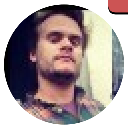
Recomm



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Co-founder of Scrimba— a new video format for conveying code. https://scrimba.com
Jun 7, 2016 · 7 min read

Boosting Sales With Machine Learning

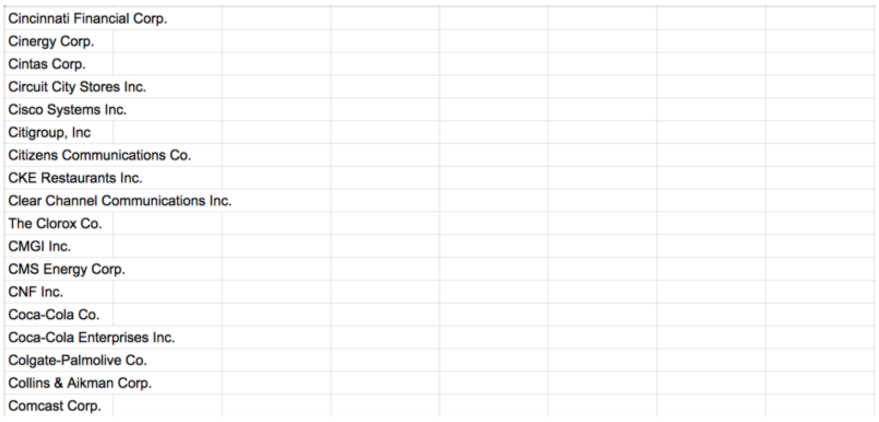
How we use natural language processing to qualify leads

In this blog post I'll explain how we're making our sales process at Xeneta more effective by training a machine learning algorithm to predict the quality of our leads based upon their company descriptions.

Head over to GitHub if you want to check out the script immediately, and feel free to suggest improvements as it's under continuous development.

The problem

It started with a request from business development representative Edvard, who was tired of performing the tedious task of going through big excel sheets filled with company names, trying to identify which ones we ought to contact.



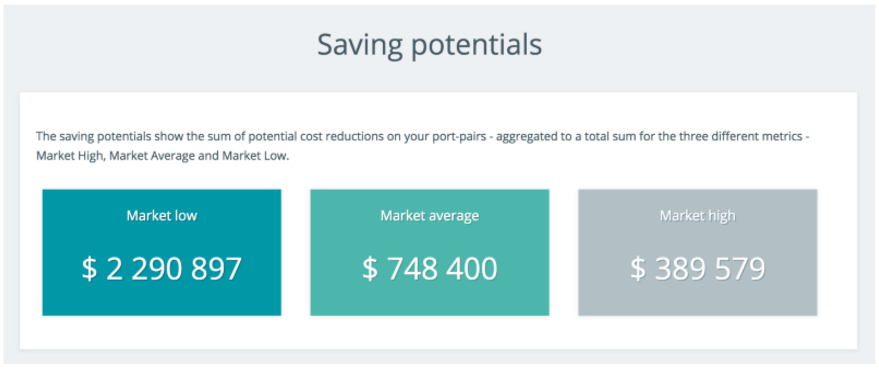
Cincinnati Financial Corp.
Cinergy Corp.
Cintas Corp.
Circuit City Stores Inc.
Cisco Systems Inc.
Citigroup, Inc
Citizens Communications Co.
CKE Restaurants Inc.
Clear Channel Communications Inc.
The Clorox Co.
CMGI Inc.
CMS Energy Corp.
CNF Inc.
Coca-Cola Co.
Coca-Cola Enterprises Inc.
Colgate-Palmolive Co.
Collins & Aikman Corp.
Comcast Corp.

An example of a list of potential companies to contact, pulled from sec.gov

This kind of **pre-qualification of sales leads** can take hours, as it forces the sales representative to figure out what every single company does (e.g. through read about them on LinkedIn) so that he/she can do a qualified guess at whether or not the company is a good fit for our SaaS app.

And how do you make a **qualified guess?** To understand that, you'll first need to know what we do:

> *In essence, Xeneta help companies that ship containers discover saving potential by providing sea freight market intelligence.*



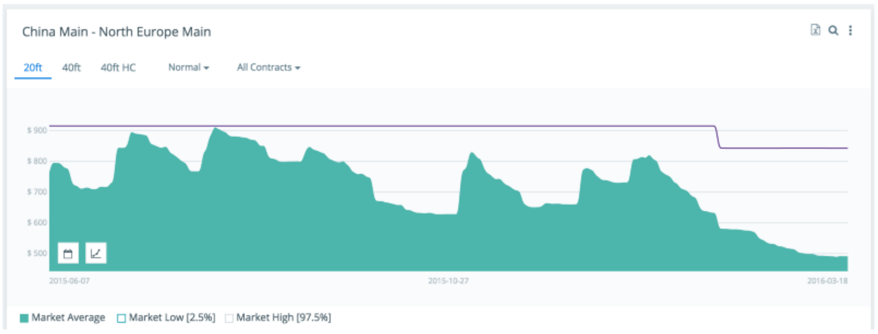
Saving potentials

The saving potentials show the sum of potential cost reductions on your port-pairs - aggregated to a total sum for the three different metrics - Market High, Market Average and Market Low.

Market low	Market average	Market high
$ 2 290 897	$ 748 400	$ 389 579

This customer had a 748K USD saving potential down to market average on its sea freight spend.

More specifically, if your company ships above 500 containers per year, you're likely to discover significant saving potential by using Xeneta, as we're able to tell you exactly where you're **paying above the market average price.**



This widget compares a customers' contracted rate (purple line) to the market average (green graph) for 20 foot containers from China to Northern Europe.

This means that our target customers are vastly different from each other, as their only common denominator is that they're somewhat involved in sea freight. Here are some examples of company categories we target:

- Automotive
- Freight forwarding
- Chemicals
- Consumer & Retail
- Low paying commodities

The hypothesis

Though the broad range of customers represents a challenge when finding leads, we're normally able to tell if a company is of interest for Xeneta **by reading their company description**, as it often contains hints of whether or not they're involved in sending stuff around the world.

This made us think:

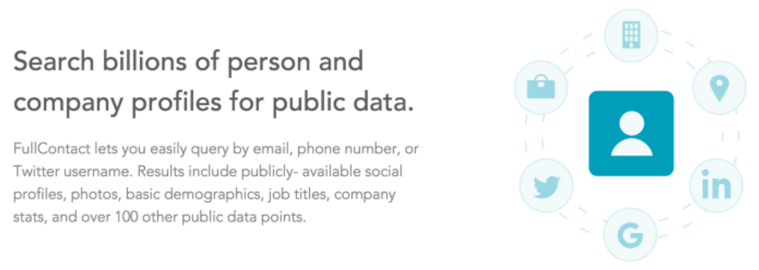
> *Given a company description, can we train an algorithm to predict whether or not it's a potential Xeneta customer?*

If so, this algorithm could prove as a huge time saver for the sales team, as it could roughly sort the excel sheets before they start qualifying the leads manually.

The development

As I started working on this, I quickly realised that the machine learning part wasn't be the only problem. We also needed a way to get hold of the company descriptions.

We considered crawling the companies' websites and fetch the ***About us*** section. But this smelled like a messy, unpredictable and time consuming activity, so we started looking for API's to use instead. After some searching we discovered FullContact, which have a Company API that provides you with descriptions of millions of companies.



Search billions of person and company profiles for public data.

FullContact lets you easily query by email, phone number, or Twitter username. Results include publicly- available social profiles, photos, basic demographics, job titles, company stats, and over 100 other public data points.

However, their API only accept company URL's as inputs, which rarely are present in our excel sheets.

So we had to find a way to obtain the URL's as well, which made us land on the following workflow:

- Using the Google API to google the company name (hacky, I know…)
- Loop through the search result and find the most likely correct URL
- Use this URL to query the FullContact API

There's of course a loss at each step here, so we're going to find a better way of doing this. However, this worked well enough to test the idea out.

The dataset

Having these scripts in place, the next step was to create our training dataset. It needed to contain at least 1000 **qualified** companies and 1000 **disqualified** companies.

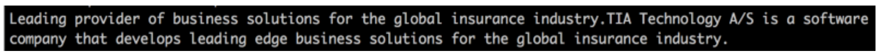
The first category was easy, as we could simply export a list of 1000 Xeneta users from SalesForce.

Finding 1000 **disqualified** was a bit tougher though, as we don't keep track of the companies we've avoided contacting. So Edvard manually **disqualified** 1000 companies.

Cleaning the data

With that done, it was time to start writing the natural language processing script, with step one being to clean up the descriptions, as they are quite dirty and contain a lot of irrelevant information.

In the examples below, I'll go though each of the cleaning techniques we're currently applying, and show you how a **raw description** ends up as an **array of numbers.**



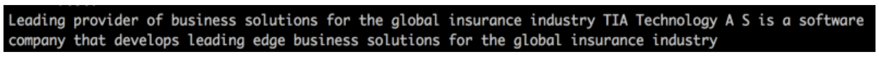
```
Leading provider of business solutions for the global insurance industry.TIA Technology A/S is a software
company that develops leading edge business solutions for the global insurance industry.
```

An example of a raw description.

RegExp

The first thing we do is to use regular expressions to get rid non-alphabetical characters, as our model will only be able to learn words.

```
description = re.sub("[^a-zA-Z]", " ", description)
```



```
Leading provider of business solutions for the global insurance industry TIA Technology A S is a software
company that develops leading edge business solutions for the global insurance industry
```

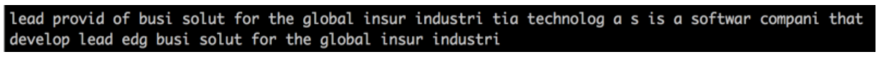
After removing non-alphabetical characters.

Stemmer

We also stem the words. This means reducing multiple variations of the same word to its stem. So instead of accepting words like **manufacturer, manufaction, manufactured & manufactoring,** we rather simplify them to **manufact.**

```
from nltk.stem.snowball import SnowballStemmer
stemmer = SnowballStemmer('english')
description = getDescription()

description = [stemmer.stem(word) for word in description]
```



```
lead provid of busi solut for the global insur industri tia technolog a s is a softwar compani that
develop lead edg busi solut for the global insur industri
```

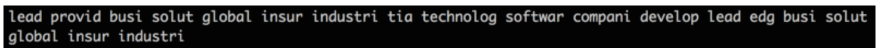
After stemming the words.

Stop words

We then remove stop words, using Natural Language Toolkit. Stop words are words that have little relevance for the conceptual understanding the text, such as ***is, to, for, at, I, it etc.***

```
from nltk.corpus import stopwords
stopWords = set(stopwords.words('english'))
description = getDescription()


description = [word for word in description if not word in
stopWords]
```



```
lead provid busi solut global insur industri tia technolog softwar compani develop lead edg busi solut
global insur industri
```

After removing stop words.

Transforming the data

But cleaning and stemming the data won't actually help us do any machine learning, as we also need to transform the descriptions into something the machine understands, which is numbers.

Bag of Words

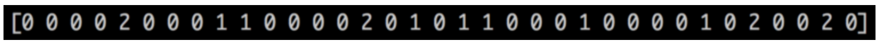
For this, we're using the Bag of Words (BoW) approach. If you're not familiar with BoW, I'd recommend you to read this Kaggle tutorial.

BoW is a simple technique to turn **text phrases into vectors,** where each item in the vectors represents a specific word. Scikit learn's CountVectorizer gives you super simple way to do this:

```
from sklearn.feature_extraction.text import CountVectorizer


vectorizer = CountVectorizer(analyzer = ‘word’,
max_features=5000)
vectorizer.fit(training_data)
vectorized_training_data =
vectorizer.transform(training_data)
```

The **max_features** parameter tells the vectorizer how many words you want to have in our vocabulary. In this example, the vectorizer will include the 5000 words that occur most frequently in our dataset and reject the rest of them.



```
[0 0 0 0 2 0 0 0 1 1 0 0 0 0 2 0 1 0 1 1 0 0 0 1 0 0 0 0 1 0 2 0 0 2 0]
```

An example of a very small (35 items) Bag of Words vector. (Ours is 5K items long).

Tf-idf Transformation

Finally, we also apply a **tf-idf** transformation, which is a short for **term frequency inverse document frequency.** It's a technique that adjusts the importance of the different words in your documents.

More specifically, tf-idf will emphasise words that occur frequently in a description (**term frequency**), while de-emphasise words that occur frequently in the entire dataset (**inverse document frequency**).

```
from sklearn.feature_extraction.text import TfidfTransformer
tfidf = TfidfTransformer(norm='l1')


tfidf.fit(vectorized_training_data)
tfidf_vectorized_data =
tfidf.transform(vectorized_training_data)
```

Again, scikit learn saves the day by providing tf-idf out of the box. Simply **fit** the model to your vectorized training data, and then use the **transform** method to transform it.

The vector after applying tf-idf. (Sorry about the bad formatting)

The algorithm

After all the data has been **cleaned**, **vectorised** and **transformed**, we can finally start doing some machine learning, which is one of the simplest parts of this task.

I first sliced the data into 70% training data and 30% testing data, and then started off with two scikit learn algorithms: Random Forest (RF) and K Nearest Neighbors (KNN). It quickly became clear that RF outperformed KNN, as the former quickly reached more than 80% accuracy while the latter stayed at 60%.

Fitting a scikit learn model is super simple:

```
def runForest(X_train, X_test, Y_train, Y_test):
 forest = RandomForestClassifier(n_estimators=100)
 forest = forest.fit(X_train, Y_train)
 score = forest.score(X_test, Y_test)
 return score


forest_score = runForest(X_train, X_test, Y_train, Y_test)
```

So I continued with RF to see how much I could increase the accuracy by tuning the following parameters:

- **Vocabulary:** how many words the CountVectorizer includes in the vocabulary (currently 5K)
- **Gram Range:** size of phrases to include in Bag Of Words (currently 1–3, meaning up until '3 word'-phrases)
- **Estimators:** amount of estimators to include in Random Forest (currently 90)

With these parameters tuned, the algorithm reaches an accuracy of 86,4% on the testing dataset, and is actually starting to become useful for our sales team.

The road ahead

However, the script is by no means finished. There are **tons** of way to improve it. For example, the algorithm is likely to be biased towards the kind of descriptions we currently have in our training data. This might become a performance bottle neck when testing it on more real world data.

Here are a few activities we're considering to do in the road ahead:

- Get more data (scraping, other API's, improve data cleaning)
- Test other types of data transformation(e.g. word2vec)

- Test other ml algorithms (e.g. neural nets)

We'll be pushing to GitHub regularly if you want to follow the progress. And feel free to leave a comment below if you have anything you'd like to add.

Cheers,

Per Harald Borgen

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Thanks for reading! We are Xeneta—the world's leading sea freight intelligence platform. We're always looking for bright minds to join us, so head over to our website if you're interested!

You can follow us at both Twitter and Medium.