Marketing Material

Step by Step Guide to Natural Language Processing: Extract ESG Sentiment from Company Reports

RAM Systematic Equity Team

06.10.2022

ACTIVE INVESTMENTS

Table of Content

- Natural Language Processing
  - Rule based
  - Statistics based
  - Machine learning based

- Applications to Sustainable Finance
  - Sentiment extraction
  - Implementation demo

Demo on Google Colaboratory

Structured and Unstructured Data

Structured Data

	A	B	C	D	E	F	G
1	Date	Open	High	Low	Close	Volume	
2	23-Aug-16	52.77	52.77	51.69	52	536708	
3	22-Aug-16	52.04	52.62	51.61	52.12	505987	
4	19-Aug-16	51.5	52.77	51.5	52.15	532715	
5	18-Aug-16	51.37	51.7	51.06	51.61	455721	
6	17-Aug-16	51.31	51.59	51.01	51.42	574666	
7	16-Aug-16	51.76	52.04	51.22	51.48	574858	
8	15-Aug-16	51.25	52.3	51	51.89	745329	
9	12-Aug-16	50.98	51.25	50.7	51.18	492953	
10	11-Aug-16	51	51.24	50.15	50.9	601622	
11	10-Aug-16	50.72	51.06	49.97	50.75	746181	
12	9-Aug-16	51.03	51.17	50.51	50.95	795285	
13	8-Aug-16	50.83	51.72	50.58	50.91	1141620	
14	5-Aug-16	49.24	50.48	49.15	50.46	1099180	
15	4-Aug-16	48.4	49.25	48.3	49.01	947769	
16	3-Aug-16	48.55	49.04	48.03	48.3	908821	
17	2-Aug-16	49.22	49.3	48.09	48.57	1738877	
18	1-Aug-16	48.5	49.54	47.84	49.46	1470115	
19	29-Jul-16	49.55	49.68	47.86	48.59	2333035	
20	28-Jul-16	46.33	50	46	49.82	7145374	

Unstructured Data

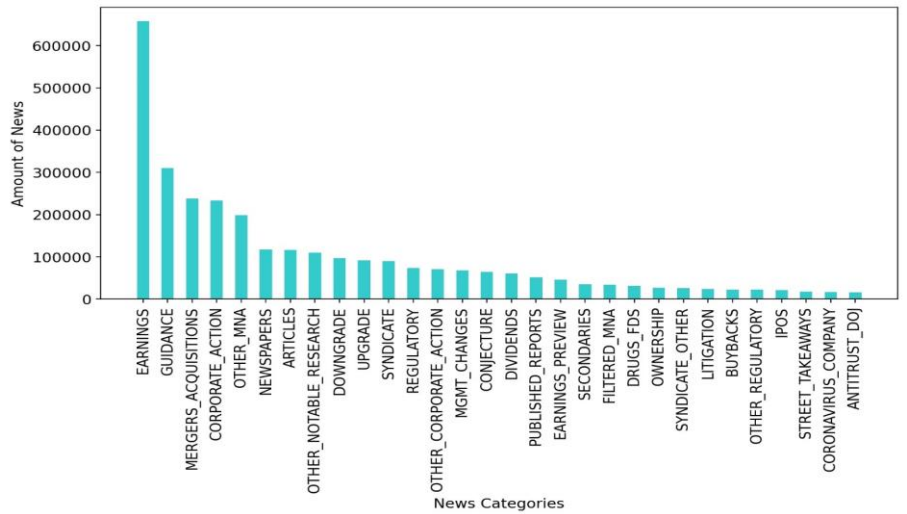
Financial news

Headline:

MWD says ABT lost Red Cross contract

Content:

The firm said they did not believe the contract to be that important to ABT, but that it could cause pressure in the stock as the news is disseminated.



Source: RAM Active Investments, StreetAccount, Factset.

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Quantitative Analysis

$$\mathbf{x} \in \mathbb{R}^d \quad y \in \mathbb{R} \quad \hat{y} = f(\mathbf{X})$$

$$\hat{y} = \sum_{i=1}^{d} w_i x_i + b$$

$$\hat{y} = \mathrm{w}^\top \sigma(\mathbf{W}\mathbf{x} + \mathbb{B}) + b$$

Structured and Unstructured Data

Unstructured Data

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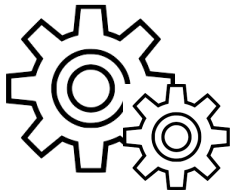
Transformation



1/1/2017	279,206	695,533	400,000	187,259
2/1/2017	387,480	799,862	400,000	215,348
3/1/2017	571,995	919,842	400,000	247,650
4/1/2017	844,187	1,057,818	400,000	284,797
5/1/2017	1,217,208	1,216,491	400,000	327,517
6/1/2017	1,706,182	1,398,964	400,000	430,451
7/1/2017	2,274,695	1,608,809	400,000	495,018
8/1/2017	2,988,486	1,850,130	400,000	569,271

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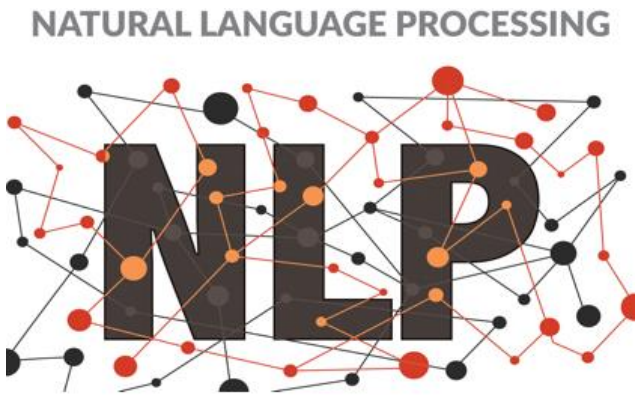
Natural Language Processing



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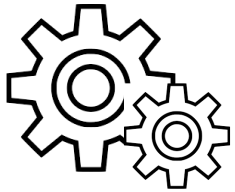

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Source: Chris Kuo/Dr. Dataman, "Looking into Natural Language Processing", https://medium.com/dataman-in-ai/natural-language-processing-nlp-for-electronic-health-record-ehr-part-i-4cb1d4c2f24b, 2018

Natural Language Processing

NLP development phases:

- Rule based
- Statistics based
- Machine learning based

“In the early 1900s, a Swiss linguistics professor named Ferdinand de Saussure almost deprived the world of the concept of “Language as a Science.”

“NLP makes computers capable of ‘understanding’ the contents of documents”

Source: Keith D. Foote, “A Brief History of Natural Language Processing”, https://www.dataversity.net/a-brief-history-of-natural-language-processing-nlp/, 2019.

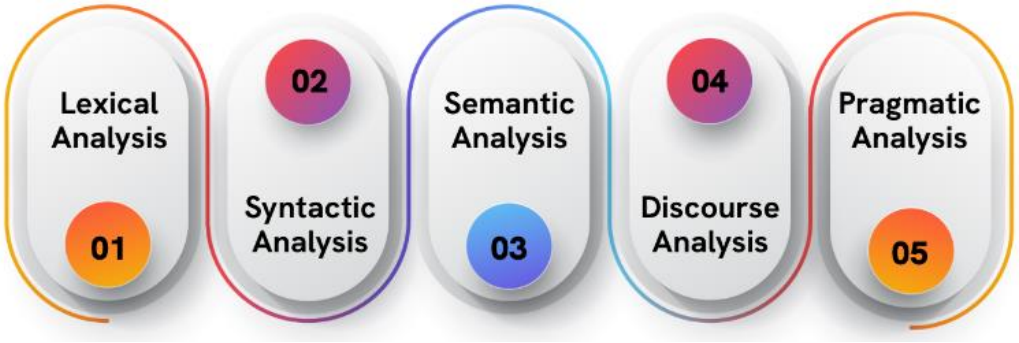
Natural Language Processing

Rule-based

- Automatic parsing and information extraction
- Discretionary analysis

NLP development phases:

- Rule based
- Statistics based
- Machine learning based



Source: OptiSol, “The 5 phases of natural language processing”, https://www.optisolbusiness.com/insight/the-5-phases-of-natural-language-processing, 2022

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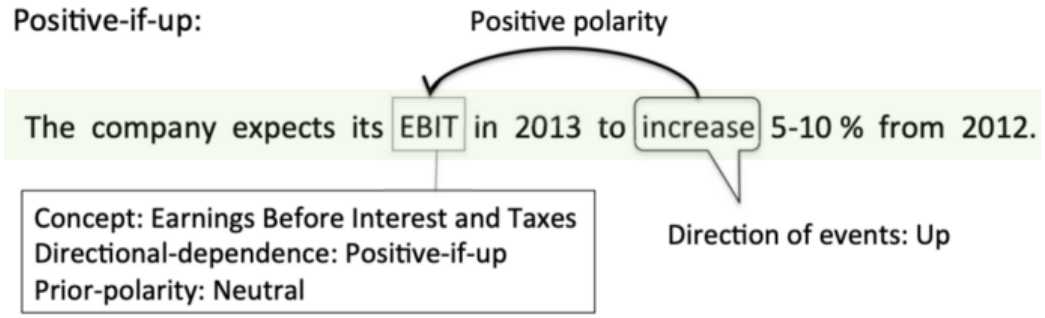
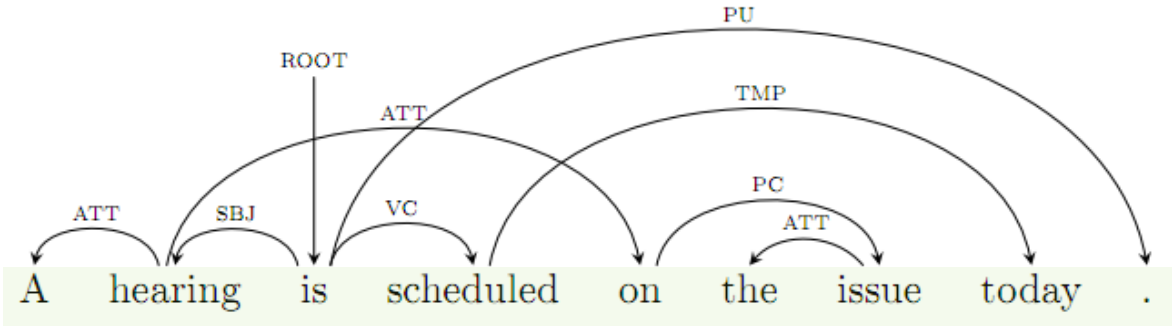




Source: Neo Yi Peng," How NLP has evolved for Financial Sentiment Analysis", "https://towardsdatascience.com/how-nlp-has-evolved-for-financial-sentiment-analysis-fb2990d9b3ed, 2020.
Matt Payne, "7 NLP Techniques for Extracting Information from Unstructured Text using Algorithms", https://www.width.ai/post/extracting-information-from-unstructured-text-using-algorithms, 2021.

Natural Language Processing

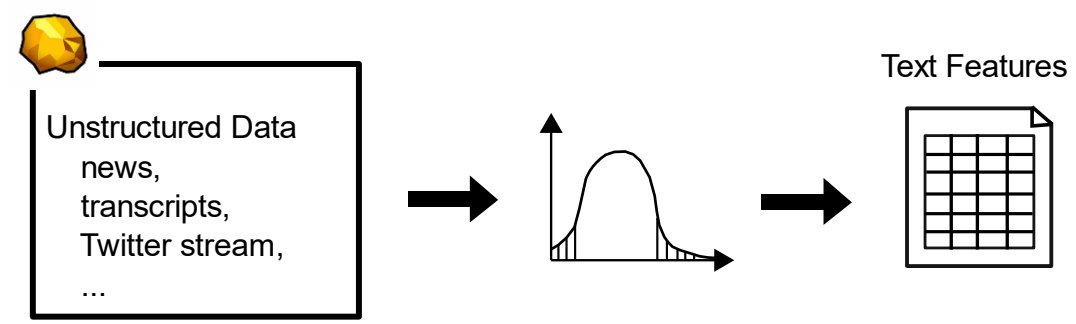
Statistics-based

- Language models
- Topic models
- Linguistic feature extraction

NLP development phases:

- Rule based
- Statistics based
- Machine learning based

Data



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Language models

(probability) Generative models

$$P(w_1 w_2 \ldots w_n) = \prod_i P(w_i \mid w_1 w_2 \ldots w_{i-1})$$

$$P(\text{next word} = ? \mid \text{The company expects its})$$

e.g., EBIT, annual return, etc.

Applications: machine translation,
speech recognition,
spelling correction, etc.

Tower of Babel

Source: Wikipedia

Natural Language Processing

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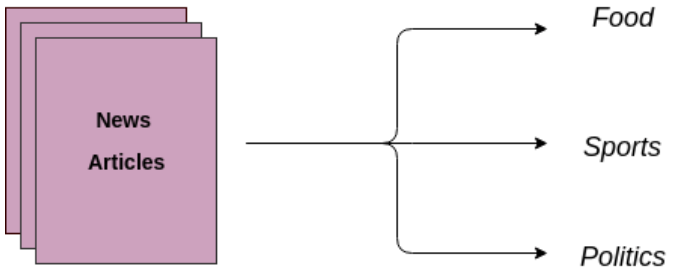
Topics models

Generative latent variable models

Latent Dirichlet allocation

$$P(\boldsymbol{Z}, \boldsymbol{W}; \alpha, \beta) = \int_{\boldsymbol{\theta}} \int_{\boldsymbol{\varphi}} P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta)\, d\boldsymbol{\varphi}\, d\boldsymbol{\theta}$$

$$P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta) = \prod_{i=1}^{K} P(\varphi_i; \beta) \prod_{j=1}^{M} P(\theta_j; \alpha) \prod_{t=1}^{N} P(Z_{j,t} \mid \theta_j) P(W_{j,t} \mid \varphi_{Z_{j,t}}),$$



Source: Khuyen Tran, ”pyLDAvis: Topic Modelling Exploration Tool That Every NLP Data Scientist Should Know”, https://neptune.ai/blog/pyldavis-topic-modelling-exploration-tool-that-every-nlp-data-scientist-should-know, 2022.

Natural Language Processing

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NLP development phases:

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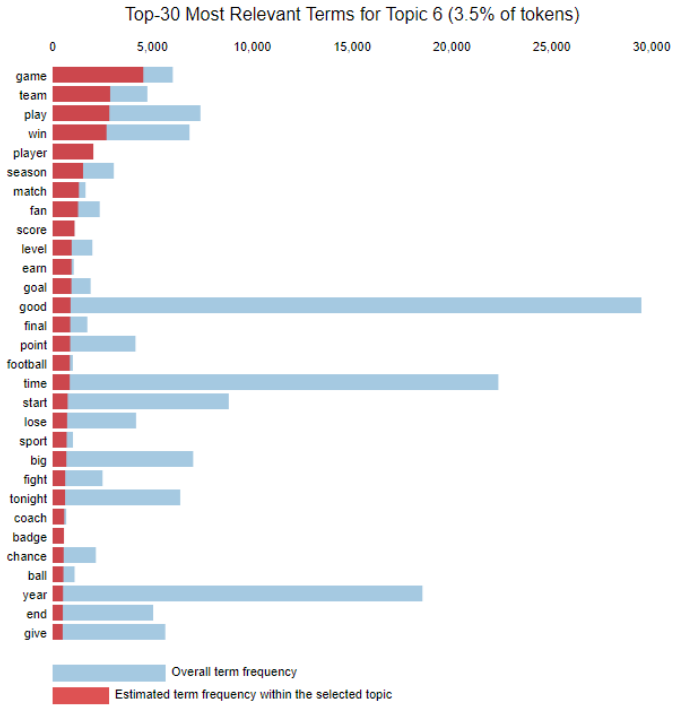
Topics models

Generative latent variable models

	Topic 1	Topic 2	Topic 3	Topic 4
1	blackstone	settlement	xbox	goog
2	bids	parties	processor	google
3	bidders	termination	dvd	aapl
4	bidding	litigation	sne	msft
5	auction	connection	game	ipod
6	situation	inc	processors	apple
7	private	entered	models	nflx
8	citing	agreement	players	software
9	people	agreements	gb	itunes
10	unit	relating	series	windows



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Natural Language Processing

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NLP development phases:

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Topics models: Generative latent variable models

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Doc. 1	32%	59%	4%	2%	3%
Doc. 2	25%	26%	23%	12%	13%
Doc. 3	65%	4%	3%	4%	24%
Doc. 4	34%	4%	14%	9%	39%
Doc. 5	14%	25%	2%	17%	41%
Doc. 6	16%	6%	2%	18%	59%
Doc. 7	21%	9%	27%	7%	36%
Doc. 8	5%	3%	21%	49%	21%
Doc. 9	10%	3%	17%	48%	23%

Source: Boemer, Dominik. "Topic modeling of investment style news." (2020).

	Topic 1	Topic 2	Topic 3	Topic 4
1	blackstone	settlement	xbox	goog
2	bids	parties	processor	google
3	bidders	termination	dvd	aapl
4	bidding	litigation	sne	msft
5	auction	connection	game	ipod
6	situation	inc	processors	apple
7	private	entered	models	nflx
8	citing	agreement	players	software
9	people	agreements	gb	itunes
10	unit	relating	series	windows

Natural Language Processing

Statistics-based

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- Statistics based
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Linguistic feature extraction

Domain-specific lexicons

e.g., positive, negative, litigious, polarity, risk, readability, fraud, safe, certainty, uncertainty, and sentiment.

	ticker	text2score	positive	negative	certainty	uncertainty	risk	safe	litigious	fraud	sentiment	polarity	readability
0	AMZN	Management's Discussion and Analysis of Financ...	0.098471	0.035031	0.044420	0.034790	0.051402	0.058505	0.041652	0.042013	0.075	0.475203	18.28
1	MSFT	STATEMENT OF MANAGEMENT'S RESPONSIBILITY FOR F...	0.110902	0.054511	0.080827	0.046992	0.069549	0.084586	0.084586	0.067669	0.110	0.340909	24.43
2	GOOG	MANAGEMENT'S DISCUSSION AND ANALYSIS OF FINANC...	0.103122	0.038239	0.046985	0.036408	0.052273	0.069257	0.030001	0.032442	0.069	0.458993	21.83
3	27904	This section of this Form 10-K does not addres...	0.097858	0.031033	0.044836	0.032366	0.036173	0.062922	0.028939	0.026559	0.113	0.518464	14.80
4	UBER	The following discussion and analysis of our f...	0.105012	0.041169	0.047998	0.037987	0.058671	0.070406	0.038186	0.034275	0.106	0.436735	23.16

Source: Sanjiv Das, Bodhisatta Saha, Daniel Zhu, and Derrick Zhang, "Create a dashboard with SEC text for financial NLP in Amazon SageMaker JumpStart", https://aws.amazon.com/blogs/machine-learning/create-a-dashboard-with-sec-text-for-financial-nlp-in-amazon-sagemaker-jumpstart/, 2021.

Natural Language Processing

Rule-based

- Automatic parsing and information extraction
- Discretionary analysis

Statistics-based

- Language models
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Drawbacks

- Lack of semantic distinguishability
- Lack of end-to-end development
- …

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Doc. 1	32%	59%	4%	2%	3%
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"NOK hopes its N-Gage mobile phone will boost sales and attract younger generation…"

"HBC and BCS upgraded to outperform from peer perform at Bear Stearns… "

"BEAS upgraded to overweight from equal weight at ThinkEquity…"

Source: StreetAccount

Natural Language Processing

Machine learning based

Text embedding: define meaning with coordinates/vectors

An introductory example:

	Country	Capital	Greek	Italian
Italy	1	0	0	1
Rome	0	1	0	1
Athens	0	1	1	0

$$X = \text{Italy} - \text{Rome} + \text{Athens}$$

Greece	1	0	1	0

NLP development phases:

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Source: Yuli Vasiliev, “Using Word Vectors to Mathematically Find Words with Similar Meanings”, https://towardsdatascience.com/using-word-vectors-to-mathematically-find-words-with-similar-meanings-fc9eadac3dbe, 2020.

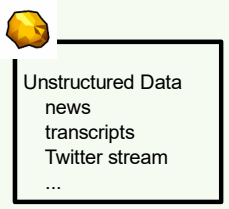
Natural Language Processing

Machine learning based

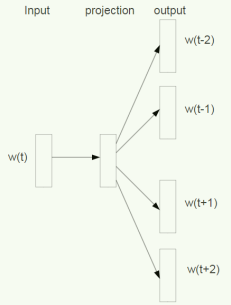
Text embedding
- High-dimensional vectors in the semantic space
- hundreds of dimensions
- Downstream tasks

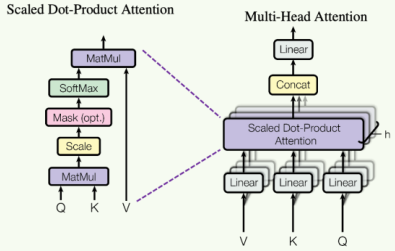
Data:
- Large generic corpus
- Domain-specific data

Wikipedia

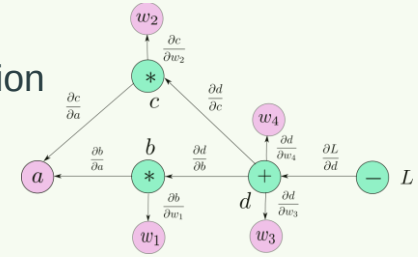


Model architecture:
- Similarity
- Relevance
- …





Model training:
- Automatic differentiation
- Computing power



Source:
(1) Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." Advances in neural information processing systems 26 (2013).
(2) Yasuto Tamura, ”Multi-head attention mechanism: “queries”, “keys”, and “values,” over and over again”, https://data-science-blog.com/blog/2021/04/07/multi-head-attention-mechanism/, 2021.
(3) Ayoosh Kathuria, ”PyTorch 101, Part 1: Understanding Graphs, Automatic Differentiation and Autograd”, https://blog.paperspace.com/pytorch-101-understanding-graphs-and-automatic-differentiation/, 2020.

NLP development phases:
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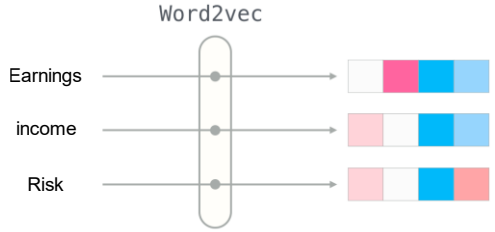
Natural Language Processing

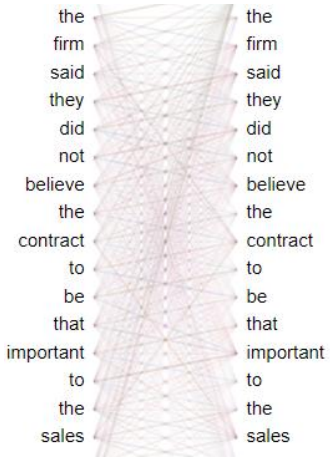
Machine learning based

Text embedding

- Word embedding



- Contextualized embedding
  - through large language models



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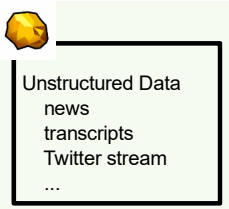
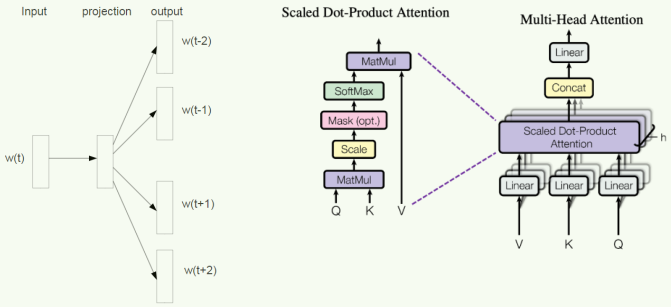
- Domain-specific data

Wikipedia



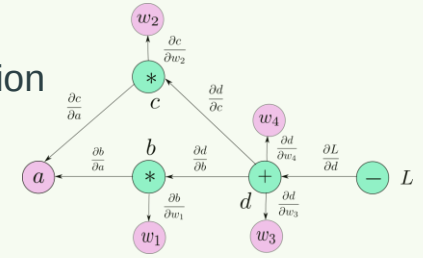
Model architecture:

- Similarity
- Relevance
- …



Model training:

- Automatic differentiation
- Computing power



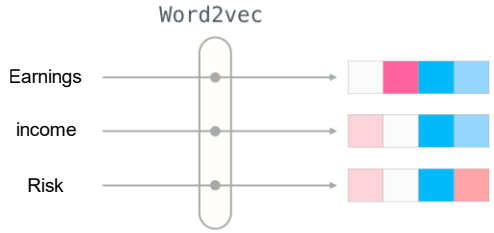
Source:
(1) Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." Advances in neural information processing systems 26 (2013).
(2) Yasuto Tamura,"Multi-head attention mechanism: "queries", "keys", and "values," over and over again", https://data-science-blog.com/blog/2021/04/07/multi-head-attention-mechanism/, 2021.
(3) Ayoosh Kathuria, "PyTorch 101, Part 1: Understanding Graphs, Automatic Differentiation and Autograd", https://blog.paperspace.com/pytorch-101-understanding-graphs-and-automatic-differentiation/, 2020.
(4) Jay Alammar, "The Illustrated Word2vec", https://jalammar.github.io/illustrated-word2vec/, 2019.

Natural Language Processing

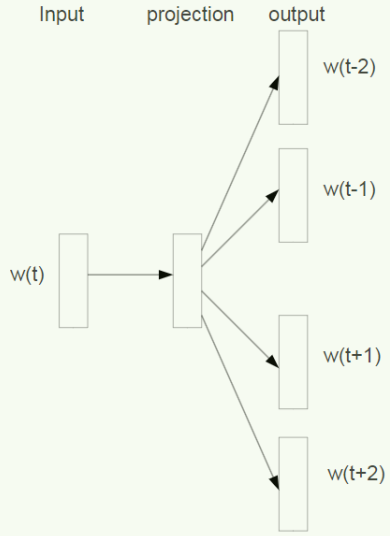
Machine learning based

Text embedding

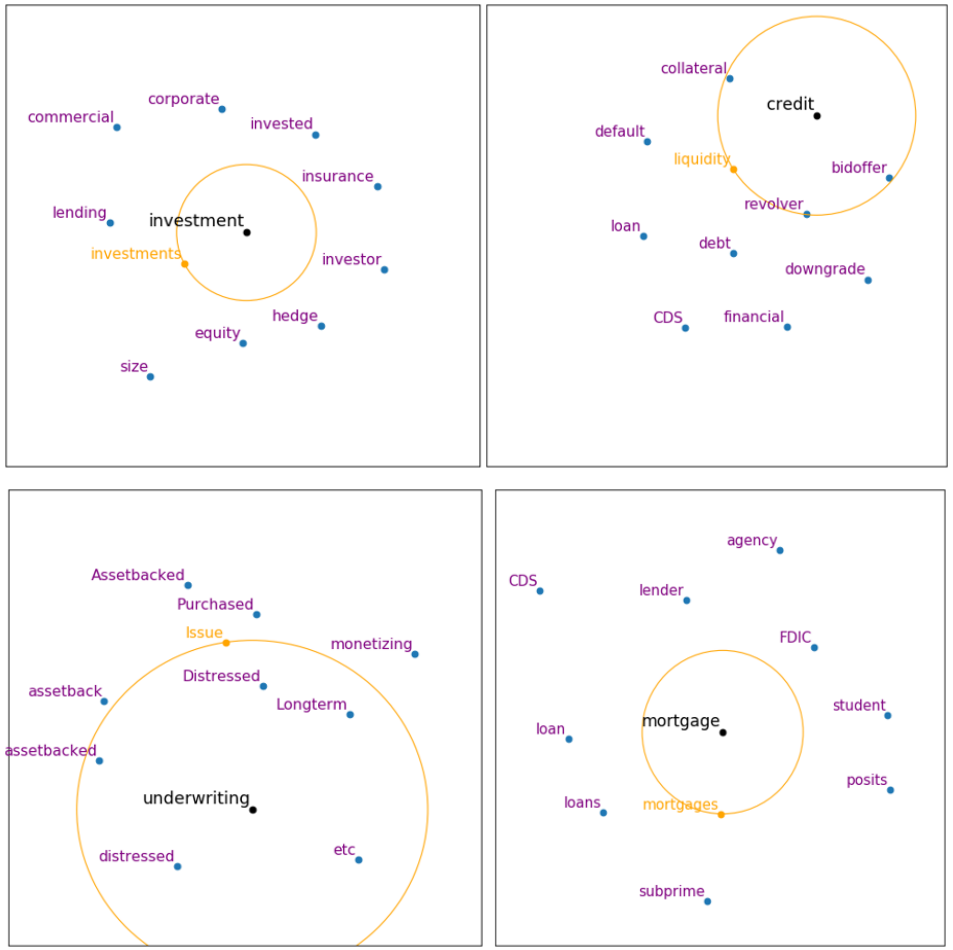
- Word embedding



"The firm said they did not believe the contract to be that important to the sales."



Minimize $\log \sigma(v'_{wO}{}^{\top} v_{wI}) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P_n(w)} \left[\log \sigma(-v'_{w_i}{}^{\top} v_{wI}) \right]$



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(2) Manu Siddhartha, "BankFin Embeddings : Customized word embeddings Pre-Trained on Financial Text corpus for Financial NLP tasks", https://github.com/sid321axn/bank_fin_embedding, 2020.

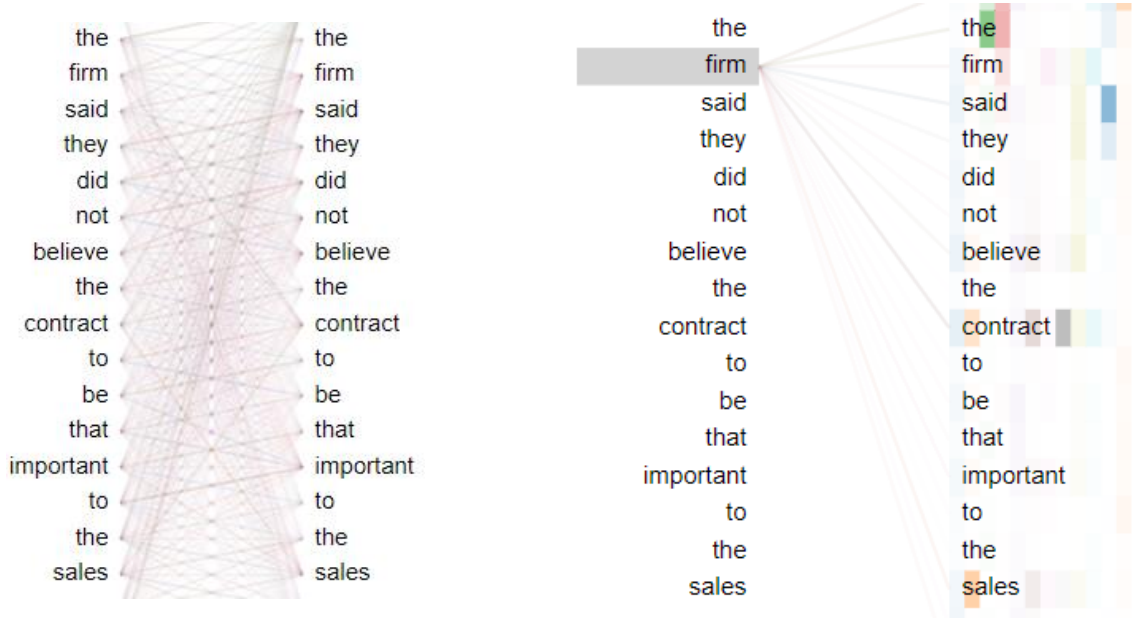
Natural Language Processing

Machine learning based

Text embedding

- Contextualized embedding

“The firm said they did not believe the contract to be that important to the sales."



Source:
(1) Jesse Vig, ”Visualize Attention in NLP Models”, https://github.com/jessevig/bertviz, 2022.
(2) Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems* 30 (2017).

Natural Language Processing

Machine learning based

Text embedding

- Contextualized embedding

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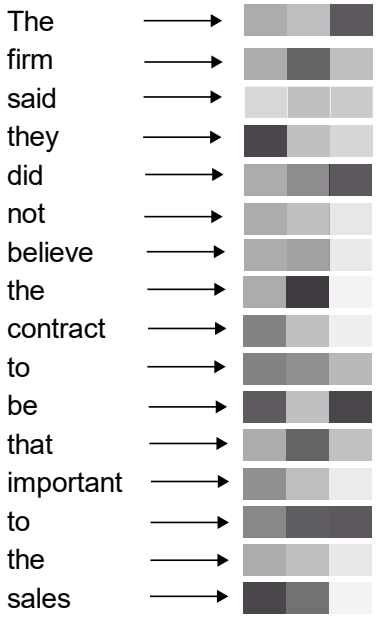

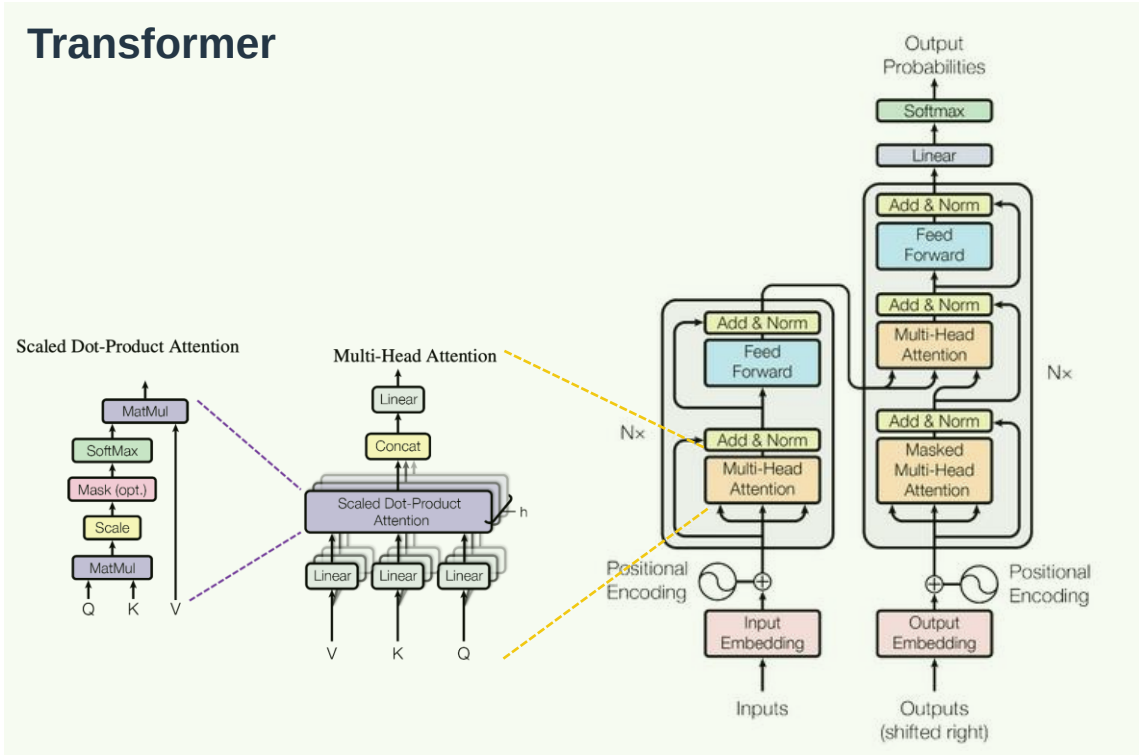

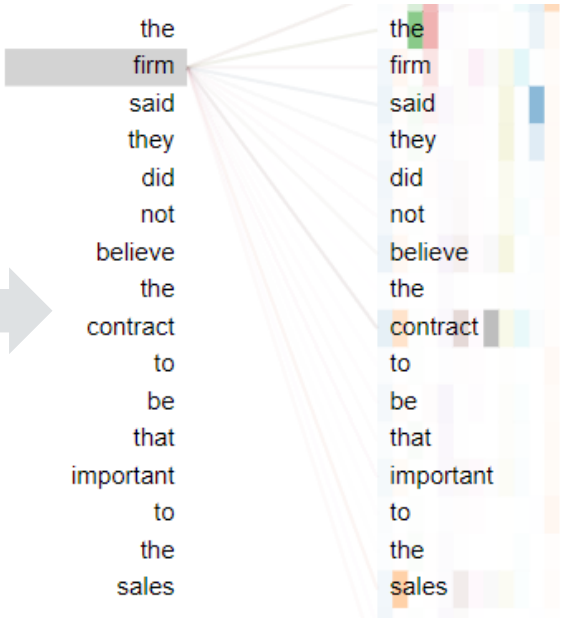

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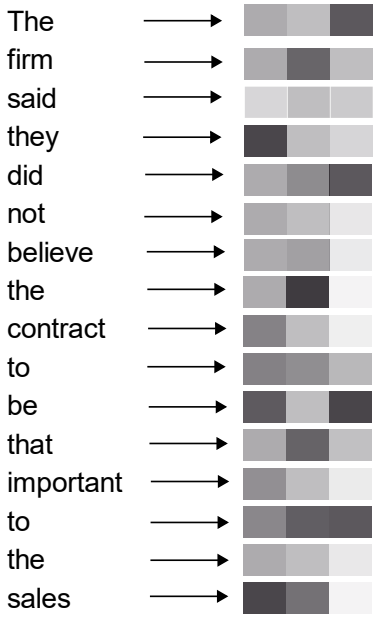
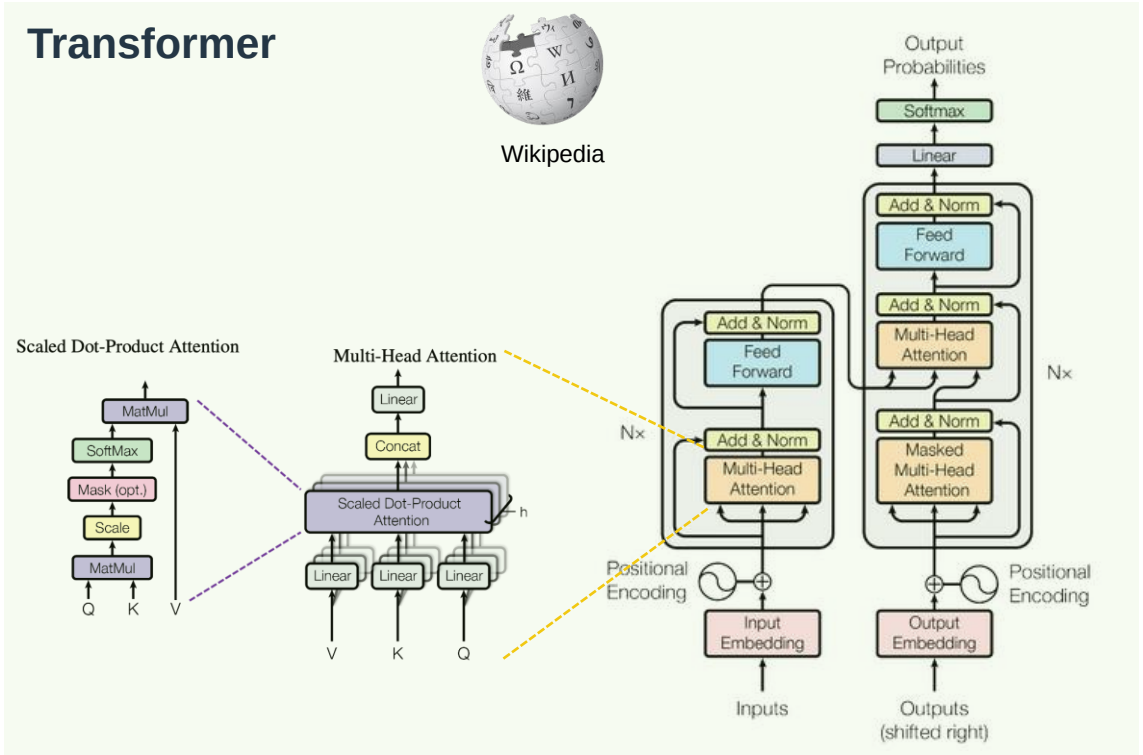
Natural Language Processing

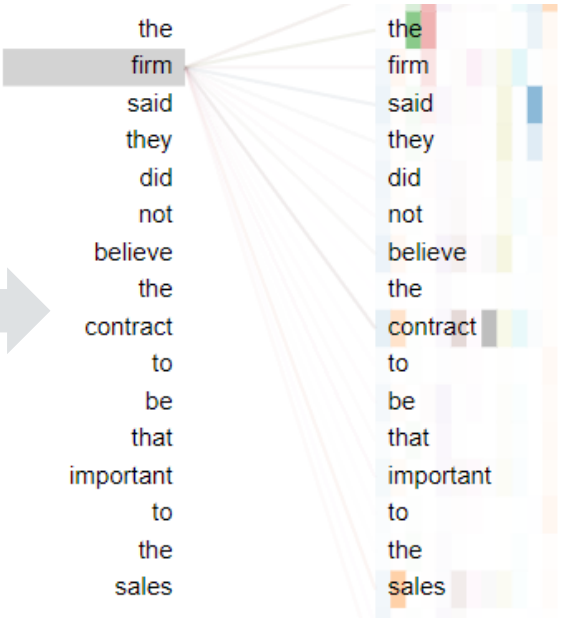
Machine learning based

Large language models

- Training tasks: (randomly) masked words, next sentence prediction, etc.







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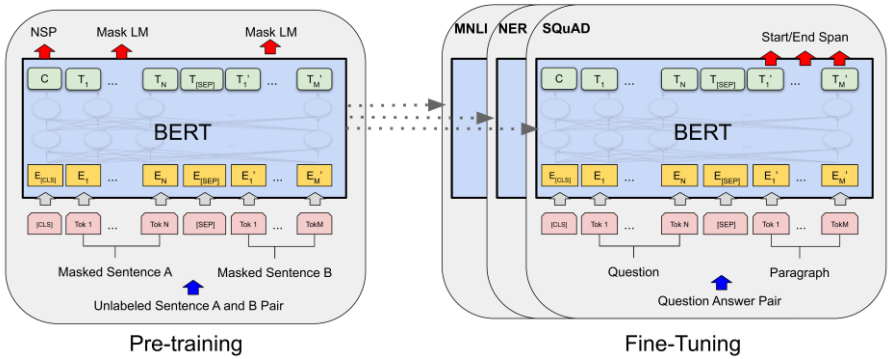
Natural Language Processing

Machine learning based

Large language models

- Pre-trained on large and general language corpus
- Fine-tuned on application specific data

Wikipedia



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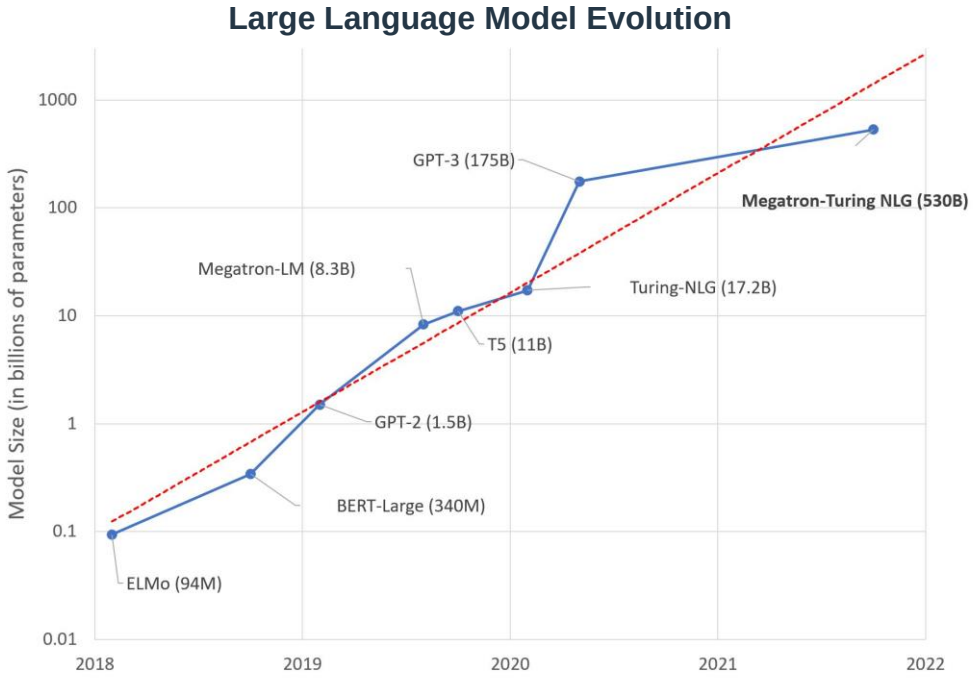


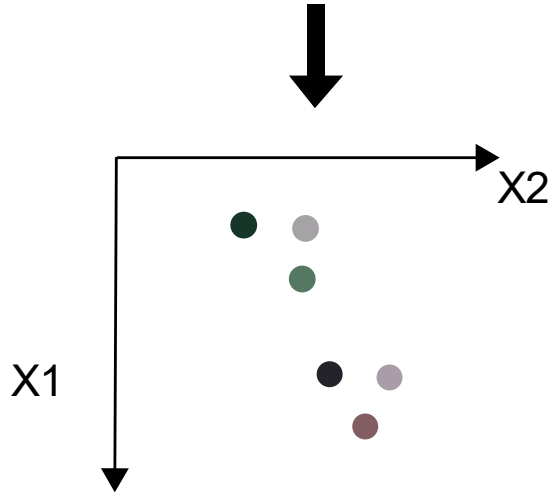
Source: Julien Simon, https://huggingface.co/blog/large-language-models, 2021.

Natural Language Processing

Applications of text embedding

- Text semantic similarity
- Text clustering
- …

- "...warms up to idea of potential acquisitions in new markets..."
- "...reports preliminary Q1 adjusted EBITDA €535M; raises FY outlook..."
- "Fundamentals in Residential Systems segment continue to be strong, driven by the new housebuild sector..."
- "A third of dealer network is closed and a third operating with limited capacity..."
- "...have cooled down merger negotiation talks due to the uncertainties surrounding coronavirus..."
- "...comments on a significant decrease of its share price over the last few days..."

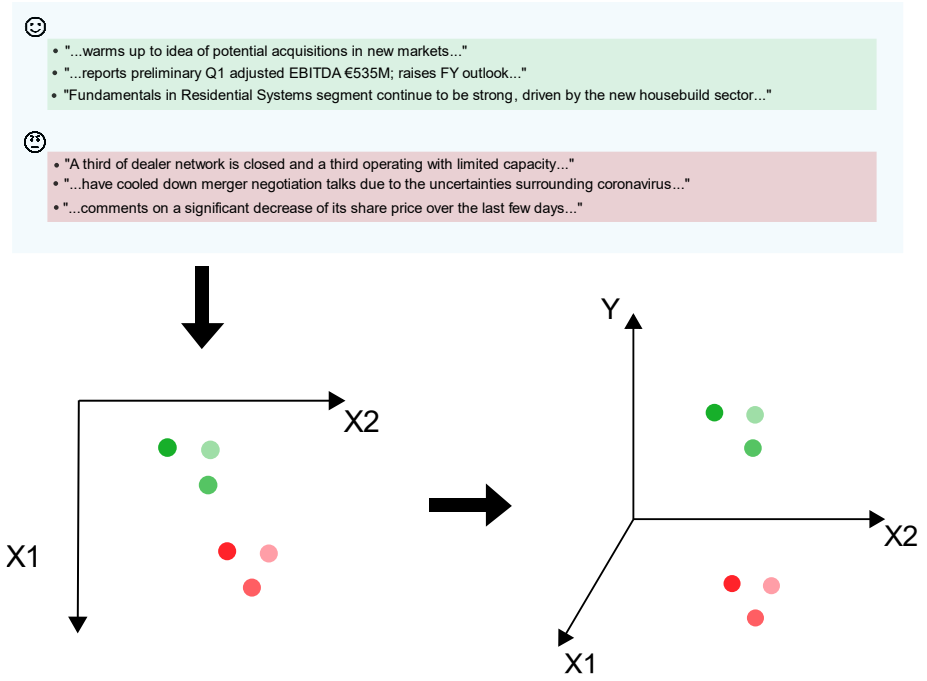


Natural Language Processing

Applications of text embedding

- Text semantic similarity
- Text clustering
- …

- Supervised learning and fine-tuning
  - Sentiments
  - ESG controversies
  - Stock Movements
  - …



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Source: P. Malo and A. Sinha and P. Korhonen and J. Wallenius and P. Takala, https://huggingface.co/datasets/financial_phrasebank/, 2020.

Natural Language Processing

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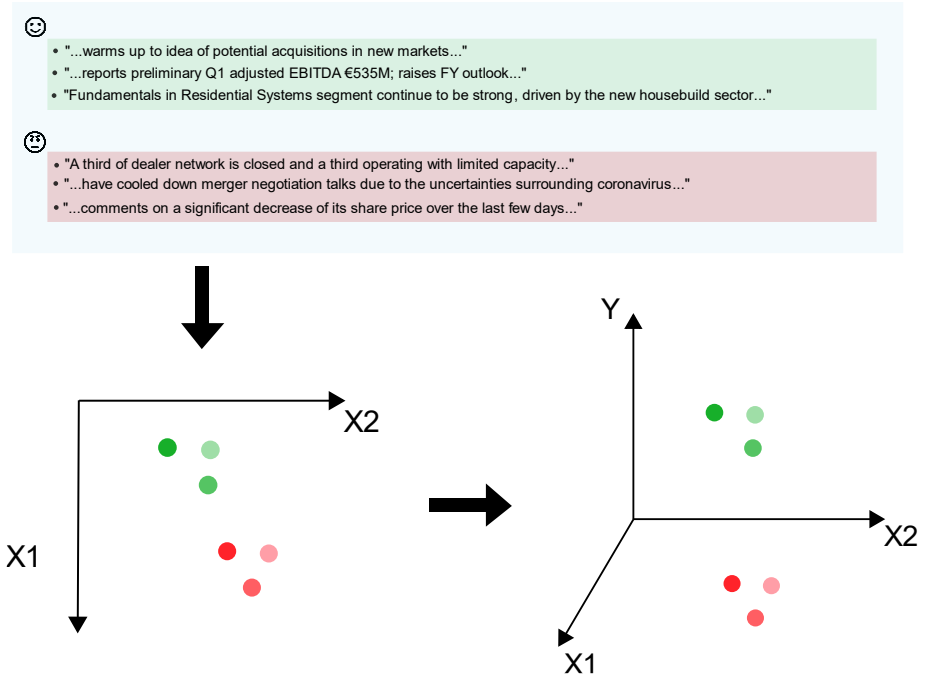

ESG Controversy
Accounting
Anti-Competition
Business Ethics
Consumer Complaints
Customer Health & Safety
Diversity & Opportunity
Employee Health & Safety
Environmental
General Shareholder Rights
Human Rights
Insider Dealings
Intellectual Property
Management Compensation
Management Departures
No Controversy
Privacy
Public Health
Responsible Marketing
Tax Fraud
Wages or Working Condition

Source: Nugent, Tim, Nicole Stelea, and Jochen L. Leidner. "Detecting ESG topics using domain-specific language models and data augmentation approaches." *arXiv preprint arXiv:2010.08319* (2020).

Natural Language Processing

Applications of text embedding

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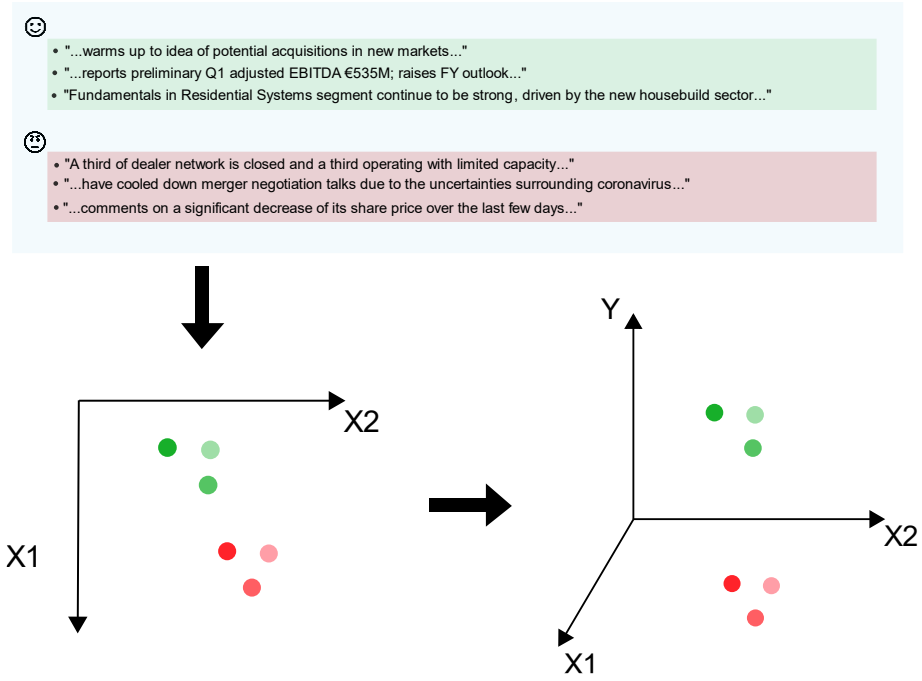
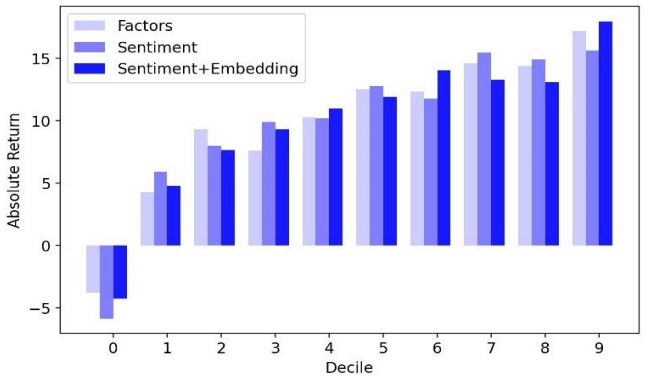


Source: RAM Active Investments

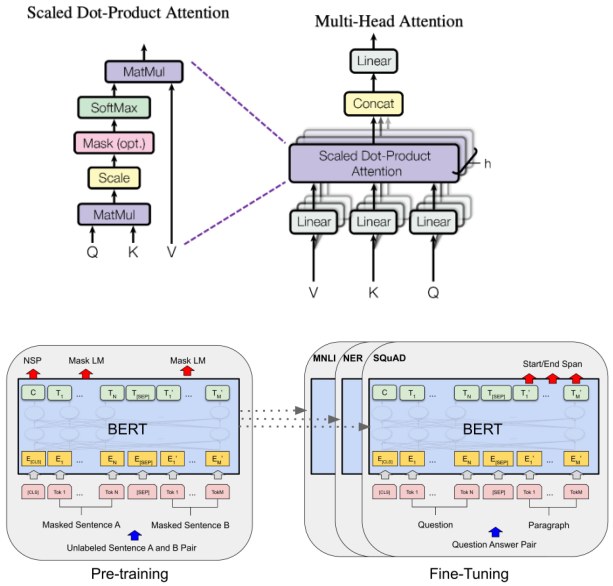


* Past performance is not a reliable indicator of future results.

Summary

$$P(\boldsymbol{Z}, \boldsymbol{W}; \alpha, \beta) = \int_{\boldsymbol{\theta}} \int_{\boldsymbol{\varphi}} P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta)\, d\boldsymbol{\varphi}\, d\boldsymbol{\theta}$$

$$P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta) = \prod_{i=1}^{K} P(\varphi_i; \beta) \prod_{j=1}^{M} P(\theta_j; \alpha) \prod_{t=1}^{N} P(Z_{j,t} \mid \theta_j) P(W_{j,t} \mid \varphi_{Z_{j,t}}),$$



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python™

```
import torch
from transformers import BertTokenizer, BertForSequenceClassification
```

Source:https://commons.wikimedia.org/wiki/File:Python_logo_and_wordmark.svg

ram ACTIVE INVESTMENTS

Demo

“If I had five minutes to chop down a tree, I'd spend the first three sharpening my axe.”

- Abraham Lincoln


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Demo

Data resources and Development tools

Google Dataset Search

https://datasetsearch.research.google.com/

Ceres SEC Sustainability Disclosure Search Tool

https://tools.ceres.org/resources/tools/sec-sustainability-disclosure/

PyTorch

https://pytorch.org/

Hugging Face Transformers

https://github.com/huggingface/transformers

pandas

https://pandas.pydata.org/

NLTK

https://www.nltk.org/#

ram ACTIVE INVESTMENTS

Demo

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Demo

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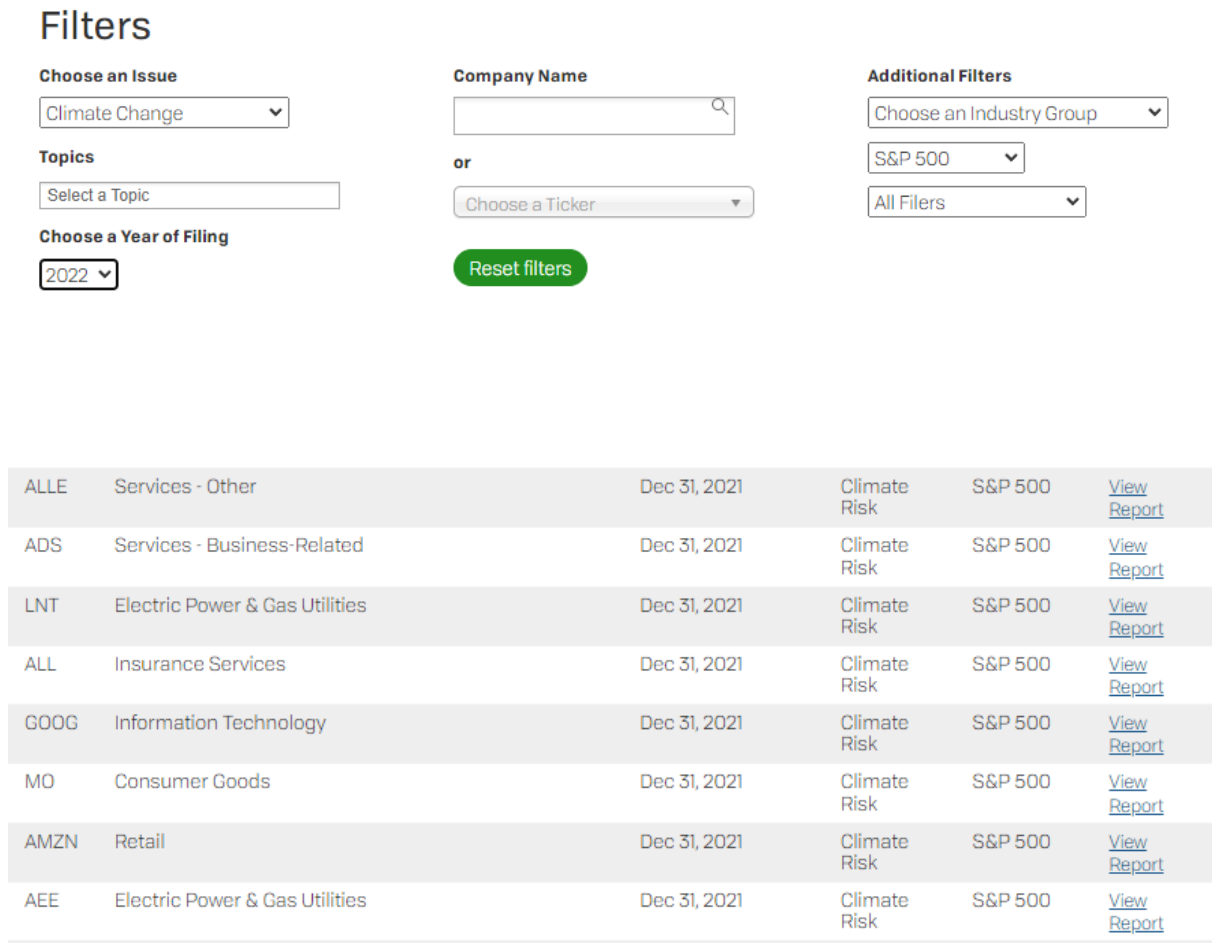

Demo

Data resources and Development tools

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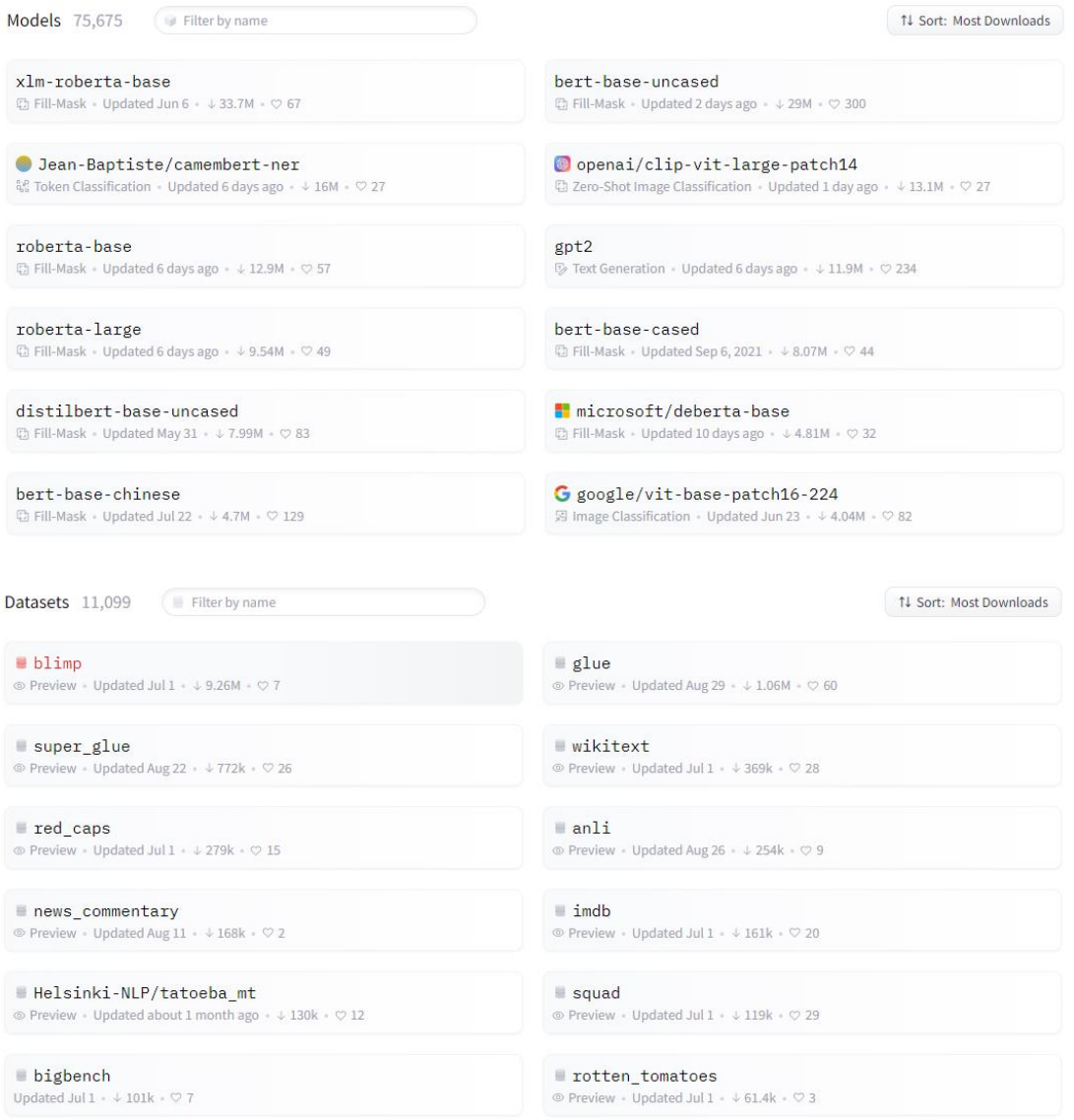

Demo

Demo on Google Colaboratory

```
import numpy as np
import pandas as pd
```

```
!pip3 install nltk

!pip install transformers[torch]
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: nltk in /usr/local/lib/python3.7/dist-packages (3.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages (from nltk) (1.1.0)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.7/dist-packages (from nltk) (2022.6.2)
Requirement already satisfied: click in /usr/local/lib/python3.7/dist-packages (from nltk) (7.1.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from nltk) (4.64.1)
```

```
# --- load data

report = {
    'cocik': '6281',
    'coname': 'ANALOG DEVICES INC',
    'p_date': '2009-12-31',
    'sector': 'Electronic Technology',
    'filename': '0000950123-09-065635',
    'abstracts': ["  We have developed products specifically for the automotive market which are used in such applications as:&amp;nbsp;*&amp;nbsp;Crash sensors in airbag systems Roll-over sensing Global positioning satellite (GPS)
    }
```

Demo

```python
# --- GPU or CPU

import torch
import os

import nltk
nltk.download('punkt')

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

```python
# --- import pre-saved model, e.g., FinBert finetuned on financial sentiment data

from nltk.tokenize import sent_tokenize, word_tokenize
from transformers import BertTokenizer, BertForSequenceClassification

finbert = BertForSequenceClassification.from_pretrained(
    'yiyanghkust/finbert-tone',
    num_labels = 3,
).to(device)

tokenizer = BertTokenizer.from_pretrained(
    'yiyanghkust/finbert-tone',
)
```

Demo on Google Colaboratory

Demo

```python
# extract a list of sentences from text paragraphs
sent_list = []
for tmp_text_parag in report['abstracts']:
  sent_list += sent_tokenize(tmp_text_parag)

tmp_tokenized_input = tokenizer(
    sent_list,
    max_length = 100,
    truncation = True,
    return_tensors = "pt",
    padding = True,
)
tmp_outputs = finbert(
    **tmp_tokenized_input.to(device),
    return_dict = True,
    output_hidden_states = True,
)
```

Demo on Google Colaboratory

Demo

```
# output the results

for idx, tmp in enumerate( tmp_outputs['logits'] ):
    print('\n',  'sentiment:', sentiment_logits_normalization(list(tmp.detach().cpu().numpy()),),  '; content:', sent_list[idx], )
```

```
sentiment: Positive ; content:   We have developed products specifically for the automotive market which are used in such applications as:&amp;nbsp;*&amp;nbsp;Crash sensors in airbag systems Roll-over sensing Global positi

sentiment: Neutral ; content:   New climate change regulations could require us to change our manufacturing processes or obtain substitute materials that may cost more or be less available for our manufacturing ope

sentiment: Neutral ; content: In addition, new restrictions on carbon dioxide or other greenhouse gas emissions could result in significant costs for us.

sentiment: Neutral ; content: Greenhouse gas legislation has been introduced in Massachusetts and the United States legislatures and we expect increased worldwide regulatory activity in the future.

sentiment: Negative ; content: The cost of complying, or of failing to comply, with these and other climate change and emissions regulations could have an adverse effect on our business plans and operating results.
```

Conclusion

$$P(\boldsymbol{Z}, \boldsymbol{W}; \alpha, \beta) = \int_{\boldsymbol{\theta}} \int_{\boldsymbol{\varphi}} P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta)\, d\boldsymbol{\varphi}\, d\boldsymbol{\theta}$$

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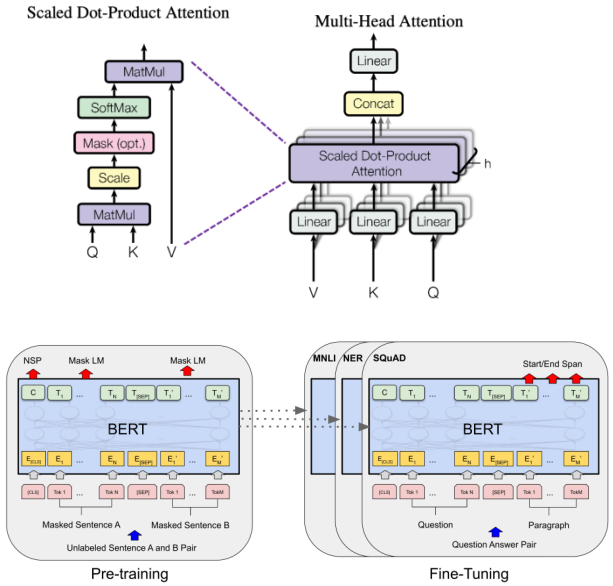

Source: generated by https://beta.dreamstudio.ai/dream via the Stable Diffusion technique.

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https://sfh22.sparkboard.com/projects

Build a Bad Buzz Factory for ESG Controversy Detection!

What is a Bad Buzz factory?

It is a machine learning infrastructure that generates artificial news articles about companies involved in ESG controversies.

What are ESG controversies?

They are negative events related to environmental, social and governance (ESG) topics.

Why do we need a Bad Buzz factory?

We aim to detect ESG controversies as soon as they occur to improve the sustainability of our equity portfolios. Training a machine learning model is an efficient method to detect such controversies within the news flow in an automatic and data-driven way. However, a large dataset is needed for the model training, and real-life news articles pose a real challenge in terms of data availability, labelling, copyrights, etc.

Could the solution be a Bad Buzz Factory that synthetically generates all the articles needed to train our model?

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