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AI In Investment Management: The Advancement Of Learning

Amundi Investment Solutions

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AI In Investment Management: The Advancement Of Learning

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Abstract

At Amundi, we have previously explored NLP approaches but were disappointed by their instability - small changes in input words or word order often led to significant shifts in interpretation. In our recent research, we revisited modern Transformer-based NLP models. Much like their revolutionary impact on language translation, we found that Transformer-based approaches brought an unexpected level of analytical precision to Natural Language Processing tasks. Our findings show that AI, combined with Big Data, has the potential to deepen our understanding of financial markets. For example, we were able to quantify economic narratives using news data. This allows us to test the intuitions of renowned academic researchers whose work has shaped financial and economic reasoning in our industry. As finance becomes increasingly intertwined with AI, new questions will emerge for practitioners, especially as knowledge is now processed and accessed in entirely new forms. Concepts have become vectors. It is our responsibility to leverage AI tools to enhance the robustness of portfolio management.

Keywords: LLM, NLP, AI

JEL classification: G11, O33, C55.

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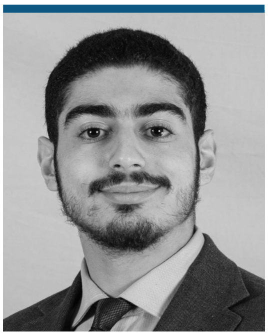
Takaya Sekine, CFA is the Deputy Head of Quant Portfolio Strategy within Amundi Investment Institute (formerly known as the Quantitative Research Team of Amundi). In this role, he works on the practical implementation of quant research, artificial intelligence and alternative data for investment strategies.

He joined Amundi in 2000 and is in his current position since July 2018. Prior to that, he was Deputy CIO at Amundi Japan (between 2011 and 2018) with a focus on global quantitative strategies, Head of Index and Multi-Strategies at Amundi Japan (between 2010 and 2011), Fund Manager (between 2007 and 2010) and Financial Engineer (between 2001 and 2007). He has been involved in macro and policy related investment strategies for both retail and institutional clients. Takaya began his career as an IT Manager at Amundi Japan's predecessor company (between 2000 and 2001).

Takaya is a CFA charterholder since 2005. He received the Ingénieur Civil des Mines degree from Ecole des Mines de Nancy in 2000.



Imad AMRI

Imad Amri joined Amundi in July 2024 as an intern in the Quant Portfolio Strategy team of Amundi Investment Institute. His work focuses on applying AI tools to financial markets, particularly in topic modelling and information network analysis. He has worked on supply chain mapping using NLP and novel topic identification, extracting insights from financial reports and news databases.

Imad is an engineering student at CentraleSupélec. He has a strong background in applied mathematics, statistics, and machine learning, complemented by research experience in numerical optimization and risk modeling. He also holds a Bachelor's degree in Applied Economics from Université Paris-Dauphine, PSL.

Théo LE GUENEDAL

Théo Le Guenedal is the Head of Prospective and Quantitative Solutions at the Innovation Lab of Amundi Technology. Prior to this, he worked in the Quantitative Research department of the Amundi Institute since 2018, starting with a project on the performance of ESG investing in the equity market. Since then, he has been involved in an extensive research project on incorporating ESG factors, alternative signals and climate risks into asset allocation strategies. In 2020, he co-authored a paper titled “Credit Risk Sensitivity to Carbon Price,” which was awarded the GRASFI Best Paper Prize for Research on Climate Finance, a prestigious honor sponsored by Imperial College London. He also made significant contributions to the academic field of physical risk assessment by developing the Tropical Cyclone Generation Algorithm. Théo completed his Ph.D. thesis, “Financial Modeling of Climate-related Risks” in Applied Mathematics at the Institut Polytechnique in December 2023, covering both transition and physical risks. Recently, he has focused on integrating advanced climate metrics, stress tests, and analytics into investment tools at Amundi Technology’s Innovation Lab.

Amina CHERIEF

Amina Cherief is a Fixed Income Quant Researcher at Amundi Investment Institute. She conducts research projects closely linked with portfolio management platforms, the risk department and Amundi Intermediation.

Amina joined Amundi’s Quantitative Research Team in April 2017 to work on the development of a multi-factor risk and performance analysis tool. She worked from 2017 to 2018 as a Financial Engineer at Natixis AM and from 2018 to 2019 as a Cross-Asset Strategist at Natixis CIB where she was in charge of support and research (equity & commodity strategies, new portfolio allocation) for the QIS team. In 2019, Amina joined SG CIB in New York as a Cross-Asset Financial Engineer in the QIS team for two years; she was in charge of research and portfolio construction of systematic equity and commodity strategies. She developed tools for the sales and traders. Amina re-joined Amundi as a Quantitative Researcher in December 2020. Her areas of research are factor investing, sustainable investing and AI-ML in both fixed-income and equities. Recent advanced topics covered by Amina have been the integration of machine learning algorithms in the investment process of a fixed income team or the creation of innovative allocation in portfolios.

Amina holds a Master’s Degree (with honors) in Risk and Asset Management from Paris-Saclay University.

Sofia SAKOUT

Sofia Sakout, PhD is Lead Data Scientist in Natural Language Processing and Generative AI within the Innovation Lab of Amundi Technology. Sofia plays a central role in harnessing open source text data and in the development of NLP pipelines, with a particular focus on question-answering (QA) systems. Her focus at Amundi Technology is to channel innovation, data science, artificial intelligence toward practical applications in Amundi.

Sofia holds an engineering degree from École Mohammadia d'Ingénieurs, a Master's degree from École des Ponts ParisTech, and a PhD from the Sciences, Ingénierie et Environnement Doctoral School in partnership with École Polytechnique.

Sonja TILLY

Sonja Tilly, PhD, CFA joined Amundi as a Quantitative Analyst in 2024. Commencing her career in 2008 in London, Sonja started out as an Investment Analyst, then transitioning to Quantitative Analyst roles. Her time at Stanhope Capital, Aberdeen Asset Management, and Hiscox honed her skills in investment analysis, financial asset modelling, economic scenario development, and stress-testing portfolios.

While working as Quantitative Researcher at Qoniam Asset Management, Sonja created a filtering method based on deep learning for processing extensive news text, extracting signals that were transformed into a systematic equity trading strategy. Sonja's experience working in traditional Finance is complemented by her insights into the crypto space, gained as Quantitative Researcher at decentralised finance start-up Allora Network, where she led the creation of loan terms for fully automated NFT-backed on-chain loans.

Sonja holds a PhD in Computer Science from University College London. Her research focuses on the impact of news narrative on the economy and financial markets, blending methodologies from data science and econometrics. Further, she is a CFA Charterholder.

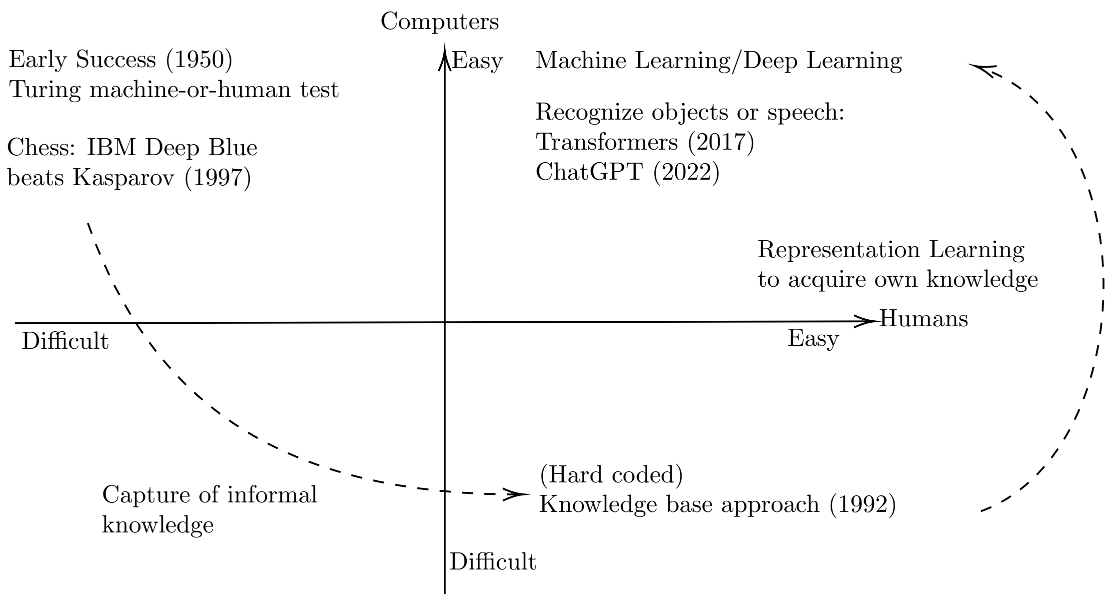
Key takeaways

- NLP processes that incorporate modern Transformer-based models have been able to synthesize complex knowledge with accuracy levels approaching 90% when compared to human experts.
- When combined with Big Data, AI (specifically NLP) enables us to bring to life the intuitions of the pioneers of our industry from the 1980s. For instance, we have been able to quantify economic narratives using news data.
- AI introduces new questions, as it reshapes how knowledge is represented and consumed. It is our responsibility to harness AI to enhance our investment processes. Doing so will require a clear understanding of both our investment philosophy and the technologies and alternative data sources necessary to support our AI strategy.

1 Introduction

The objective of "Artificial Intelligence" [AI] is to bring computers to perform human tasks. The term itself was coined in the nineteen fifties (McCarthy *et al.*, 1955). Goodfellow *et al.* (2016) propose a back-and-forth between the progress of computers achieving human tasks such as Newell and Simon (1956) running proofs of mathematical theorems; and computers failing at cognitive tasks which can be achieved by human babies such as object or speach recognition. We illustrate this computer vs. human chase in Exhibit 1.

Figure 1: The Computer vs. Human chase



Source: Goodfellow *et al.* (2016), illustration by Amundi Investment Institute

The attention mechanism of the transformer models (Vaswani, 2017) was a game changer. The Transfomer architecture uses a multi-layer context-identification (attention) which is the key to the revolution of AI. For instance, it stabilized a key component, the translation context issues and prepared the widespread adoption of AI. Unbeknownst to most, the name of the now mainstream Chat"GPT" of OpenAI stands for Generative Pre-trained Transformer.

The paper is organized as follows: Section 2 presents the test which is the basis of our conviction that AI is usable in an investment decision setting. In Section 3 we will illustrate how the combination of big data and AI has brought us closer to the original thinking of the famed researchers who have established the industry. Also we will show the parallel between the mean-variance revolution by Markowitz (1952) and the information revolution that we are witnessing. Finally, we will comment in Section 4 that similar to most novel fields for practitioners, we must be careful to keep our minds clear from the "tyranny of the taxonomies" which are unnecessary entry barriers. We are now at the age of RAGs and agents.

2 THE AI CASE FOR SPECIALIST KNOWLEDGE

We do not enter the Artificial General Intelligence [AGI] debate as proposed by Kokotajlo *et al.* (2025). AGI would be the next frontier with the success across the entire range of cognitive tests (Bergmann & Stryker, 2024). The chance for fund management vis-a-vis AI is that success in fund management is not a simple cognitive test. We explored the extent to which a well-constructed knowledge base and a robust Question-Answering framework could proxy the specialist knowledge from the International Energy Agency on the requirement of clean techs on minerals. Our process is illustrated in Exhibit 2 and can be simply outlined as follows. First, we construct a Dense Document Store with bibliographical elements describing the construction of clean techs or usage of various minerals. Then, we cut the Dense Document Store in elementary pieces. Next, for each elementary piece use a language model with the question answering feature to ask if the Mineral a is being used for the Clean Tech i / if the Clean Tech i requires the Mineral a. - collect the proposed answers. Finally, we run a syntactic control to check if the Mineral a and the Clean Tech i are contained in the text from which the language model derives its answer.

Further details are available in Stagnol *et al.* (2023). Ultimately we conclude that we matched the analysis of the IEA at approximatively 90% (IEA, 2021). The meaning of this result which is visually illustrated in Exhibit 2a is that by collecting enough information on the specialist knowledge, an AI process relying on open-source Pretrained Large Language Model has the capacity to prepare 90% of the synthesis work for specialized analysts. At the difference of a frontier model such as GPT3 which has 175 billion parameters (Brown *et al.*, 2020), the models used here are extremely light as they only have hundreds of millions of parameters (Hugging Face *et al.*, 2020) [1]. We add a purely syntactic layer which acts as a very efficient false positive safety net by removing about 70% of the candidate responses generated by alBERT. We illustrate an example of exclusion in Exhibit 1. The purpose of this example is not to infer the fallacy that all other situations can be solved by AI. Our purpose is to state that with a relatively simple and open-source language model and with the utilization of very down-to-earth regular expressions, we managed to convert a knowledge base into a result consistent at 90% with the synthesis of human experts. We do not infer that all other cases will be manageable with AI, but we simply state that this significantly positive result has encouraged further research for us.

Table 1: Word similarity control in application

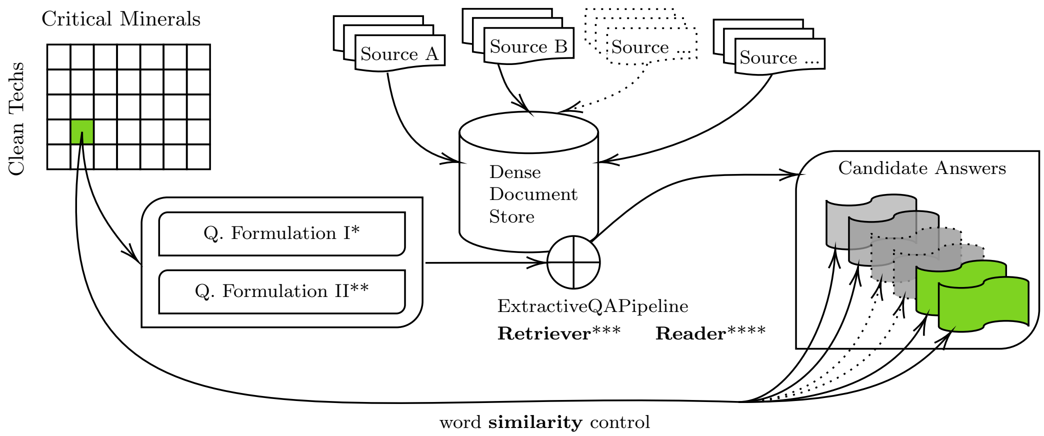
critical material	clean energy tech	context	alBERT	material to context	clean energy tech to context	Final
Aluminium	Solar PV	**Aluminium** is an important input to the clean energy transition, with the production of several clean technologies, including **solar PV** installations and EVs, requiring significant amounts	✓	✓	✓	✓
Iridium	EVs and battery storage	**EVs and battery storage** grows nearly tenfold in the STEPS and around 30 times in the SDS over the period to 2040. By weight, **mineral** demand in 2040	✓	✗	✓	✗

Source: Authors' calculations, IEA (2022, 2023), Amundi Investment Institute

We would like to complement this accuracy analysis by stating the obvious. Given sufficient calculation capacity, memory and time, the computer will actually analyze the entire

[1] this particular result was achieved with alBERT_xxlargev1_squad2_512 [alBERT] which is a model fine-tuned for question answering tasks

Figure 2: Information extraction



Note: ⋆: Is ***mineral*** necessary for ***techno*** ?, ⋆⋆: Does ***techno*** require ***mineral*** ?, ⋆⋆⋆: we test retrievers, ⋆⋆⋆⋆: multiple readers are tested for the question answering (QA) task.

Source: Amundi Investment Institute

Table 2: Critical mineral needs for clean tech

(a) QA Pipeline

	Cu	Co	Ni	Li	REEs	Cr	Zi	PGMs	Al
Solar PV	●	○	○	○	○	○	○	○	●
Wind	●	○	○	○	●	○	●	○	○
Hydro	○	○	○	○	○	○	○	○	○
CSP ⋆⋆⋆	●	○	○	○	○	○	○	○	●
Bioenergy	●	○	○	○	○	○	○	○	○
Geothermal	○	○	●	○	○	●	○	○	○
Nuclear	○	○	○	○	○	○	○	○	○
Elect Net⋆	●	○	○	○	○	○	○	○	●
EVs / BS⋆⋆	●	●	●	●	●	○	●	○	●
Hydrogen	●	○	●	●	○	○	○	●	○

Source: *Authors' calculations*

(b) IEA (2022)

	Cu	Co	Ni	Li	REEs	Cr	Zi	PGMs	Al
Solar PV	●	○	○	○	○	○	○	○	●
Wind	●	○	◍	○	●	◍	●	○	◍
Hydro	◍	○	○	○	○	◍	◍	○	◍
CSP	◍	○	◍	○	○	●	◍	○	●
Bioenergy	●	○	○	○	○	○	◍	○	◍
Geothermal	○	○	●	○	○	●	○	○	○
Nuclear	◍	○	◍	○	○	◍	○	○	○
Elect Net⋆	●	○	○	○	○	○	○	○	●
EVs / BS⋆⋆	●	●	●	●	●	○	○	○	●
Hydrogen	○	○	●	○	◍	○	○	●	◍

Source: *IEA*

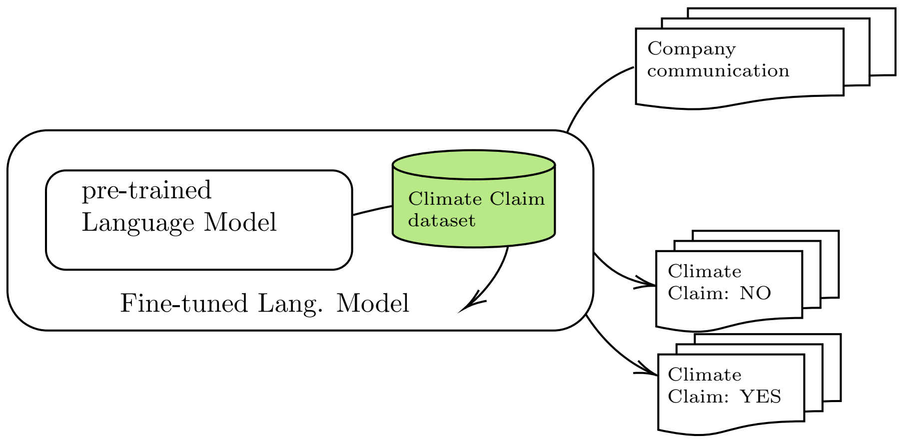
Note: for Subtable 2b: ● = high, ◍ = moderate, ○ = low; ⋆: Electricity Networks; ⋆⋆: Electric Vehicles and battery storage; ⋆⋆⋆: we display the results for the string "Concentrated Solar Power" rather than "CSP"; m: for permanent magnets.

set of text segments that we will have prepared. In this sense, it is a perfect complement to a human analyst who does not have the capacity to maintain a constant attention through multiple days without interruption, or who cannot parallelize his/her workflow to maximize his/her capacity.

In a forthcoming paper, Tilly *et al.* (Forthcoming) propose a framework using GenAI tu complement the engagement framework of Amundi. In early experiments, we ran climate claim classifications as illustrated in Exhibit 3. We use RobertaForSequence-Classification, a pre-trained BERT with an untrained classification head. We fine-tune (Sun *et al.*, 2019) the model with the climate claim dataset used by Stammbach *et al.* (2022). This dataset has 2640 claims, out of which 25% are classified as true. One striking example of the added-value of this AI supported approach was the analysis of a Water company. We analyze twenty one reports from the company published over a five year period. We split them into 5835 slices comparable in size (a.k.a chunks).

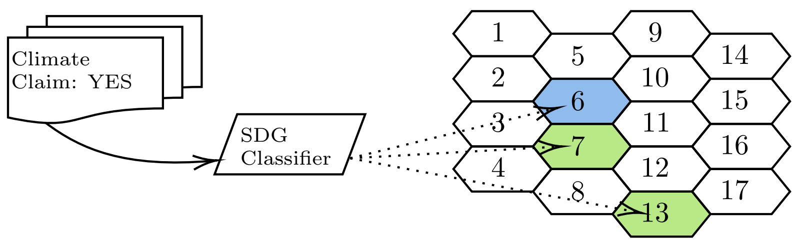
Out of the four hundred and twenty nine claims retained by our fine-tuned model to

Figure 3: Fine-tuning - training of the classification layer



Source: Amundi Investment Institute

Figure 4: SDG Classification



Source: Amundi Investment Institute

identify climate claims, three hundred and twenty five are counter-intuitively classified as being for the water-related SDG6. We use the SDG classification model from Sadickam (2023). Only seventy-three are classified into the climate-related SDG7 and SDG13 as illustrated in Appendix A.2. For a human, this high exposure to SDG6 –while we are looking for climate related claims– might put into question the quality of the classification process itself. However our AI based process further identifies that the company has stated that *With* ***approximately 80% of our GHG emissions related to pumping water****, we work to make our pumps as efficient as possible to minimize electricity consumption and emissions. As part of our annual program to replace or refurbish pumps, we invested over $72 million in 2019 and 2020 in pumping station upgrades across our footprint, which together are projected to save over 11 million kWh of electricity annually.* In the case of this company, the water pumping efficiency is directly connected to emissions hence to climate. We have seen this connection once only in the entire corpus. By finding this needle in the haystack, it has perfectly complemented the human analyst.

We have illustrated in this section both the harvesting of true positives and the capacity to find actual positives. These two concepts are respectively referred to as Precision and Recall in the field of information retrieval (Schütze *et al.*, 2008).

3 AI BRINGS US CLOSER TO THE FOUNDER'S INTENTIONS

There is a Japanese company called Oriental Land Company which is well known for having gone back to the source of the design of Disney at great cost to construct Disney theme parks in Tokyo as close as possible to their original spirit (Imagineering, 2025). In a similar way, the lower cost of AI and Big Data enables us, investment managers to go to the original designs that the founders of our industry had in mind. Originally, Chen *et al.* (1986) intended to capture "economic news" as illustrated in Exhibit 5 but could only capture "macro indicators".

Figure 5: Capturing economic news in 1986

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Economic Forces and the Stock Market*

I. Introduction

Asset prices are commonly believed to react sensitively to economic news. Daily experience seems to support the view that individual asset prices are influenced by a wide variety of unanticipated events and that some events have a more pervasive effect on asset prices than do others. Consistent with the ability of investors to diversify, modern financial theory has focused on pervasive, or "systematic," influences as the likely source of investment risk.[1] The general conclusion of theory is that an additional component of long-run return is required and obtained whenever a particular asset is influenced by systematic economic news and that no extra reward can be earned by (needlessly) bearing diversifiable risk.

This paper tests whether innovations in macroeconomic variables are risks that are rewarded in the stock market. Financial theory suggests that the following macroeconomic variables should systematically affect stock market returns: the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low-grade bonds. We find that these sources of risk are significantly

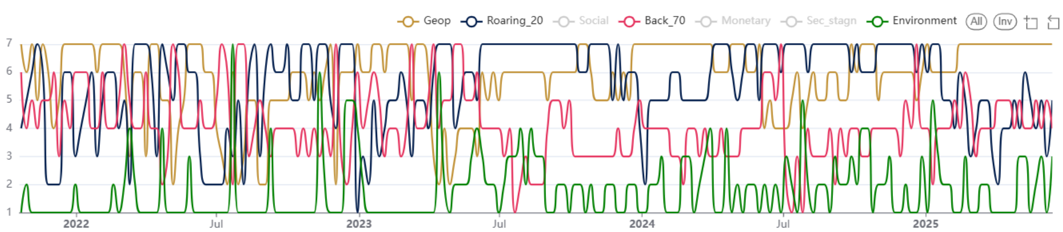
Source: Amundi Investment Institute

In Shiller (2017), the 2013 Nobel Prize laureate imagines that "advances in psychology, neuroscience, and artificial intelligence" might drive in the future the "sense of structure in narrative economics". In Blanqué *et al.* (2022), we propose a weekly quantification of four economic narratives which are inspired by identified periods of the US economy (Back to the 70s, Roaring 20s, Monetary, Secular Stagnation), together with two societal narratives (Environment and Social) and a Geopolitical Risk narrative. Our source is the Global Database of Events, Language and Tone [GDELT] (Leetaru & Schrodt, 2013) which is a Big Data (2.5 TB per year) undertaking to collect the world in the news with more than a hundred languages translated into english. The principle of GDELT v2 that we use is that each news will be processed by an event-coding engine (Schrodt, 2013). To each news will be attached the identification of locations, the sentiment of the news and the GDELT indicators from taxonomies which will identify what the news is about. Our added value has been to decide that the financial markets were following a limited number of narratives and we define which GDELT indicators belong to themes which we further integrate in each narrative. By doing a two-level narrative then theme structure we seek to balance narratives. For instance if a theme has a lot of taxonomy elements, our approach will provide a level of granularity to remove this taxonomy bias. We then compound the sentiment of the said news with the number of times the GDELT identifiers that we associate to the narrative have been present.

Once we structure our narratives for the US, we run a competition between them to identify which has the highest three month dynamics. We illustrate this battle of narratives in Exhibit 6. One remarkable feature of this battle is that the transition probability from the top rank to the bottom five ranks is not high. As we consider the second rank as a buffer rank, the probability that the top narratives remains dominant or is just second in dominance is around 70%. There is a strong stickiness of the top narrative. Indeed, we can understand that all the newsrooms in the world will not randomly allocate their subjects from one week to the other.

We have constructed economic narratives and in addition we have completed these economic narratives with societal and geopolitical risk narratives. We do not claim to have perfect foresight. Therefore we integrate a "others" category where we monitor the top-a-hundred GDELT indicators which are recurrent in the top volumes but which have not been carried in our defined narratives. For instance, after the start of the second Trump administration, we identified that we had not prepared the capture of events related to the reform of the public sector.

Figure 6: The Battle of Narratives - Ranking (inversed)



Source: Alto Studio, Amundi Investment Institute

In this section, we have described our construction of narratives. We further confirm in Blanqué *et al.* (2022) that our selected GDELT indicators carry informational content for the US equity market. This layer structured on actual news brings us closer to the original intent of Chen *et al.* (1986).

4 AI BRINGS FRESH KNOWLEDGE

Following our work on preparing specialist knowledge from subject matter documents in Stagnol *et al.* (2023), we apply the capacity to extract accurately information to news. We were monitoring the energy transition back in 2023. We applied our question answering approach to all online news in English as collected by GDELT Project (2021). We first apply a simple filter. We seek articles containing at least one of the following four words: "new", "clean", "technology" or "energy". Then we use our question answering algorithm with the following neutral question "New clean energy tech ?". We classify the resulting news relative to novelty in the clean energy field into sixteen clean tech categories ("solar","wind", "hydropower", "geothermal", "nuclear", "coal", "natural gas", "biomass", "hydrogen", "ocean and tidal", "electric vehicles", "battery and storage", "synthesis gas", "liquid fuels", "electricity networks", "carbon capture and storage CCS"). We add an "other" class to capture the emergence of new technologies. In September of 2023, a look at the "other" class revealed the emergence of the energy related questions for the new technology represented by ChatGPT as it populated approximatively 35% of this class. These components together with the transition oriented elements are displayed in Appendix A.1. Therefore from a pipeline set to capture the progress of the energy transition, we end-up with the reality of the news indicating that the world is not shifting towards energy transition but requires energy to run new technologies such as ChatGPT.

Our simple example illustrates that language models contain a new type of information. Buckmann *et al.* (2025) experiment on the added value of vector-based representations (embeddings) for the estimation of economic variables. We can draw a parallel with the mean-variance revolution brought by Markowitz (1952). Indeed practitioners who are reading this article have probably already applied the mean-variance optimization defined with a factor model in their career. This optimization is known to be sensible to slight changes in the input data (Michaud, 1989). A slight change in the factor covariance matrix or the diagonal matrix of specific variance around some eligible assets will produce significant buys or sells in the portfolio. Software which are standard in the industry will introduce line-by-line and/or global turnover constraints to control for these effects. However - with a stable expected return vector - the decision to trade on these known sensitivities of the covariance elements sits with the portfolio manager. If they decide to trade on the optimization, they could be ideally anticipating on the early movements in some segments. In a less favorable scenario they would be simply misallocating turnover. The choice remains with the human fund manager. In our case, the analysis of the "other" class guided our own researches on the implementation of AI towards sparse solutions. We are looking to optimize towards local minima and we have eliminated brute-force type solutions.

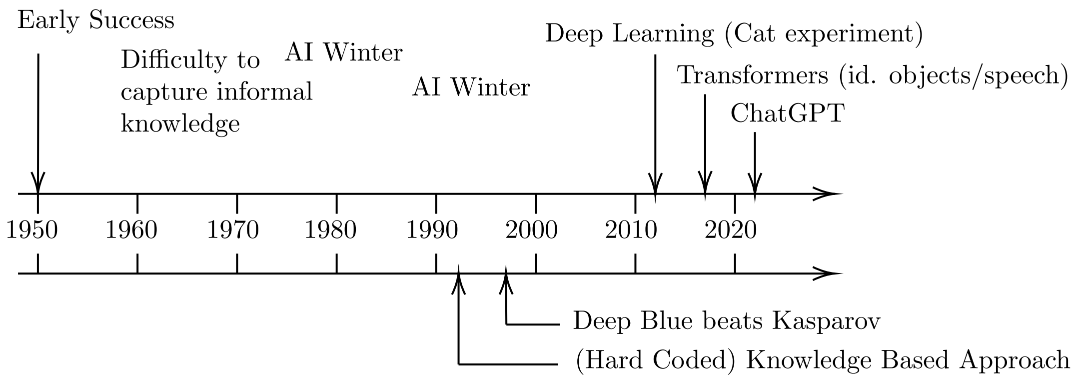
When we equip fund managers with models, we bring new questions. With the mean-variance optimization, our question was about the decision to trade on the buy and sells coming from large variance-covariance variations in the recent past. Language models will have a systematic reading of information. With modern language models, the fund managers will be able to confront their own biases to the biases systematically built-into the language models.

5 AI'S NOVELTY AND ENTRY BARRIERS

We present a timeline of AI subjects with Exhibit 7. AI subjects are not recent. Interestingly, AI has known "Winter" periods in the 1970s for eg.–the Defense Advanced Research Projects Agency (DARPA) was frustrated by the Speech Understanding Research (Juang & Rabiner, 2005); and has seen recent spectacular progress with technological improvements but also big data (Le *et al.* (2011) use 10 million 200x200 pixel images downloaded from the internet). The Investment Management community is aiming to follow the mainstream adoption of AI. Indeed in their recent survey, Boston Consulting Group *et al.* (2024) indicate that only a slight minority of asset managers (16%) have more than significant progress on their organization's data structure for adoption of GenAI while only 4% plan to sit-out any tentative of up-skilling of employees.

We have seen it when climate considerations were entering the portfolio construction space. We looked first at the existing conventions, mostly around the utilization of carbon intensity measures and we studied their trajectories (Le Guenedal *et al.*, 2020). However when looking deeper into the emissions' puzzle, we identified that the investment community was missing the Carbon Budget question. We then went one notch up and proposed net-zero carbon metrics (Le Guenedal *et al.*, 2022) focusing on the carbon emissions, not the

Figure 7: an AI timeline



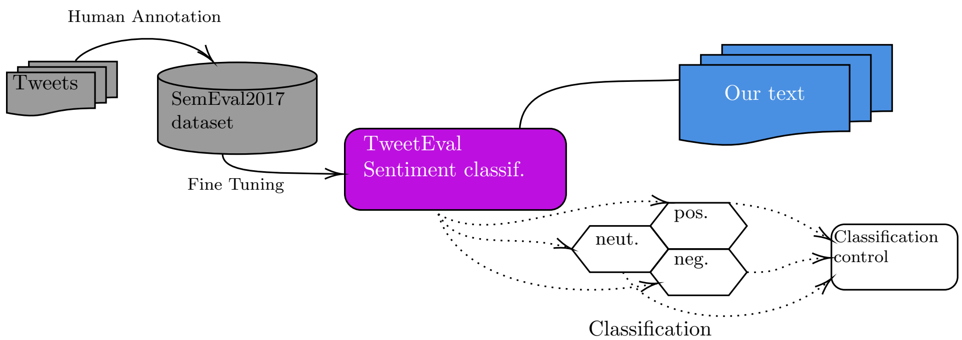
Source: Amundi Investment Institute

intensities. Indeed, the concept of intensity was introduced by the Bush administration after the US withdrew from the Kyoto protocol (Bush, 2001) which was focusing on the direct metric of carbon emissions. Bush (2002) introduces the concept of emission intensity per unit of economic output (GDP). So it is a second order metric which shows the intension to pollute less per increase in GDP, however it does not put any strict cap on absolute emissions. It so happened that the total emissions in the US diminished following the consequenes of the Global financial Crisis of 2007-2009. Our intention, especially with the technical appendix was to illustrate to the student audience that climate metrics and portfolio management could be connected through mathematical expressions. The field is known for having conceptual entry barriers (Walton, 2013). In addition, we experienced that some practitioners might have accentuated the taxonomical barrier. It took us some papers to question the concept of intensity itself which has found its way into the general practice and the regulation of this industry.

Likewise, we believe that the coming discussions in the industry on AI should not so much center on if process follow a RAG of an Agentic approach, but should rather focus on which elements of human intelligence can be augmented by agents for instance. If a practionner sits in a meeting and hears about the agentic revolution which will change the processes forever, they should simply ask what existing tasks or intelligence or knowledge are being discussed. Then what models are being utilized and most importantly what data has been utilized for these models. We have these debates internally. TweetEval (Barbieri *et al.*, 2020) for instance is fine-tuned on the SemEval2017 (Rosenthal *et al.*, 2019) dataset. By directly using the sentiment metric, we would be relying on human annotators who did not have knowledge of the double exit of the US from the Paris Agreements, of the Covid, of the war in Ukraine.

In Amundi we have run quantitative management for Japanese pension funds on the domestics and global equity markets. We have run these systematic strategies from our Tokyo office. As long-term participants to exchanges with japanese investors, our quant management processes has adopted the japanese Kaizen approach (Brunet & New, 2003) derived from the Plan-Do-Check-Act (PDCA) Cycle for factory quality control imported by Edward Demings in the 1950s in Japan (Tsutsui, 1996). We find a natural match between our quantitative approach and the Performance measure-Environment-Actuators-Sensors approach defined by Russell and Norvig (2021) for Agentic AI. Indeed:

Figure 8: Transformer based sentiment model - tracing the sentiment



- Plan matches with Performance measure
- Do matches with Actuators
- Check matches with Sensors
- Act matches with Environment

At the time of writing, we consider that Agentic AI approach still requires a construction of knowledge bases oriented by humans. For instance, the word similarity control applied in Exhibit 2 is a technique using regular expression matching which is a battle-tested programming technique (Thompson, 1968). After poor performance measures on Precision, we decided to augment the NLP pipeline with an improvement loop between its sensors and its actuators. Exhibit 1 illustrates the context which can be extracted from the question answering model. This context becomes part of the Environment in the Agentic AI sense. We use sensors on this newly generated context for the action of regular expression matching. AI enables the constitution of a Learning agent around our information extraction pipeline.

Similarly to Cherief *et al.* (Forthcoming) where we collect knowledge on human capital, we could collect academic research on the field of question-answering refinements and then test the multiple options available. We could also skip the collection of academic research by prompting a LLM directly to list a number of tests. However, we estimate that these logical steps would be complex as compared to the simplicity of the regular expression test that we have introduced.

Recent surveys indicate that AI has not yet become mainstream in the investment management process. It is already present, for example, in the simplest of the data. Company reports for example are processed by NLP pipelines before the fundamental data is inserted in databases. The real question for investment managers is the extent to which they insert AI to increase their opportunities and their understanding of the market.

6 CONCLUSION

Understanding financial markets is essential for investment managers. The challenge lies in the fact that our industry is not governed by strict, deterministic laws like those in physics. As a result, different investors can rationally make opposite investment decisions at the same time on the same securities. In our research, we were encouraged by the results of our experiment in replicating specialist expertise using language models. This experiment was made possible by the advances brought about by the Transformer revolution.

At Amundi, empirical analysis of market interpretations by experienced practitioners and academics is deeply embedded in the DNA of our quantitative research. Our goal has been to enhance the work of investment professionals by leveraging AI-driven analysis applied to targeted datasets. For example, we were able to quantify economic narratives that we believe reflect the original vision of academics such as Chen *et al.* (1986), and definitively Shiller (2017).

As knowledge is now stored and modeled in new ways, we receive a novel form of feedback from language models regarding their interpretation of the world. Developing the ability to understand and work with this feedback is a new skill we must acquire. It is important that we do not fall victim to the “tyranny of taxonomies”, which we are already beginning to see emerge. In the context of climate finance, for example, we proposed a glossary to guide interpretation (Le Guenedal, 2019). A similar approach may prove useful in future applications.

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A Appendix

A.1 The "others" category

As the news content turned, the "others" category from the clean tech invation monitor from Stagnol *et al.* (2023) started to capture:
"ChatGPT", "ChatGPT", "Global Biofuels Alliance", "digital nomad visa", "ChatGPT", "cable networks", "Thomson Sebastian", "digital nomad visa", "jet engine tech transfer", "Powerelectricity", "zigzag technology", "quantum computing", "data centers", "artificial intelligence", "quantum computing", "abatement and removal technologies", "cryptocurrencies", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "biotechnology", "iRobot OS", "abatement and removal technologies", "Ethanol-blended petrol", "biofuels", "public transport", "ChatGPT", "ChatGPT", "ChatGPT", "renewable energy era", "Digital Payment Infrastructure", "abatement and removal technologies", "tripling global renewable energy capacity", "climate change", "Reduce, recapture and repair", "baking soda or white vinegar", "abatement and removal technologies", "car screen cleaner", "ChatGPT", "renewable energy", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "ChatGPT", "blockchain", "Global Biofuels Alliance", "ChatGPT", "algorithmic trading", "USD 4 trillion", "steam turbine", "ChatGPT", "artificial intelligence", "ChatGPT", "ChatGPT", "healthcare", "digital transformation", "energy-saving technology for homeowners", "3D computer visualizations", "AMJET Turbine System", "ChatGPT", "Toyota Safety Sense 3.0", "serial production", "carbon-neutral fuels", "recycling programmes", "high-tech solutions", "transitions", "abatement and removal technologies", "AI", "Quang Ninh Province", "Quang Ninh Province", "Bring Your Own Thermostat®", "low-voltage halogen track lighting", "wind or solar", "photosynthetic pyruvate-derived bioproduction", "ThetaRay", "wind and solar power", "Global Biofuel Alliance", "artificial intelligence", "SmartValve", "air-source heat pumps and underfloor heating", "digital transformation", "battery supply chain investments", "motion sensors", "Net Zero Energy", "Free Report", "biotechnology", "ShiftCam", "ChatGPT", "ChatGPT", "wind or solar", "AI", "A remotely operated chemical mixing station", "renewable energy", "Google"

A.2 Classification of climate claims for our sample water company

Table 3: Classification of the identified Climate claims

SDG	SDG description	Nb claims
Goal 1	End poverty in all its forms everywhere	0
Goal 2	End hunger, achieve food security and improved nutrition and promote sustainable agriculture	0
Goal 3	Ensure healthy lives and promote well-being for all at all ages	3
Goal 4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all	1
Goal 5	Achieve gender equality and empower all women and girls	1
Goal 6	Ensure availability and sustainable management of water and sanitation for all	325
Goal 7	Ensure access to affordable, reliable, sustainable and modern energy for all	36
Goal 8	Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all	3
Goal 9	Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation	3
Goal 10	Reduce inequality within and among countries	0
Goal 11	Make cities and human settlements inclusive, safe, resilient and sustainable	2
Goal 12	Ensure sustainable consumption and production patterns	17
Goal 13	Take urgent action to combat climate change and its impacts[b]	37
Goal 14	Conserve and sustainably use the oceans, seas and marine resources for sustainable development	0
Goal 15	Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	1
Goal 16	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels	0
Goal 17	Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development	0
	Total claims	429

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