How Finance Uses Natural Language Processing

8 Case Studies in Banking and Investment Management

May 2020

FinText

Machines can understand text better than ever before.

Modern banks and investment managers have built their business around crunching numbers. The race to extract excess returns has been driving the sector's embrace of technology and analytical modelling. But, with access to information no longer the competitive edge it once was, pockets of value have become much scarcer.

Meanwhile, processing large volumes of text has become the new frontier for hidden market signals. Further, firms are struggling to adapt traditional processes handling written information to the ever-growing volume of analysis and news, compliance-led reports and streamed market data.

For this reason, companies are turning to Natural Language Processing (NLP), a set of techniques to intelligently process language using computers.

Applied NLP is at an inflection point. Technical and theoretical progress over the past decade, coupled with the advent of powerful open-source software (which is often free), has made intelligent text processing accessible.

This report presents eight case studies of investment companies using bespoke NLP solutions to achieve a business goal. For each, we present the objective, the solution implemented, and some of the key NLP concepts relevant to that solution.

While some off-the-shelf NLP products are available, a recent survey by the Bank of England and the Financial Conduct Authority shows that financial services firms already using machine learning solutions prefer developing applications in-house.

The applications range widely across business areas: From improving investment strategies to enhancing operations or providing better customer services, NLP helps remove text-related grunt work, allowing employees to focus on higher-value tasks.

However, increased adoption can lead to meaningful long-term implications for the industry's workforce. According to financial intelligence company Coalition, between 2012 and 2019 investment banks have shed over 16 percent of their front-office workforce globally, while investing heavily in automation.

In the wake of the COVID-19 pandemic, and facing a tougher economic climate, firms are certain to look to make the most of their resources.

Nonetheless, the existing track record for in-house NLP applications suggests that, while solutions are commonly initiated to improve an internal process, they often yield two additional gains: reduced human error, and new value-adding services.

We therefore hope this paper serves as both a source of inspiration for new potential applications, and an accessible introduction to NLP’s established terms and techniques.

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FinText

May 2020

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Case Study 1: Tracking Media Coverage

Barings Asset Management

Barings Asset Management

Tracking Media Coverage

Key to the value proposition of asset managers is their ability to extract value signals from the wealth of information available. Consequently, asset managers consume large amounts of textual information from different media sources.

From financial news to blogging and tweeting, markets are now saturated with a live-stream of text discussing and influencing asset pricing.

Especially during earnings season, when news flow becomes particularly voluminous, ingesting all this information becomes a challenge.

Barings sought to develop an internal solution to help consume information at scale and augment the investment research process.

NLP Concept: Named-Entity Recognition

Machines break texts apart into smaller particles. These units are called tokens, and the process is called Tokenisation. Usually, each word is a token.

Some tokens (or a series of tokens) represent specific names, objects or concepts. These are called Named Entities. Countries and currency, like 'France' or 'JPY', are some examples of entities. Within financial services, other entities might include companies ('BP') and regulators ('Financial Conduct Authority') .

Named-Entity Recognition is the task of automatically spotting when tokens are named entities, and labeling them correctly.

Often, clues like uppercase letters, or acronyms (such as 'FDA') help to flag a named entity. Still, company names like 'adidas' or '3i' can be challenging for rule-based named-entity recognition. This is one reason domain-specific applications usually require additional expertise, in order to update automated tools with menially labeled entity lists.

Example:

Figure 1 presents a visualisation of named-entity recognition.

Here, an open-source NLP software package correctly identifies a name, a date, and an organisation.

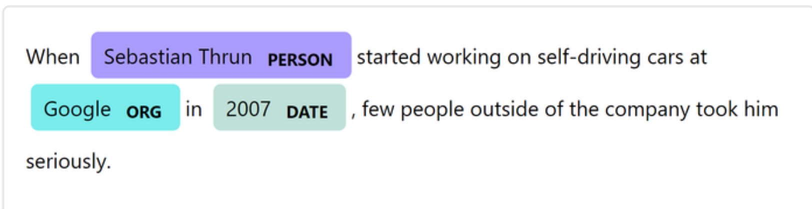

Figure 1: Named Entity Recognition
Source: spaCy

Tracking Media Coverage

Solution

Beginning in 2018, Barings researchers developed a system that helps digest media content. It identifies the relevant company discussed in a document, tags the document with the correct internal company id and generates a sentiment score for the content. (More on Sentiment Analysis on p.10.)

In addition to discovering that financial news coverage is skewed towards a small selection of companies relative to the overall investment universe, developers had to contend with the challenge of differentiating between stories discussing a popular company's product, and stories discussing the company itself. (e.g the platform named Facebook vs. the identically-named corporate entity.)

The researchers trained machine-learning models (See ML Concept below.) to tell apart the two story types, as only the former was deemed relevant.

ML Concept: Model Training

Under the hood of almost any piece of software is an excruciatingly-detailed recipe, telling the machine how to treat any input it receives. Unless the recipe itself changes, the software will behave exactly the same over time.

This is in stark contrast to how humans learn to do things. When a person learns to catch a ball, for instance, they do so without first being taught complicated motion equations. Instead, people practice. We often learn best through repeated trial and error.

For highly complicated tasks (face recognition, for example), algorithm developers struggle to specify a well-performing exact recipe. As a field, Machine Learning concerns itself with developing automated solutions that can adapt performance over time. A Model is a software component. Its performance depends on the value of a set of parameters (from as little as one parameter, to over a billion).

Model Training is the process of finding the best values for these parameters, so as to minimize the amount of mistakes the model makes when performing its task.

Training is done by showing the model many data examples. For some - or all - of the data examples, a desired outcome is also shown. Through a feedback loop, the model adjusts its parameters to improve its success rate.

Case Study 2:
Better Sustainability Investing

Deutsche Bank

Better Sustainability Investing

Demand to factor Environmental, Social and Governance (ESG) data into investment decisions has been growing, from both large pension funds and individual investors. Some evidence also suggests this added consideration helps deliver superior portfolio performance.

As figure 2 shows, the vast majority of S&P 500 companies now publish sustainability reports. However, translating non-financial ESG information into actionable data can be tricky.

A big part of the problem is 'greenwashing', whereby companies file voluminous disclosures related to sustainability, which are ultimately opaque and meaningless.

Deutsche Bank found larger-cap companies tended to receive overall higher ESG ratings, possibly because large firms have greater resources to write lengthy reports.

The bank decided to develop alternative ways to analyze sustainability reports, in order to gauge if companies are truly aligning their business with sustainable practices.

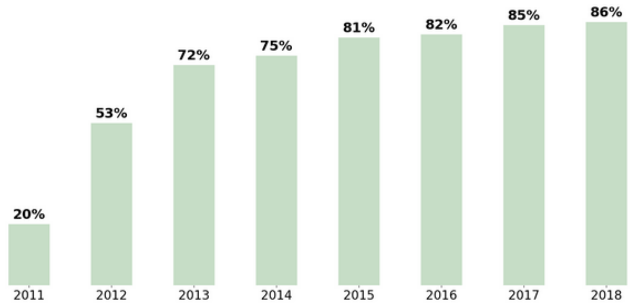

Figure 2: Percentage of S&P 500 companies that have published sustainability reports
Source: Governance and Accountability Institute

Solution

Deutsche Bank decided to investigate whether the commitments firms make to reducing carbon emissions were associated with achieved sustainability performance.

Analyzing carbon-related discussions within the reports, researchers identified five different topics, along with the top keywords associated with each topic. Table 1 on the following page shows the topics and the top associated keywords.

Companies were ranked based on their focus on the mitigation and adaptation topics. The system also scanned for numbers and quantitative words (like 'first' and 'half'), and for active (vs. passive) language.

The bank found that companies using highly active and numeric language have, on average, a 74% chance of reducing their future emissions. Also, companies that frequently discuss mitigating or adapting to climate change have a 65% higher chance to achieve reductions.

Better Sustainability Investing

footprint	mitigation	adaptation	monitoring	risks
emissions	processes	systems	monitoring	risks
impacts	responses	adaptation	usage	regulatory
ocean	plans	goals	volume	reporting
climates	requirements	threshold	percentile	policymakers
ecosystems	reported	technology	stabilizing	trends
society	estimates	operational	target	economic
reef	measures	achieving	consumption	shifts
glacier	mitigation	improvement	percent	effects
forest	research	target	capacity	changing

Table 1: Associated words for the 5 key topics in ESG reports.
Source: Deutsche Bank

NLP Concept: Topic Modelling

A text's topic is thought of as the key idea the text expresses. While certain words are likely to appear in texts irrespective of their topic (for example, 'and'), other words are likely to relate to some ideas more than to others. 'Coffee', for example, more commonly relates to 'food' than it does to 'banking'.

The set of problems dealing with linking the topics of texts with the keywords associated with those topics is known as Topic Modelling.

One such problem is identifying groups of keywords that commonly appear together, to assess the topics of a set of documents. For example, if analysis shows the words 'cost', emissions', 'economy', 'economic' and 'industry' commonly appear together in a group of articles, one might infer these articles are all discussing economic impacts relating to climate change.

A different problem is identifying which articles cover specific topics. In the example above, Deutsche Bank's researchers analysed a set of sustainability reports to identify keywords that commonly appear in sections with the above five topics. These keywords then help flag similar sections in many other reports.

As a result, researchers were able to spot whether companies' sustainability reports had sections focusing primarily on the topics of 'mitigation' and 'adaptation', and compare their success at achieving emissions reductions goals.

Case Study 3:
Uncovering Hidden Signals

American Century Investments

Uncovering Hidden Signals

Before being made publicly accessible, relatively few had access to analyst-call discussions, where company management discusses its recent accounts and responds to analysts' probing questions.

With this information no longer as exclusive, investment managers are increasingly seeking new sources of insights, which can potentially deliver an edge in identifying mispriced assets.

One approach is to use alternative data. This may include satellite images, social media postings, consumer credit and debit card data, and e-commerce transactions.

Earnings conference call recordings and transcripts are one such source of added insight. The comments made by a company's management team can be automatically scrutinised.

This can potentially capture signals that aren't reflected in the company's latest financial reports.

NLP Concept: Sentiment Analysis

Texts discussing the markets often carry a sentiment, by placing events that could impact a position, either in a negative or positive way.

Human readers can easily judge the sentiment polarity of a text, but – relative to machines – are slow readers.

Sentiment analysis is the task of automating the decision of whether a text is positive or negative, while processing large amounts of content.

Because the language cues for polarity are often subtle, this machine learning task often involves showing the model many examples of positive and negative texts, to aid its ability to tell them apart.

Solution

Asset management firm **American Century** complements its investment processes with a sentiment model that looks to detect deception in management language during quarterly earnings calls

It checks for four elements of deception: omission (failure to disclose key details), spin (exaggeration from management and overly scripted language), obfuscation (overly complicated storytelling), and blame (deflection of responsibility).

Such signals are more subtle than merely polarity (see NLP Concept above). In an effort to avoid biases, researchers accounted for both the unique style of a given management team and the collective language of its industry peers.

To develop the model, the researchers first turned to financial journals and psychology texts to identify linguistic patterns associated with deception. This was later enhanced with feedback from the investment team.

Case Study 4: Connecting Data Sources

ING Merchant Bank

Connecting Data Sources

Financial services firms receive data from many different source systems. This data often concerns specific companies, and may include stock prices, financial reporting data, corporate actions and analyst coverage reports.

However, no single company identifier exists, one which is consistently shared among different source systems. As a result, connecting different data sets can be difficult, since a company's name can differ between data sets.

Figure 3 illustrates the name-matching problem: The Ground Truth table features the company names, as might be used internally. The other tables show how data providers might name the same companies.

Financial services firms are tasked with building systems that correctly match different data sets. With millions of different company names to match across sources, this problem can become acute.

Ground Truth	Source 1	Source 2	Source 3
ABN Amro Bank	ABN Amro NV	ABN Amro N.V	ABN Amro N.V
RBS Bank	RBS LLC	RBS LLC	RBS LLC
Rabobank	Rabobank NV	Rabobank N.V	RABOBANK NV
JP Morgan	JPM USA	JP Morgan USA	JPM USA
Chase Bank	Chase	Chase	Chase Bank
HSBC Bank	HSBC	HSBC	HSBC
Goldman Sachs	GS Global	GS Global	GS Global

Figure 3: The name-matching problem
Source: ING Merchant Bank, FinText

Solution

ING Merchant Bank solves the problem using a technique that approximates name similarity. It represents company names with numbers, in a way that encodes all the different tokens (see NLP Concept on p.4.) a company name might have.

Names in the source data sets are encoded based on the tokens they *have*. 'RBS LLC', for example, has two tokens: RBS and LLC. Names in the Ground Truth table are encoded with both the tokens they have and with ones they *might have*.

Since suffixes like LLC can appear in lots of company names, they're less helpful for finding the right match. numerical representations of company names are adjusted using TF-IDF, a popular term-weighting scheme. (See NLP Concept on the following page.)

As data arrives, names are numerically represented and compared to find the closest match in the Ground Truth representations. This delivers a matching that's both accurate and - crucially, given the ever growing volume of data - fast to compute.

Connecting Data Sources

NLP Concept: TF-IDF

'The' appears often in English, and doesn't add much meaning. Conversely, rarer words are often suggestive of a text's topic (for example, 'inflation').

But the relative rarity of a word in a document depends on context. 'Inflation' is much more common in economic texts than in children's books.

Term **F**requency–**I**nverse **D**ocument **F**requency (TF-IDF) is a popular way to measure how important a word is to a document, relative to its importance in a wider collection of documents. (The collection is also known as the corpus.)

Common words in both the document and corpus won't be that important. On the other hand, rare words in the document relative to the corpus will be more significant.

In ING's case, each 'document' was simply a company name, as it arrived from one of the data sources. 'Rabobank N.V', for example, is a document, containing two tokens.

But the token 'N.V' appears in many other company names. By using a term-weighting scheme like TF-IDF, its relative importance diminishes. Among the millions of company names, the token 'Rabobank' is not that common; its relative importance will be high.

Therefore, when comparing the representations of 'Rabobank N.V' with the Ground Truth term for Rabobank, the two will appear very similar.

Case Study 5: Cutting Down Costs

JP Morgan Chase

Cutting Down Costs

JP Morgan Chase set out to improve the process of reviewing commercial-loan agreements.

Having employees menially review thousands of contracts annually was straining the bank's human resources and limiting potential growth.

The bank also sought the added benefit of decreasing loan-servicing mistakes stemming from human error.

ML Concept: Feature Selection

Imagine wanting to explain how to tell apart oranges from apples to someone who's never seen fruit.

Colour alone is not enough (oranges can be green), nor is size (apples can be big). Both colour and size are features, and to successfully tell apart apples from oranges, you'll need more than just these two. Ideally, you'd like the number of features to be low.

In machine learning, feature selection is the process of finding the best features for helping a machine separate one group from another. These can often be very different to what humans would find helpful.

JP Morgan's researchers have identified 150 different features used to tell apart different types of contracts.

As the example to the right shows, sometimes the text can offer clues for useful features.

Solution

The bank implemented a program called COIN, which stands for Contract Intelligence. The software identifies and categorizes repeated clauses. It does so by classifying clauses according to about 150 different "attributes". (Also known as features, see NLP Concept to the left.)

COIN analyses contract documents to find words or phrases relevant to these attributes. Based on these, the system extracts from the contract the relevant sections warranting human review.

If the system fails to analyze a contract, it directs it to human reviewers, for them to manually search the document.

The bank reported that the solution annually saves lawyers and work officers 360,000 hours of work.

Example:

At times, the text can offer feature-selection clues:

1. The text before the first full stop.
2. Does the clause have crucial words, like 'amount'?
3. Are there numbers? Is there a currency symbol?

1

2

Section 2.2 Initial Advance.

At closing, Lender shall advance Loan proceeds in the amount of Sixty-Eight Million Seven Hundred Thirty Thousand Dollars ($68,730,000)

3

Case Study 6:
Providing Customer Services

N26 The Mobile Bank

Providing Customer Services

Chatbots are fast becoming a must-have channel for banking services. The chatbots often help with simple transactions, such as money transfers and balance inquiries. They reduce customer frustration, improve accessibility, and offer a consistent quality of services.

Among the many banks already deploying chatbot personal assistants are **Wells Fargo**, **Capital One**, **Santander**, **HDFC** and **Hang Seng**.

Leading the pack, though, is **Bank of America**, whose chatbot, Erica, already completed over 100 million client requests. Over a hundred people were needed to develop the application. This level of investment is only accessible to the largest financial institutions.

Open source natural language processing has opened up possibilities for smaller companies as well.

N26, the mobile bank, has grown to over 3.5 million customers in just a few years. To improve customer experience, the bank decided to develop a chatbot, using open source software.

Solution

When exploring potential chatbot solutions, N26 felt limited by the customization options offered by existing cloud-based solutions. Data-protection considerations were also a factor.

Using Rasa, an open source chatbot software, N26 was able to get from idea to production within four weeks. The bank's chatbot, Neon, now handles 20% of all support requests through the bank's mobile app.

Neon performs customer support tasks that range in complexity, from simple requests such as updating contact details to back-and-forth conversations, like reporting a lost or stolen card.

Crucially, as N26 operates in several European markets, the chatbot now provides services in five different languages.

Computing Concept: Open-Source Software

Under the closed-source software (or proprietary software) paradigm, the user pays for the right to use a piece of software, and intellectual rights, including the right to change the software, are reserved to its publisher.

This model implies that, to perform a task using software, users either have to pay for a license of an existing software product, or develop a bespoke one from scratch.

Software companies and independent developers are increasingly opting to provide open-source software.

Under this paradigm, users can use and customize the software for free. Open-source licensing can limit commercial terms like re-selling or patenting.

Open-source software has radically reduced the barriers to developing bespoke applications (like chatbots) for companies and individuals.

Case Study 7:
Extracting Research Insights

State Street

Extracting Research Insights

The volume of research information available currently overwhelms analysts. **State Street** has estimated that top financial research teams can produce enough content to consume 12,000 sheets of paper per day.

With limited time, investors may overlook or miss important research insights. In this environment, making sense of information quickly can become a competitive edge.

Additionally, owing to the European MIFID-II regulations, investment firms now need to pay for research. Understanding which research adds value helps optimize this expense.

State Street decided to develop a solution that helps investment professionals efficiently read and interpret lengthy research reports. The system was rolled out internally, with a view of expanding it as a service to clients.

NLP Concept: Extractive Summarisation

To quickly decide if a long article is worth reading, it can be helpful to have a short summary featuring the content's highlights.

One way to generate such a paragraph is to identify within the text several key sentences, which are likely to contain the most crucial information.

Extractive Text Summarisation is the task of automatically identifying which of the sentences are the best choice.

This is done by scoring sentences using automated text-analysis criteria, which attempts to rank the sentences by importance.

One such criterion is ranking sentences based on the relative rarity of the words they contain, using a term-weighting scheme. (See NLP Concept on p.13.)

Often, a combination of measurements is used to decide which are the most potent sentences.

Example:

The output of an extractive summarisation task is usually the relevant sentences in the order they appear in the original text.

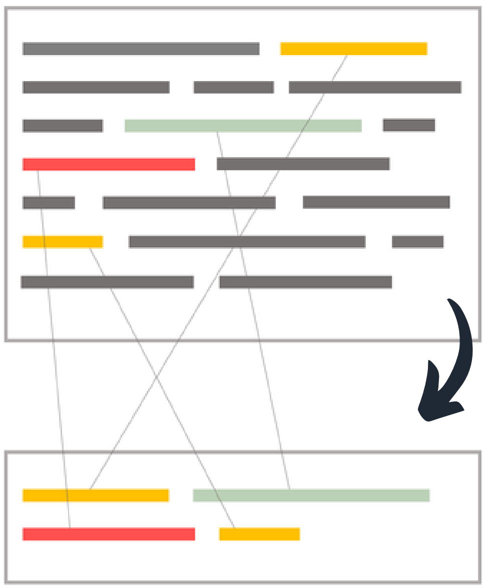

Figure 4: A Conceptual outline of Extractive Summarisation

Extracting Research Insights

Solution

In 2017, State Street launched its Quantextual Ideas Lab, to improve investment research. The lab launched a research aggregation software, which reviews lengthy research reports and, in addition to tagging and classifying documents, also summarises their content.

Analysts and portfolio managers can quickly extract findings relevant to their investment strategies. The algorithm identifies words and phrases (including financial terms), and uses the keywords to classify documents into topics, asset classes and regions. (See Topic Modelling, p.8.) The system automatically tags and categorizes research, while allowing human reviewers to add and refine tags. Additionally, users can query the research in everyday language.

To help researchers analyse search results, text summarisation algorithms condense the research into shorter snippets, while preserving their nuanced academic or economic tone.

Case Study 8:
Aligning Marketing With Sales

FinText

Aligning Marketing With Sales

The mutual-fund and active-management industry has witnessed its market radically change in the past decade. The rise of platforms and passive investing played a part, as did the surge in available investment products. Overall, this has led to outflows and fee compression.

All the while, clients have moved online. Recent evidence shows advisors are more influenced by website content than by roadshows, and by social media more than by printed marketing materials.

Content marketing is therefore becoming an integral part of the sales process.

Surveying the top 200 investment management firms reveals that 88% produce content regularly, and that 95% are active on LinkedIn.

However, those who create content – portfolio managers and the marketing teams – are not in direct regular contact with clients, and rarely have access to clients' cares and concerns. Little of the content is used by sales teams to secure inflows.

Thus, while marketers know that some content marketing is effective, they lack hard data to decide which content is worth the investment.

NLP Concept: Text Analytics

While the field of NLP is rich with tools and techniques, these often concern highly specific tasks, contrasting sharply with how humans ingest and reason about written content.

Text Analytics (also known as Text Mining) is the process of bridging between the high-level information needs for intelligibly processing text, and the algorithm-level techniques.

Text analytics breaks questions concerning texts to smaller sub-tasks, and later integrates the various outcomes.

Individually, sub-tasks offers merely a glimpse of a text's structure and meaning. To produce higher-level insight, combinations of building blocks are tailored to specific text processing problems.

Examples of some of the building-block techniques used to extract information (which include linguistic, statistical, and machine learning algorithms) appear throughout this report.

Such sub-tasks include (but are not limited to) named-entity recognition (p.4), text summarisation (p.19), sentiment analysis (p.10) and document clustering (for instance, when conducting topic modelling, see p.8).

Aligning Marketing With Sales

Solution

To add new value, it helps to know what investors are already reading. Such content may include news, thought leadership and online discussions, among others. Through comparative text analytics, **FinText** identifies both stylistic choices and emerging topics, to create measurably-better marketing content.

For example, clients often want insightful financial content but reject thought leadership written in overly-complex terms. Traditional readability tests (developed by the US military to make technical manuals easy to read) fail to advise on how to strike this balance for highly-educated readers.

Instead, FinText compares measures (including word difficulty, sentence length and opening-paragraph punchiness) to content investors enjoy. This enables marketers to adjust content readability to match client preferences.

Further, to keep in touch with prospects, sales teams require content that speaks to clients' concerns. But analysis points to excessive use of the first person ("We", "I" and "Our") in investment marketing. Using such signals, along with insights into what's currently concerning clients, empowers marketers to create useful, client-centric collateral.

Example:

Figure 5a below shows how seven investment managers' content compare in complexity. Relative to financial news covering the same period, most investment content is phrased in language that's much harder to read.

Figure 5b shows how often the first person is used in the same content. In some cases, one out of every four or five sentences is self-referential. While still costly to produce, inward-focusing collateral tends to appeal less to clients, often proving less affective.

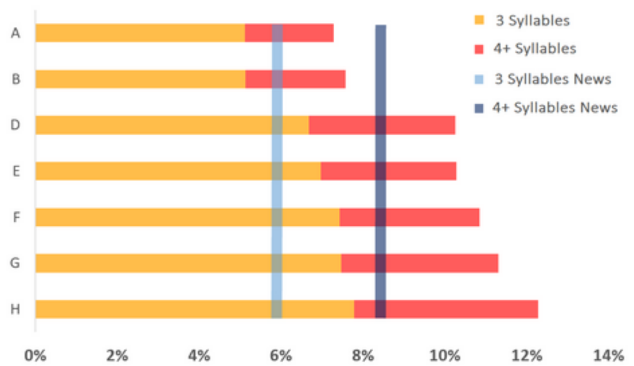

Figure 5a: Average percentage of words with three syllables or more
Source: FinText

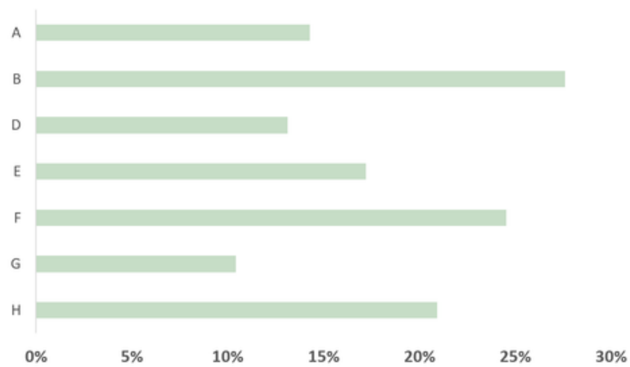

Figure 5b: Average percentage of sentences using "We", "I" or "Our"
Source: FinText

Key Learnings:
Unlocking Value With NLP

Key Learnings

Unlocking Value With NLP

Collectively, the case studies point to five aspects of financial-services NLP applications.

1. What's possible today was not available to most companies a decade ago.
Underlying trends leading to the current inflection point include surging research (most notably within large tech companies); the rise in computational power; and access to large textual databases.

Crucially, the shift to open source software made the progress accessible to the wider business community.

2. Successful NLP applications originate with a business process.
Typically, a challenge arises when a company's existing processes are ill-matched to the volume of text data that the company wants or is required to process.

3. The benefits can be substantial.
Monetary benefits are easiest to measure in terms of savings (as was the case with JP Morgan Chase) or excess returns (as was the case with Deutsche Bank).

But the greater impact can be witnessed with companies eradicating existing competitive moats (for example, N26), or creating an entirely new class of services (for example, State Street).

4. NLP techniques alone are not enough.
For tangible gains, domain knowledge is still critical. Solutions would typically target repetitive tasks and require specific tailoring to the relevant use case. Invariably, this involves domain expertise.

5. Text crunching as a competitive advantage.
While knowledgeable individuals can quickly gain high-level comprehension of written information, they are strictly limited in their ability to process large amounts of texts.

Consequently, deriving reliable insight from large bodies of texts lies outside the scope of the human workforce. Employees working alongside machines presents a new competitive edge.

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