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Data Science Methods

Natural Language Processing: Grammar Rules for Event Detection in Corporate Transcripts

We see natural language processing (NLP) as one of the most promising ways to apply data science to investment research. Event detection, using NLP methods to find expressions of specific ideas in texts, stands out as an especially promising approach, so we have developed a method for building these features:

Grammar rules can systematically apply concrete relationships in language to identify specific events. They are straightforward, flexible, cost-effective, and low-risk relative to other approaches for this particular language processing task.

We can also leverage the expertise of Barclays analysts in an iterative development procedure:

- **Investment analysts define an event detection feature of interest,** establishing characteristics of a concept they think would be useful to identify in text;
- **Open-source tools like SpaCy are used to create a rule for the event;** that rule then generates a short list of candidate sentences drawn from a set of training data;
- **Then the analyst manually classifies a small number of examples**, identifying which ones fit the idea, and which ones do not;
- **The rule is refined,** using repeated cycles of sentence detection and analyst classification until it is performing at acceptable levels of precision and recall in the training sets (or the return on further effort is deemed to be too low to justify further investment);
- **Once it is finalized, the rule is applied to the full transcript dataset using Spark on a computing cluster;**
- **Reserved testing data is used to measure the out-of-sample precision and recall of the rule.** Additional out of time validation data can be reserved for testing the rule's relationship with outcomes like returns or corporate key performance indicators.

We include an example the development of a rule to detect discussions of reducing capital expenditures in earnings call transcripts; the rule was applied to forecasting aggregate capital spending in *U.S. Equity Strategy: Management Sentiment NLP Model Implies Subdued Capex Growth*, September 24, 2019.

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METHOD: GRAMMAR-BASED EVENT DETECTION

Our General Framework for Natural Language Processing Embraces Diverse Methods and Outputs

For natural language processing (NLP), we have established a framework that separates the features we want to create from the tools and models that are used to create them. The features are quantitative representations of text which are appropriate for modelling or analysis. The tools and models are the algorithms that take texts and create these representations. Some examples of representations are:

- A binary feature representing whether an "event of interest" occurs, on some pre-defined universe of events, as in grammar rule–based event detection (the focus of this report)
- A categorical feature representing the "topic" the text is written about, or a vector representing proportions of topics, as in latent dirichlet allocation (LDA)
- A real-valued vector that captures the "meaning" of a piece of text, in a way that is sufficient for some prediction task, as with intermediate embeddings for language translation
- Two real-valued scalars, representing the "sentiment" of the text, under some definition of sentiment, and its magnitude, as with Google's sentiment API

Tools and models are usually inspired by an abstract concept, and are meant to build features that can represent that concept. A sentiment model, for example, will often give a positive number when text represents "good" sentiment, and a negative number to represent "bad' sentiment.

There are many approaches to represent a given concept, each with its own strengths and weaknesses. Keeping with the example above, to represent the sentiment of a text, you might:

- Divide the text into individual words (tokenize it), then use a dictionary to assign a sentiment score to each word, and sum up the scores to get an overall sentiment; or
- Have readers assign sentiment scores to a set of past example texts, convert the texts to a bag-of-words vector, train a supervised learning model (e.g. logistic regression) on the human-scored examples, and use this model to estimate the new statement's sentiment; or
- Apply the same labelling procedure as above, but learn a representation to encode the text, as in a neural network model, or
- Train a model for a completely different purpose, (e.g. predicting the next character in an Amazon product review), and hope that it happens to discover "sentiment" as a side effect, as described in "Learning to Generate Reviews and Discovering Sentiment"[1]

All of these models are very different from one another, but they all generate a quantitative representation of the concept of "sentiment." These will typically perform very differently on any given task for which sentiment is an input. It's up to the analyst to choose a tool that balances simplicity (saving implementation, maintenance, and compute cost), risk (you can fail to successfully build a neural network model, and invest significant resources in that failure) and performance.

[1] Radford, Jozefowicz, and Sutskever. Learning to Generate Reviews and Discovering Sentiment. (2017) *https://arxiv.org/abs/1704.01444*

Event Detection in Transcripts

We think a promising NLP task for investment research is to detect language "events," with a particular focus on earnings call transcripts. The event is the expression of a concept in the text; in an earnings call transcript that would mean that something spoken by a participant in the call. For example, this could be

- A company's management talking about:
  - "cutting capital expenditures," or
  - "launching a new product," or
  - "earnings were better than expected," or
  - "we would be receptive to merger bids"; or
- An analyst stating that revenue was surprisingly strong, or
- Any participant inquiring about the company reducing their debt; or
- If a particular speaker is using language thought to be affiliated with deceptiveness

Our event definition could also be conditional on meta-data: the sentence must be said by a speaker with a specific role, or in a specific section of an earnings call, or made by a company with some other permanent or temporary characteristic.

The event definition can also require non-grammatical aspects of the text. For example, sentiment could also be a factor. In that case, we might say that one "event" would be "company planning to reduce CapEx" with positive sentiment, and the same idea with negative sentiment could be an independently detected event.

In general, our target output would be to create a data feature at the transcript level that would be a 1 if the event was detected at least once in a transcript, and a 0 otherwise.

Using Grammar Use Rules for Event Detection

We chose to use grammar rules as our tool because they're simple enough to be understood by non-experts, have low risk of failure, can capture some of the non-linearity in text, are flexible enough to answer a wide range of questions, and require only a modest investment in total human resources to create a working detection.

To make things easier to understand, we'll use a demonstration event as a running example to illustrate our definitions and procedures: any occurrences of any participant in an earnings call discussing a future reduction of capital expenditures. The circumstance we're looking for would include any variations of that discussion, but would also need to exclude general discussion of capital spending plans, reductions that have already take place, or times when capex is increasing (or NOT being reduced).

To represent a concept with grammar rules, you need to systematically encode the grammar for how that concept is talked about. This requires a lot of exploratory analysis. Figure 1 shows some of the example statements we've found in our transcript data.

FIGURE 1

Examples of Sentences About the Idea of "CapEx Reduction" That We Would Want Our Event Detection Algorithm to Find

Forms	Sentences
Continuous Tense	"You guys are reducing your CapEx."
Passive voice	"First one, just capital spending, the CapEx guidance or the plan for capital spending was reduced."
Complex Sentence Structure	"So going through CapEx, that is a pretty deep cut from what you had anticipated previously from $180 million to $100 million if I heard that right."
Question	"Okay, with the one thing, you are talking about more out-sourcing, will that reduce capital expenditures going forward?"
Noun phrase	"And then our reduction in our capital expenditure."

Source: Refinitiv, Barclays Research

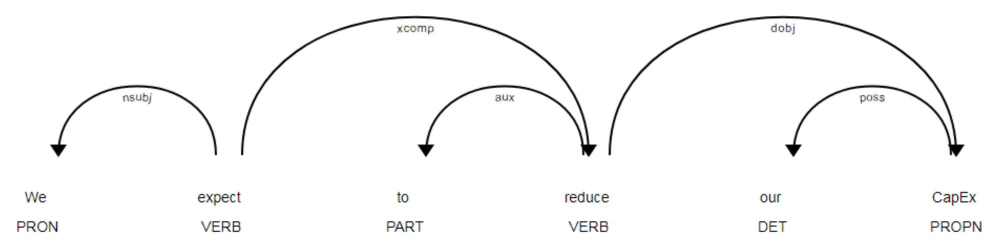
Each sentence could take a different grammar rule to detect it, so our event detector would require a collection of grammar rules. All of these rules are meant to codify the same idea. They are a way to make our subjective concept of the "event" objective.

As a concrete example, in the statement "We expect to reduce our CapEx," the subject "we," is acting on the object, "CapEx," through the verb "reduce." If we can find all phrases where the subject refers to a company, the object is synonymous with CapEx, and the verb is synonymous with reduction, then we have a precise way to talk systematically about conversation about "CapEx reduction."

There are multiple open source NLP tools and frameworks in high-level scripting languages. The Python Natural Language Toolkit, an open-source suite of tools for various NLP tasks, has been around since 2001; we are using SpaCy – a more recent python NLP library released in 2015. Both of these tools support parsing grammatical dependencies, and so can be used to build grammar rules. A SpaCy dependency parsing example can be seen in Figure 2.

FIGURE 2

Visualization of Dependency Parsing



Source: spaCy, Barclays Research

We can write logic rules that act on this "parse tree": if we detect the word "reduce" and its "direct object" (dobj) is "CapEx", we have a "CapEx reduction" detection. We can run through a similar process to find detections of each of the structures in Figure 1, and we'll have a good start for an event detector.

Grammar Rules Make Non-Linearity Cheap (in Terms of Human Investment and Computational Time)

Grammar rules are a simple step past bag-of-words representations. Instead of just tagging occurrences of "CapEx" in the same sentences as "reduction," we're using binary indicators for relationships between terms. That lets us look for more nuanced structure, where we're sure "CapEx" is the thing being reduced, and we can check that "reduction" is not being negated.

This approach falls short of natural language understanding. Our model doesn't understand broader context, and so can't resolve pronoun references. We'll miss cases where "CapEx" is being represented by the word "it," for example. Term disambiguation is partly handled by default components of SpaCy's processing pipeline. We can improve it by upgrading the Part of Speech (POS) tagger or entity recognition module.

SpaCy's decoupling of its components into replaceable models means we can improve our entity recognition model in the future without necessarily having to change our grammar rules. For the use cases we've tested, the default components work well enough, and we just have a cheap and simple way to engineer non-linear features from text.

It's easy to see why this non-linearity is important. We've used lemmatized search, an advanced version of term detection, to try to identify concepts like "capex reduction" and "debt reduction." These searches have a precision in the ballpark of 50%: about half of the phrases we identify capture the wrong concept. You can see some examples in Figure 3 where a search would give us an incorrect detection, but the non-linearity inherent in understanding grammar fixes the problem.

FIGURE 3

Term Matching vs Grammar Rules on "CapEx Reduction" Detection

Sample sentences	Term matching	Grammar rules	Actual
Got it, and then looking at your capital ratios after declining for a number of quarters they ticked up slightly in the third quarter.	Detection	No detection	No CapEx reduction mentioned
There had been a $10 million working capital reduction in the first quarter.	Detection	No detection	No CapEx reduction mentioned
I think reduce our need to access the capital markets, as well as enhance our credit profile.	Detection	No detection	No CapEx reduction mentioned
It is a new INVI-care product and it is more expensive from a capital standpoint, but it reduces the amount of labor.	Detection	No detection	No CapEx reduction mentioned

Source: Refinitiv, Barclays Research

This approach is scalable. We run our grammar rules on a cluster using PySpark, and so it's easy to leverage SpaCy at scale. The fast rule development time we get from using a high-level scripting language like Python makes the whole pipeline cheap to use.

Modern Methods Can Work Well, but Can Be Costly and Risky

There are more performant ways to encode information from text which might require less specialized work than grammar rule development. We've seen proof-of-concept work for using recurrent neural networks to build dense vector representations of text. Then, if you provide a small collection of examples, you can find similar statements using nearest-neighbor search. This worked well for event detection in the limited test cases we tried.

We also didn't use the most sophisticated implementation of the tools we chose. The SpaCy package is extensible, and can use domain-specific components instead of its generic default components, even within the framework of using grammar rules. In particular, we haven't tested the part of speech tagger extensively in the finance domain. To reduce the cost of our proof-of-concept work, we opted to use the default pipeline components. They worked well in our experiments, and were measured with part-of-speech tag accuracy around 96%, and named-entity recognition accuracy around 87% in their training domains[2].

[2] English SpaCy Models Documentation, v2.1.0.. *https://spacy.io/models/en#en_core_web_lg*

Modern text processing models have exceeded the performance of older methods, but they require time and resources to build and use. Google translate is an instructive example. The creators describe using 96 Tesla K-80 GPUs working around nine days[3], and achieve performance at the level of the product we're all familiar with. At current pricing, this would take around $9300 for a nine-day training run at the $0.45/GPU * hr pricing currently listed on their website. Considering model construction takes many training runs, often around 10-20, that puts the pricing at the low end around $93,000. Hyperparameter search can easily push the training run count closer to 100, and the million-dollar range (for one model!) is feasible if you aren't careful to use early stopping criteria and other specific methods aimed at mitigating costs. It requires significant expertise to do this well.

With all of this in mind, we opted to use an older method with a clear, iterative process for refinement. We're able to balance cost by deciding whether further improvement is warranted, and "fail fast" when we see an event detection just isn't working.

Our Procedure

Our process lets you repeatedly adjust your rule and measure its performance. If you notice vanishing performance gains as the effort increases, you have distinct points at which you can stop and decide whether your rule is good enough.

This event detection is based on writing a collection of logic rules, so you also have a stronger guarantee that it won't simply fail to identify the phrases of interest as might happen with more sophisticated neural language models. You'll typically get better-than-guessing performance, which is often enough performance to be useful.

Step 1: Lemmatized Search: Surfacing Candidates

We start by defining keywords of interest, and doing lemmatized search with those keywords. The goal at this stage is very high recall (trying to capture as many instances of the event as possible), and very low precision (also getting lots of incorrect detections). The result is a set of candidate sentences.

Step 2: Manual Classification by Domain Experts

From these candidates, we select a random sample of 100 sentences to pass along to a domain expert for them to manually classify as correct or incorrect detections of the event. These sentences have much higher positive detection rates than the corpus overall, so we have enough positive test examples to work with.

Step 3: Iterative Rule Improvement

Next, we have a cycle where we write and test rules in the set of 100 sentences we've selected and manually classified. The cycle goes:

- Refine or add rules to our pipeline, where we look for specific grammar structures with each rule
- Measure the new precision and recall on the set of manually classified examples
- If we improve precision without losing too much recall (i.e. without excluding positive examples), keep the new rule. Otherwise, revise or remove the rule, and repeat the cycle.

Through this process, we manage precision and recall against our baseline, and can stop when we decide the results are "good enough" on this test set. What is good enough depends on your use case.

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3 Wu et al. Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation. (2016). *https://arxiv.org/abs/1609.08144*

Step 4: Re-Sample and Evaluate Performance

Finally, we must make sure we don't "over-train" by tailoring our rules to a limited number of cases in which our model works well. We re-run our random selection process to generate 100 new examples, manually classify these, and check our precision and recall with our rules in this new set. At this stage, if the performance metrics decrease too much, we should repeat the whole process starting at step 2 on this new test set until the performance is good enough on a newly selected random test set.

Step 5: Spot-Check Out-of-Sample Recall

This step is nuanced because of our low event rates. It's hard to find out-of-sample points to make sure we've detected them. The best ideas we've come up with are:

1. Test against some observed metric which should correlate with the event. While it's an objective measure, in practice you won't likely know whether the event should correlate with the metric even if your rule is perfect.

2. Leverage domain knowledge where analysts can point you to transcripts where they know the event of interest occurred, and make sure you were able to detect it. This suffers from small sample sizes, and biased sampling (it's based on human memory). It's not a great measurement, but can surface failure modes of your event detector to provide more routes for improvement.

Step 6: Running at Scale

At this point, we have a set of grammar rules that work well on random samples from a larger corpus, so we can expect them to work comparably across the corpus. We run the logic rules against all sentences from all transcripts, and so have (Company, Date) pairs with positive detections that we can use as a potential investment signal.

Problems and Solutions with Rule Development

We've laid out our basic goal: to take a set of earnings call transcripts as input, and create a panel of abstract "event detections" as output, represented as a binary panel. This panel contains a 1 for each day and company where our rules register an event detection on that day, and a zero otherwise.

This task is easy to do, but difficult to do well for a number of reasons.

- **No Ground Truth.** We don't have any way to test our rule performance over all transcripts, because that would mean we already know the result we're writing the rule to measure. Instead, we can evaluate performance on a set of manually tagged examples.

- **Events Are Rare.** Instead of manually tagging the whole corpus, we'd like to test our rule performance on a random subset of manually tagged examples. There are generally too few positive examples to have any positive cases in a small sample, so we use our lemmatized search to find a non-random sample that over-indexes for positive cases.

- **Performance Metrics Are Biased.** In a non-random sample, our performance metrics are biased. Our precision should be unbiased, but recall is still biased. That's a problem we address on a case-by-case basis.

Example: "CapEx Reduction" in the S&P 1500

Now we'll complete our example by presenting some real-world results from our rule development process. Our testing results are based on the available earnings call transcript data from Refinitiv. This data set contains around 85% of total S&P 1500 company's earnings call transcripts since 2002.

Step 1: Lemmatized Search: Surfacing Candidates

Our goal is to detect events where the concept "conversation about CapEx reduction" has happened. First, we come up with the list of terms shown in Figure 4. In this step, instead of creating any grammar rules, we simply do lemmatized search, meaning if a sentence contains any of the CapEx Synonyms *and* any of the reduction synonyms, we keep the sentence as a candidate for "conversation about CapEx reduction." We apply these to all sentences in all transcripts to get a set of candidates for detection which are much more likely to be talking about CapEx reduction.

FIGURE 4

List of Terms in Broad Rule Matching

CapEx Synonyms	Reduction Synonyms
"Capex," "CapEx," "capex," "capital," "expenditure"	"reduce," "reduction," "decline," "cut"

Source: Barclays Research

Step 2: Manual Classification

We randomly select 100 sentences from step 1 and pass them to a domain expert to manually classify as "conversation about CapEx reduction" or not. The confusion matrix is shown in Figure 5, The precision is 40% (if we treat being surfaced by the search as a detection) and recall is 100% (by definition). Note that this is in-sample recall, and not recall that will generalize to the whole corpus.

FIGURE 5

Confusion Matrix of Lemmatized Matching

	CapEx reduction mentioned	No CapEx reduction mentioned
NLP detected	40	60
NLP not detected	0	0

Source: Refinitiv, Barclays Research

At this stage, we did exploratory analysis to understand the grammar of the detected events (according to our domain expert), and figured out how to write rules to capture as many events as possible with as few rules as possible. There is a little art to this part of the process, and it gets easier with experience.

Some examples of classifications by our domain expert are in Figure 6. You can see some of the grammar can be complicated. The more complicated the grammar, the harder it is to write a rule to capture it. Some of these structures are complicated and rare enough that it makes sense to ignore them.

FIGURE 6

Sample Detections of Lemmatized Matching

Correct detections	False detections
You guys are reducing your CapEx.	That's where all these cost savings, working capital reduction initiatives help support.
We think we've really reduced expenditures.	In fact, we have also spent a lot of capital on cost reduction with belt lines and so forth.
But I just wondered if you have capital spending forecast for the year and whether you maybe kind of cut back on what your original CapEx plans were, given what happened here.	So as more and more of that business moves to a central counterparty, that capital charges associated with it will actually be significantly reduced.
I mean, that CapEx number, sounds like it's going to get to cut in half.	The reason for the decline in the U.S. at higher rates than we said before has been capital.

Source: Refinitiv, Barclays Research

Step 3: Iterative Rule Improvement

Notice that if we kept simple lemmatized search as our definition for our rule, we only would have around 40% precision. 60% of cases would be incorrect detections. Depending on your use case, that might be accurate enough. For us, we wanted to make sure we got rid of some of these extra detections.

We used SpaCy to build grammar rules to find the sentences that actually talk about CapEx reduction. We used our set of 100 manually classified sentences to test and improve our grammar rules by adjusting the rule, calculating our validation metrics, keeping the adjustment if it improved performance, and repeating. The final confusion matrix is in Figure 7. The precision is 69% and recall is 67.5%.

FIGURE 7

Confusion Matrix of Grammar Rule Matching

	CapEx reduction mentioned	No CapEx reduction mentioned
NLP detected	27	12
NLP not detected	13	48

Source: Refinitiv, Barclays Research

Step 4: Re-Sample and Evaluate

To test whether our grammar rules “over-train” the train sentences or not, we randomly select another set of 100 sentences, manually classified them and run the updated grammar rules on them. The out-of-sample sentences confusion matrix is show in Figure 8.

FIGURE 8

Confusion Matrix of Grammar Rules on Out-of-Sample Test Set

	CapEx reduction mentioned	No CapEx reduction mentioned
NLP detected	24	7
NLP not detected	12	57

Source: Refinitiv, Barclays Research

The out-of-sample precision is 77.4% and recall is 66.7%. Hence our rules did not over-train the training set.

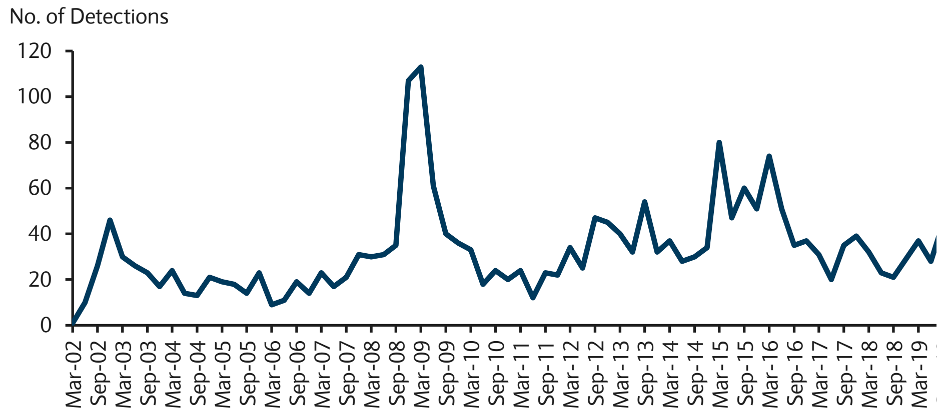
Step 5: Spot-Check Out-of-Sample Recall

Next, we wanted to check out-of-sample recall. We don’t have a good solution for this problem in general, and so this is a point on which to evaluate whether these tools are appropriate for your use case.

Figure 9 shows the count of detections over time for the available SP1500 companies earnings call transcript data from Refinitiv.

FIGURE 9

Number of "CapEx Reduction" Detections by Quarter from 2001 to 2019



Source: Refinitiv, Barclays Research

Of the companies mentioning CapEx reduction, we found that 52.0% actually did reduce CapEx over the next fiscal year. You can compare this with the marginal rate of companies reducing CapEx of 42.5% over the same time period to see that companies mentioning reducing CapEx are far more likely than chance to actually reduce CapEx. The confusion matrix is show in Figure 10.

FIGURE 10

The Confusion Matrix of CapEx Reduction on the Whole Available SP1500 Transcripts

	CapEx reduction	No CapEx reduction
NLP detected	884	816
NLP not detected	6966	9812

Source: Refinitiv, Barclays Research

The odds ratio is 1.52 (1.34 to 1.74 at the 99% CL), showing that companies who we detect mentioning CapEx reduction are around 50% more likely than companies we don't detect to mention CapEx reduction to actually reduce their CapEx.

Now we can ask whether we're in the right ballpark in recall. The overall rate of CapEx reduction is 42.5%. We would hope that our rule identifies all of these companies, but expect many of them to reduce CapEx without mentioning it on their calls. The proportion of companies we measured mentioning CapEx reduction is 9.2%, indicating that while the rule has some predictive power for CapEx reduction, its recall for predicting instances of CapEx reduction is relatively low.

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