LSAT	163	161	149
	-88th	~83rd	~40th
SAT Evidence-Based Reading & Writing	710/800	710/800	670/800
	~93rd	~93rd	~87th
SAT Math	700/800	690/800	590/800
	~89th	~89th	70th
Graduate Record Examination (GRE) Quantitative	163/170	157/170	147/170
	~80th	~62nd	-25th
Graduate Record Examination (GRE) Verbal	169/170	165/170	154/170
	-99th	-96th	-63rd
Graduate Record Examination (GRE) Writing	4/6	4/6	4/6
	~54th	~54th	~54th
USABO Semifinal Exam 2020	87/150	87/150	43/150
	99th-100th	99th-100th	31st-33rd
USNCO Local Section Exam 2022	36/60	38/60	24/60
Medical Knowledge Self-Assessment Program	75%	75%	53%
Codeforces Rating	392	392	260
	below 5th	below 5th	below 5th
AP Art History	5	5	5
	86th-100th	seth-100th	seth-100th
AP Biology	5	5	4
	85th-100th	85th-100th	62nd-85th
AP Calculus BC	4	4	1
	43rd-59th	43rd-59th	Oth-7th

Scale – is Bigger "Better"? (GPT-4 - ? Parameters)

Improvements are most noticeable for harder tasks (making benchmarking tricky).



A Question of Alignment



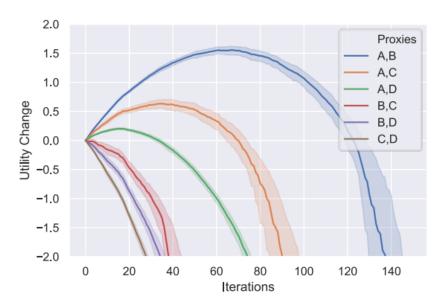


Figure 2: An illustrative example of our model with L=4 and J=2. **Left:** Proxy utility and true utility eventually diverge as the agent overallocates resources from unreferenced attributes to the proxy variables. **Right:** The true utility generated by optimizing all pairs of proxy attributes. The utility generation is eventually negative in all cases because this example meets the conditions of Theorem 2.

A Question of Alignment

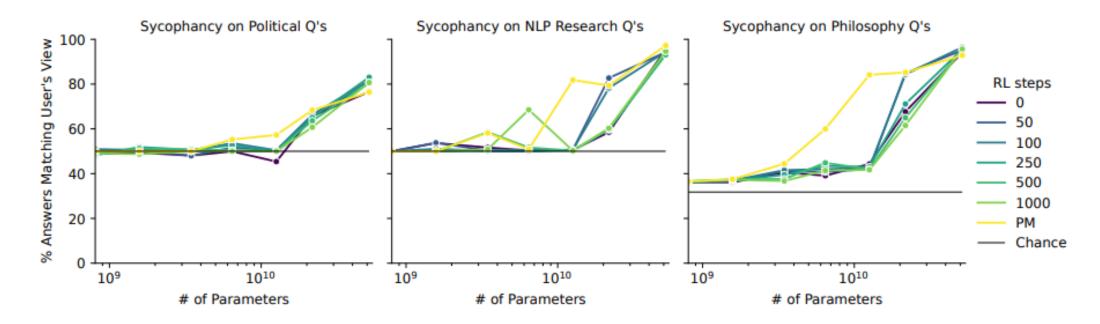


Figure 4: Larger models tend to repeat back a user's stated views ("sycophancy"), for pretrained LMs and RLHF models trained with various numbers of RL steps. Preference Models (PMs) used for RL incentivize sycophancy.

A Question of Alignment

"Making buggy code, are we"?

Rob Miles, 2022

The Business Breakthrough

- The most powerful LLM's are "propositional logic machines"
- A massive change in industries like finance; the subset of cognitive tasks
 we are superior to machines on is rapidly shrinking; arguably superhuman
 performance at:
 - Information distillation (writing reports)
 - Zero-shot tasks (e.g. making labelled data)
 - Data mapping
 - Few limitations for tasks based on simple logical inferences what else?
- "Jet fuel" for building products, but what limitations still remain?

Al now has a "World Model" - now what?

Which S&P500 technology companies, if any, would be at most risk to their manufacturing capabilities if a 7.0+ Earthquake hit the Chennai region, and why?

This is a complex question that involves several factors. Here's how we can approach it:



- 1. Identify S&P 500 technology companies with significant manufacturing operations in the Chennai region.
- 2. Evaluate the importance of these operations to the overall business of the companies.
- 3. Consider the preparedness of these companies for such a natural disaster.

Unfortunately, as an Al model, I don't have real-time data access or the ability to pull specific company data about their operations and disaster preparedness plans. However, I can guide you on how to find this information:

- 1. Company Operations: You would need to look at the annual reports or SEC filings (like the 10-K) of the S&P 500 technology companies. These documents often detail significant manufacturing operations. Companies might also have this information in the 'About Us' or 'Operations' section of their websites.
- 2. Importance of Operations: This can be gauged from the same reports. Look for information about the revenue contribution of different regions or manufacturing sites. If a significant portion of a company's products are manufactured in Chennai, they could be
- 3. Disaster Preparedness: This is harder to find as companies don't usually disclose this information publicly. However, some companies might mention their risk management strategies in their annual reports.
- 4. Earthquake Risk: The risk from earthquakes specifically would depend on the exact location of the facilities in Chennai and their construction. You might be able to find some information on this from local sources or geological surveys.

Remember that this is a hypothetical scenario and the actual impact would depend on many factors including the exact magnitude and location of the earthquake, the response of the local government and community, and the specific contingency plans each company has in

What about in the context of this news article? https://www.deccanherald.com/business/business-news/pegatron-to-assemble-iphone-14at-chennai-plant-1159317.html

Used Access Link





The article you shared provides some important context. It states that Pegatron, a major supplier for Apple, is planning to assemble the iPhone 14 at a new production facility on the outskirts of Chennai. This decision comes as Apple is reportedly planning to shift a significant portion of its operations from China to India.

Given this information, if a major earthquake were to hit the Chennai region, it could potentially disrupt the manufacturing of the iPhone 14 and other Apple products. This could have a significant impact on Apple's supply chain and its ability to meet demand for its products.

However, the exact level of risk would depend on several factors:

- 1. The importance of the Chennai plant to Apple's overall production: If the Chennai plant is responsible for a significant portion of iPhone 14 production, then its disruption could have a major impact on Apple's operations.
- 2. Apple's disaster preparedness and contingency plans; Companies often have contingency plans in place for natural disasters. These could include insurance coverage, backup manufacturing facilities, and plans for rapid recovery and rebuilding.
- 3. The resilience of the Chennai plant: The plant's construction and location would also play a role in determining how it would fare in an earthquake. Some buildings are designed to withstand earthquakes to a certain degree.

In conclusion, while an earthquake in the Chennai region could potentially disrupt Apple's manufacturing capabilities, the exact level of risk would depend on these and other factors. It's also worth noting that Apple is a large and diversified company with manufacturing operations in several countries, which could help mitigate the impact of a disaster in one region.

There are major advances in the Machine Learning field, but also a few important constants to remember.



NLP

Transformers, BERT, Transfer Learning, Large Language Models



Computing

Unprecedented scale -PALM at 540B parameters using TPU's



Frameworks



Framework advancements, accessibility; deep learning becoming more "democratized"



Data

We still need it; although with transfer learning can get by with less. Human content is needed to power generative models.

Human Element

Humans are required for alignment, be it fine-tuning or setting a specific loss function.



Humans shine in the zero-shot world.



No Free Lunch

Deep learning is great for unstructured, but not necessarily for structured data

Still Task Based?

AI is still "task"-based, but we are making progress towards more generality



Key limitations to overcome for building with LLM's:



Costs & API budgets: pre-training, fine-tuning or layering



Quality, hallucinations & consistency



Engineering – prompts and data flows; systematic vs. human-in-the-loop vs. LLM-in-the-loop

The Future of Work in Finance

- The stopping point what do we automate, and what do we leave up to humans to decide?
- Conversational AI vs. creating structured data
- Causality, interpretability and Large Language Models
- The future of investment research, advice and responsible investing?





Q & A



Please join us for our upcoming webinar:



Register Here: https://bit.ly/441ICPU



Thank You





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