2023 Future of finance conference

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<https://www.rebellionresearch.com/cornell-financial-engineering-manhattan-rebellion-research-2023-future-of-finance-conference>

Format: one day series of panels and keynote debates with participants from investment banks, asset managers, hedge funds, financial services etc.

In the below, I am including highlights from most of the relevant panels (for details on the panelists please check the link above).

## Panel 1: Chat-GPT & The Future of Ai in Finance

Highlights:

* LLMs adoption in financial services is growing and is primarily in marketing , sales , and operations.
* LLMs are more useful in entity resolution, coding, Automate document generation and processing, less relevant in sentiment analysis.
* BlackRock sales and marketing distribution team leverages ML/NLP/LLM to target asset allocators (in particular , looking at general news whenever institutional investors are mentioned, they look at certain cues that indicate that they are maybe ready to allocate in certain areas and feed that in formation to the sales team, which requires entity resolution/recognition, event detection and redundancy removal )
* There is no big concern on the impact of AI on the labor market.
* AI/LLM will be most impactful on accelerating the access to information.
* Sales industry will be the most impacted by LLMs.

## Panel 2: The quantitative investment Process

Highlights:

* Quantitative investment in words: data, logic, words
* Systematic vs Quantitative: should not be confused, an investment process can be highly quantitative (but still includes decisions based on human judgment) but not systematic (fully automated)
* Even with a systematic investment process, the role of human is crucial not only in framing the problem and setting up the system, it is also in the continuous monitoring, adjusting, enhancing of the system.
* A strong statement from Gregory Pelts (Scotiabank): there is no such thing of a fully systematic strategy or fully discretionary strategy. A fully systematic strategy is not in reality systematic as it is subject to numerous discretionary interventions (configuration changes, exit points decisions, even bug fixes). A fully discretionary strategy is not in reality discretionary as it is for the most part relying on some quantitative idealization of the world.
* Jim Liew thinks it is time to think of coming with new benchmarks (in lieu of standard market cap weighted indices) based on AI/ML/NLP & the unstructured data that is coming out of which he calls “fundamental benchmarks”. I don ‘t seem to find a trace of a publication on this idea
* Judith Gu claims that it was hard for her team to establish a clear lag/lead relationship between news sentiment and stock returns which pointed her in the direction of causal inference (vs statistical inference ) and used Google’s causal impact model:
  + Kay Brodersen et al, 2015, [Inferring causal impact using Bayesian structural time-series models](https://storage.googleapis.com/pub-tools-public-publication-data/pdf/41854.pdf)
  + https://google.github.io/CausalImpact/CausalImpact.html

## Panel 3: Changing Landscape of investing

Highlights:

## Keynote Debate: Future of Data Science & Machine learning

## Panel 4: Encountering real world data sets

## Panel 5: Understanding the future of NLP

Highlights:

* The moderator framed the discussion to revolve around:
  + lower level: save time (take voice and translate to text)
  + second level: predict prices via building a thing called sentiment , embed text into a number and examine the correlation to price moves
  + GPT-like: text generation , completion, topic modeling, prompt engineering, answering questions
* Chat based models are less likely to help with returns forecasting since it relies on prompt engineering and it is easy for the prompt to include the user’s biases.
* Minh Trinh thinks that we will eventually get to a point of augmented real transcription of speakers (e.g. analysts on CNBC), with real time fact checking, sentiment, confidence, sincerity quantification
* Recently pretrained models should be used carefully when extracting signals/embedding and back-testing them since they include a look-ahead bias.
* AI in finance really require knowing AI and Finance (can’t agree more)
* [Retrieval augmented generation](https://arxiv.org/pdf/2005.11401.pdf) (RAG) is probably the right approach to use LLMs in finance
* [Rohit Singh](https://www.linkedin.com/in/rohit-singh-0b509b2/) is a Co-Founder of [martini.ai](https://martini.ai/) that claims bringing the power of DL to alpha generation and credit rating of US corporate bonds. We probably should set up a demo with them to learn what they are doing.
* Papers from the panelists that are worth glancing at:
  + [FinEAS: Financial Embedding analysis of sentiment](https://arxiv.org/pdf/2111.00526.pdf)
* Future research tips:
  + Aggregation: embedding + shallow model (e.g. ridge regression )
* General tips:
  + Set [custom instructions for ChatGPT](https://openai.com/blog/custom-instructions-for-chatgpt)
* Datasets:
  + [Financial phrase bank](https://huggingface.co/datasets/financial_phrasebank) (what FinBert was trained on)
  + [Commoncrawl](https://commoncrawl.org/)

## Keynote debate: AI vs Markowitz

Statistical analysis vs AI/ML

Highlights:

* (Simonian) ML can accommodate covariates and signals that go beyond returns and covariance matrix.
* (Ritter) Theorem: If you have a market with N assets , the return of these assets follow a multivariate distribution that has the [elliptical symmetry property](https://arxiv.org/pdf/1911.08171.pdf). In addition, for any reasonable investor’s utility function, the maximum expected utility model is equivalent to doing mean-variance optimization.
* (Ritter) Mean-variance keeps reappearing in several frameworks such as [Almgren-Chris](https://static1.squarespace.com/static/5df018ec4c9d61288094246c/t/5e39db229a16b072d97fce9b/1580849954431/Optimal+Execution+of+Portfolio+Transaction+_+Almgren%26Chriss+1999.pdf) framework and it is less likely to be completely overtaken by ML.
* (Ritter) reacts with skepticism to the idea that AI can construct a portfolio for you, maybe AI can help refine the inputs to the portfolio construction , he says, but you still need to use mean-variance to achieve optimality.
* (Simonian) It is possible to use econometrics (e.g. regime switching models) to identify folds for ML cross-validation evaluation. Econometrics methods are backward looking (not entirely correct) and therefore inferior at forecasting compared to ML methods.
* (Ritter) Econometrics is far from dead
* (Ritter) if you have N assets , and less than N time periods, the inverse to your covariance matrix cannot possibly exist. For a Markowitz portfolio to exist, the covariance matrix should be able to tell you something about the future correlation.

I think it is worth looking at both [Ritter](https://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=1082751) and [Simonian](https://scholar.google.com/citations?hl=en&user=xidZlHYAAAAJ&view_op=list_works&sortby=pubdate) list of papers.

## Panel 6: Capturing alpha and quantitative strategies and global outlook

Highlights:

* Panelists agree that the future of quant finance revolves around more data, generative ai, LLMs for automation, reinforcement learning
* Prompt engineering is nothing other than RL for Sudip Gupta.
* Arun Verma said Bloomberg is looking into leveraging AI/ML in augmenting classic quantitative pricing models

## Panel 7: Deep learning vs RL vs causality in Finance

Highlights:

* There is healthy hyper around chat GPT because it opens the door to discussing AI and potentially figuring out what works and what not.
* Prediction: moving from general purpose LLMs to specialized LLMs
* Generative AI can be useful in the context of stress testing via generating realistic scenarios
* Causality in finance (Alejandro Rodriguez):
  + primary goal was to estimate portfolio constituents sensitivities with respect to their optimal drivers
  + In principal we can reconstruct the causality structure using [Reichenbach’s common cause principle](https://plato.stanford.edu/entries/physics-Rpcc/)
  + Once optimal common drivers are discovered through a causality analysis, constituents sensitivities are approximated/estimated using neural networks & hierarchical clustering

[Alejandro Rodriguez](https://www.linkedin.com/in/alejandro-rodriguez-dominguez-66b48015b/) was an interesting discovery for me and it looks like few of his [papers](https://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=3370936) on ssrn are worth reading/studying:

* 2023,  [Measuring Cause-Effect with the Variability of the Largest Eigenvalue](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4510020)
* 2023, [Portfolio optimization based on Neural Networks Sensitivities from Assets Dynamics Respect common drivers](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4234186)
* 2023, [A clustering algorithm for correlation quickest hub discovery mixing time evolution and random matrix theory.](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4241975)

## Keynote debate: machine learning in finance vs micro-predictions

Highlights:

* Micro-prediction: repeated prediction over short horizon and often time pertain to a real time operation process
* Markets are better than models for short horizon predictions: collective wisdom of a group can lead to a more accurate short horizon predictions compared a single individual (model) no matter how “smart” they are (statement elaborated in Cotton’s book: [micro-predictions](https://www.amazon.com/Microprediction-Building-Open-AI-Network/dp/0262047322/ref=sr_1_1?crid=3MLDZ9DT0A8RH&keywords=microprediction&qid=1696176029&sprefix=microprediction%2Caps%2C99&sr=8-1)
* Which I ordered and going to read).
* A paraphrase: markets are better predictors than bureaucracy.
* Igor Halpering agrees with Cotton’s on the above.
* Counter example of the supremacy of the wisdom of the crowd: why did [quantopian](https://en.wikipedia.org/wiki/Quantopian) fail ?