Natural Language Processing – Business Applications

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Executives worry about their businesses.

They often have to navigate, with limited resources, a stormy market made of customers, competitors, and regulators, and the interactions between all these actors make finding answers to business questions a complex process.

But recently, machines have demonstrated their abilities to help shine some light on this chaos and provide, if not direct answers, context clues that help guide executives in using AI to to handle business problems.

In this article, we delve into examples of how natural language processing (NLP) business applications can be applied at scale to address 5 pressing business questions.

Five NLP Business Applications

1 – Customer service: *"How can I keep my customers happy?"*

NLP is used by computers to manipulate human language, whether to extract meaning, generate text, or for any other purpose. The interaction computer-language is categorized according to the task that needs to be accomplished: summarizing a long document, translating between two human languages, or detecting spam email are all examples of tasks that today can be decently accomplished by a machine.

While this wasn't the case 30 years ago, most of NLP today is based on machine learning i.e. statistical methods that are able to simulate what a human would do in similar circumstances.

NLP is heavily used in customer service. The interactions between customers and companies contain a lot of useful breadcrumbs that point towards the reasons for customer dissatisfaction, and the interaction itself can be cause of discontent.

In order to keep a finger on the pulse of consumers' intent, many companies now transcribe and analyze customer call recordings. They also deploy chat bots and automated online assistants to provide an immediate response to simple needs and decrease the load for customer service reps. Relevant NLP tasks include:

- **Speech recognition**, which converts spoken language into text. Advances in deep learning over the last 10 years have allowed major players to deploy this technology in commercial systems like Siri, Google Now, Skype's translator etc. with good performances.

- **Question answering**, which involves exactly that—answering questions posed by humans in a natural language. When in 2011 IBM's Watson outclassed the two best humans at Jeopardy!, Ken Jennings wrote on his video screen: "I, for one, welcome our new computer overlords." The task was especially hard for the machine, since the game is renowned for its convoluted and often opaque questions about general knowledge. Similar technology is used today by many companies for chatbots, both for internal (HR, operations) and external (customer service, IoT) projects.

2 – Reputation monitoring: *"What are people saying about me?"*

In the 1980s, companies started using software to find patterns in their own data and make better decisions. Optimization of supply chains, inventories and warehouses, sales processes and many other applications gave rise to what we now call business intelligence. But what's inside a company's walls is not nearly as much (or as valuable) as what's outside of them.

As the cost of computation kept dropping and algorithms kept improving, businesses started adopting tools that allowed them to look beyond their databases. This kind of data is commonly referred to as external data, public data, or open-source intelligence (OSINT).

While some of this data is structured and ready to be analyzed (e.g. census data, stock prices), most of its value remains tapped in unstructured, human-generated text such as news; blog posts; forums; patents; job postings; reports; SEC filings; social media; company websites; etc. These sources contain a plethora of precious information about how competitors, customers and the market as a whole are evolving.

An example of how this kind of data can be used is reputation monitoring. It's no secret that most customers check reviews online before buying a product, whether it's a phone or a falafel. According to the most recent BrightLocal survey, 92 percent of customers read online reviews and 86 percent won't buy a product with fewer than 3 out of 5 stars.

And as consumers have started voicing their complaints on Twitter and Facebook, reputation monitoring and management has become a top priority for businesses. Companies can now scan the entire web for mentions of their brand and products and recognize cases when they should take action.

Relevant NLP tasks for this application include:

- **Sentiment analysis**, which determines the attitude, emotional state, judgment or intent of the writer. This is done by either assigning a polarity to the text (positive, neutral or negative) or trying to recognize the underlying mood (happy, sad, calm, angry…). What about the times when multiple attitudes need to be accounted for in the same sentence? For example, "The pizza was amazing, but the waiter was awful!"

In the case above, the text is split into clauses, and polarity and mood are assessed for each. So, the previous text becomes something like:

{“clause”: “The pizza was amazing”,
“polarity”: 0.92,
“mood”: “happy”},

{“clause”: “but the waiter was awful!”,
“polarity”: -0.95,
“mood”: “angry”}

- **Coreference resolution**, which connects pronouns to the right objects. This is a hard task, but it’s essential to interpret the text correctly. For example, if a customer writes: “A guy from the dealer called to ask if I liked my new car. Well, no man, it sucks?”, it’s important to recognize that “it” refers to the car and not the guy. The customer is complaining about the product, not the service. As Elon Musk says, “Brand is just a perception”. Right now, your customers are talking about you, influencing the way other consumers perceive your brand. NLP can help you stay on top of your in-the-trenches reputation.

3 – Ad placement: *“Who is interested in my product?”*

Media buying is usually the largest line in a company’s advertising budget, so any targeting that can be done to ensure that ads are presented to the right eyeballs is of paramount importance. While in the past marketers have focused on demographics (race, economic status, sex, age, etc.) and psychographics (values, personality, attitudes, opinions, etc.), they’ve quickly adapted to the new digital area.

Our emails, social media, e-commerce and browsing behaviors contain a lot of information about what we’re really interested in. The huge potential of this kind of unstructured data is confirmed by the fact that 2 of the 10 largest companies today generate most of their revenue selling ads (Google and Facebook). Relevant NLP tasks for this application include:

- **Keyword matching**, which checks whether words of interest are included in some text. This is one of the easiest tasks in NLP, and at the same time one of the most remunerative. While this first approximation is often good enough, its lack of sophistication can produce pretty inappropriate results.
- **Sense disambiguation**, or identification of which sense of a word is used in a sentence. While the human brain is pretty good at this task, a computer won’t necessarily find it easy to recognize that the term pounds in the sentence, “I gained 20 pounds since the wedding!”, most likely refers to the unit of mass rather than the currency. This is still an open problem in NLP.

4 – Market intelligence: *“What’s happening with my competitors?”*

Markets are influenced by information exchange – between company/shareholders, government/citizens or simply individuals. Knowing the status of an industry is essential to developing an effective strategy, but the channels of content distribution today (RSS feeds, social media, emails) produce so much information that it's becoming hard to keep up.

This is especially true in financial markets, which is why [hedge funds routinely use NLP] to improve their models. Relevant NLP tasks for this application include:

- **Event extraction**, which recognizes what's happening to an entity. M&As, employment changes, deal closings and everything else that happens to organizations or people can be extracted automatically. For example, "Howard Schultz Stepping Down As Starbucks CEO" can be parsed as:

{"company": "Starbucks",
"position": "CEO",
"person": "Howard Schultz",
"event": "end of employment"}

A structured database of events about companies, governments and people is an extremely powerful tool for analyzing the business ecosystem.

- **Sentence classification,** or putting a sentence in a predefined set of buckets. This is often used as a first pass to extract relevant content from large repositories, like the SEC's EDGAR system. For example, "We expect a 15% increase in revenue next year," can be classified as a forward-looking statement.

5 – Regulatory compliance: *"Is my product a liability?"*

A crucial example of compliance is pharmacovigilance i.e. the studies done after a drug has been marketed (phase IV of clinical trials) to gather information on its side effects. A lot of information about adverse drug events (ADEs) resides in what's called unstructured clinical narratives, or patients' reports about their health.

Pharma companies extract ADEs from 1) electronic health records (EHRs), social media and forums for patients complaining about a problem, and 2) web search trends and patterns for patients looking for a solution. Relevant NLP tasks for this application include:

- **Named entity recognition (NER)**, which extracts the names of drugs, diseases, patients, and pharma companies using rule-based or statistical methods. Applying NER to a sentence will be able to convert it from, "Valium makes me sleepy," to "{drug} makes me {symptom}."
- **Relation detection**, used to identify the context in which the ADE is mentioned. This is often done with frames, or patterns of words that correspond to a concept, e.g. "I felt {symptom} after taking {drug}" is a pattern that matches the presence of side effects.

By applying these two tasks consecutively, we've identified that the patient is linking the drug Valium to the side effect sleepy. Both these tasks benefit from using ontologies i.e. structured domain knowledge (in this case biomedical) that provides the object dictionary and the relations between objects.

What’s next in AI for BI

Over the last 10 years, companies have been able to carve the most promising NLP business applications out of academic research, and use them to improve their business intelligence. The NLP market size, which is about $7.5B today, is estimated to grow to $16B by 2021.

Still, computers are not able to process or understand text like humans do, at least not yet.

As mentioned before, most of the methods employed in NLP are statistical in nature, and statistics can only go so far without context or semantics. The algorithms behind the applications described above simulate human understanding and can do that at scale, but they are still brittle in that they can’t simulate a behavior they haven’t seen before.

For example, every time Siri tries to answer a question that has not been programmed to respond, it fails miserably, and it will keep failing until Apple’s engineers implement the fix.

The future of this field is about moving from NLP to natural language understanding (NLU), where a deeper connection between the concepts communicated and facts about the world is established. In artificial intelligence, this is considered an AI-hard problem: to be solved, computers have to be as intelligent as people.

But while the future is still in the works, present NLP technologies can still provide businesses with useful answers to bounded questions