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

Today’s Topic:

Large Language Models in Finance: Advances and Impact
Large Language Models in Finance
1990s-2010’s
[The NLP Winter]

2013
[First Forays into Deep Learning]

2014
[Recurrence & Machine Translation]

2017
[“Attention” is All We Need]

2018
[BERT – One Model to Rule Them All]

2023
[The “Zero-Shot” World?]
The field of AI is experiencing unprecedented progress that will disrupt every industry; this is driven by 3 main factors.

1. Advancements in machine learning and open source toolsets
2. Enormous growth of data
3. Advancement in hardware and optimization, making better predictions cheaper
Datasets for Creating Language Models

Introduction
The Evolution of AI in Finance

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

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

Introduction
The Evolution of AI in Finance

GPT unsupervised objective: predict the next word

```python
def gpt_loss(preds, targets):
    """
    B = batch size, T = seq length, C = token classes
    preds are logits with shape (B, T, C)
    targets are token classes with shape (B, T)
    """
    preds = preds.view(B*T,C)
    targets = targets.view(B*T)
    return F.cross_entropy(preds, targets)
```
Next-token prediction unlocks a formidable set of skills:

**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:** 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”.

Chowdhery et al. (2022), PaLM: Scaling Language Modeling with Pathways.
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Scale – is Bigger “Better”?

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The Evolution of AI in Finance

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.

Brown et al. (2020), Language Models are Few-Shot Learners.
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The Evolution of AI in Finance

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.

Chowdhery et al. (2022), PaLM: Scaling Language Modeling with Pathways.
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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)

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

Hoffmann et al. (2022), *Training Compute-Optimal Large Language Models*.
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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.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.

Step 3
Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

## Introduction

The Evolution of AI in Finance

### Scale – is Bigger “Better”? (GPT-4 - ? Parameters)

<table>
<thead>
<tr>
<th>Simulated exams</th>
<th>GPT-4 estimated percentile</th>
<th>GPT-4 (no vision) estimated percentile</th>
<th>GPT-3.5 estimated percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uniform Bar Exam (MBE+MEE+MPT)¹</td>
<td>298/400</td>
<td>298/400</td>
<td>213/400</td>
</tr>
<tr>
<td>LSAT</td>
<td>103</td>
<td>101</td>
<td>149</td>
</tr>
<tr>
<td>SAT Evidence-Based Reading &amp; Writing</td>
<td>710/800</td>
<td>710/800</td>
<td>670/800</td>
</tr>
<tr>
<td>SAT Math</td>
<td>700/800</td>
<td>690/800</td>
<td>590/800</td>
</tr>
<tr>
<td>Graduate Record Examination (GRE) Quantitative</td>
<td>163/170</td>
<td>157/170</td>
<td>147/170</td>
</tr>
<tr>
<td>Graduate Record Examination (GRE) Verbal</td>
<td>165/170</td>
<td>165/170</td>
<td>154/170</td>
</tr>
<tr>
<td>Graduate Record Examination (GRE) Writing</td>
<td>4/8</td>
<td>4/8</td>
<td>4/8</td>
</tr>
<tr>
<td>USABO Semifinal Exam 2020</td>
<td>87/150</td>
<td>87/150</td>
<td>43/150</td>
</tr>
<tr>
<td>USNCO Local Section Exam 2022</td>
<td>36/60</td>
<td>36/60</td>
<td>24/60</td>
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<tr>
<td>Medical Knowledge Self-Assessment Program</td>
<td>75%</td>
<td>75%</td>
<td>53%</td>
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<tr>
<td>Codeforces Rating</td>
<td>392</td>
<td>302</td>
<td>260</td>
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<tr>
<td>AP Art History</td>
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<td>5</td>
<td>5</td>
</tr>
<tr>
<td>AP Biology</td>
<td>5</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>AP Calculus BC</td>
<td>4</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

OpenAI Gpt-4 blog post: https://openai.com/research/gpt-4
Introduction
The Evolution of AI in Finance

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.

Zhuang et. Al. (2020), Consequences of Misaligned AI
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The Evolution of AI in Finance

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.

Perez et. Al. (2022), Discovering Language Model Behaviors with Model-Written Evaluations
“Making buggy code, are we”?
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?
Introduction
The Evolution of AI in Finance

AI 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 7.5+ 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 AI 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 their "About Us" or Operational 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 at risk.

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 place.

What about in the context of this news article?

The article you shared provides some important context. It states that Pagatron, 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.

**Introduction**

**The Evolution of AI in Finance**

**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?
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Unleashing the Power of Neural Networks:
A Personal Journey into Creating and Harnessing a Neural Network for Trading Stocks

Tom Pickel, CAIA, FDP
Founder, Gagge, Independent Consultant,
Pickel Global Finance

Hossein Kazemi, CFA
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