Actuarial Applications of Large Language Models

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Tutorial

www.actuarialdatascience.org

https://arxiv.org/abs/2206.02014

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Actuarial Data Science

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Actuarial Data Science Tutorials

On this page we present all the tutorials that have been prepared by the working party. We are intensively working on additional ones and we aim to have approx. 10 tutorials, covering a wide range of Data Science topics relevant for actuaries.

All tutorials consist of an article and the corresponding code. In the article, we describe the methodology and the statistical model. By providing you with the code you can easily replicate the analysis performed and test it on your own data.

Case Study 12: Actuarial Applications of Natural Language Processing Using Transformers: Case Studies for Using Text Features in an Actuarial Context

Article on arXiv

Code on GitHub ; Notebook (Part 1) ; Notebook (Part2)

Actuarial Applications of Natural Language Processing Using Transformers

Case Studies for Using Text Features in an Actuarial Context

Andreas Troxler * Jürg Schelldorfer **

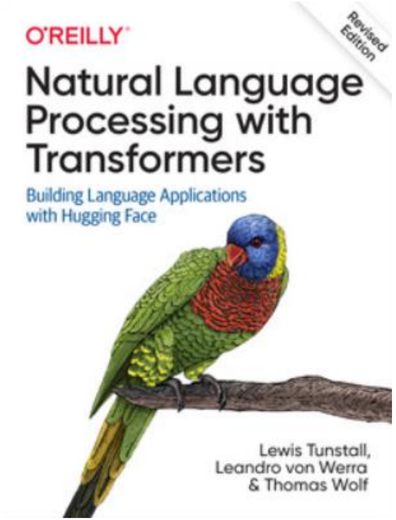
v1, 3 June 2022

Abstract

This tutorial demonstrates workflows to incorporate text data into actuarial classification and regression tasks. The main focus is on methods employing transformer-based models. A dataset of car accident descriptions with an average length of 400 words, available in English and German, and a dataset with short property insurance claims descriptions are used to demonstrate these techniques. The case studies tackle challenges related to a multi-lingual setting and long input sequences. They also show ways to interpret model output, to assess and improve model performance, by fine-tuning the models to the domain of application or to a specific prediction task. Finally, the tutorial provides practical approaches to handle classification tasks in situations with no or only few labeled data. The results achieved by using the language-understanding skills of off-the-shelf natural language processing (NLP) models with only minimal pre-processing and fine-tuning clearly demonstrate the power of transfer learning for practical applications.

Keywords. Natural language processing, NLP, transformer, multi-lingual models, domain-specific fine-tuning, integrated gradients, extractive question answering, zero-shot classification, topic modeling.

Book



Natural Language Processing with Transformers

Table of Content

Introduction

Definitions

- **Transformer**: A transformer is a **deep learning architecture** […]. The modern transformer was proposed in the 2017 paper titled 'Attention Is All You Need'. (Wikipedia)
- **Language Model:** A language model is a **probabilistic model of a natural language** that can generate probabilities of a series of words, based on text corpora in one or multiple languages it was trained on. (Wikipedia)
- **Large Language Model:** A large language model (LLM) is a language model characterized by its large size. Its size is enabled by AI accelerators, which are able to process vast amounts of text data, mostly scraped from the Internet.LLMs are **artificial neural networks which can contain a billion to a trillion weights**, and are (pre-)trained using self-supervised learning and semi-supervised learning. Transformer architecture contributed to faster training. Alternative architectures include the mixture of experts (MoE) […]. (Wikipedia)
- **Generative AI**: Generative artificial intelligence (also generative AI or GenAI) is artificial intelligence capable of **generating text, images, or other media**, using generative models. (Wikipedia)
- **HuggingFace:** Hugging Face, Inc. is a French-American company that develops tools for building applications using machine learning, based in New York City. It is most notable for its transformers library built for natural language processing applications and its **platform that allows users to share machine learning models and datasets** and showcase their work in a space. (Wikipedia)

Data

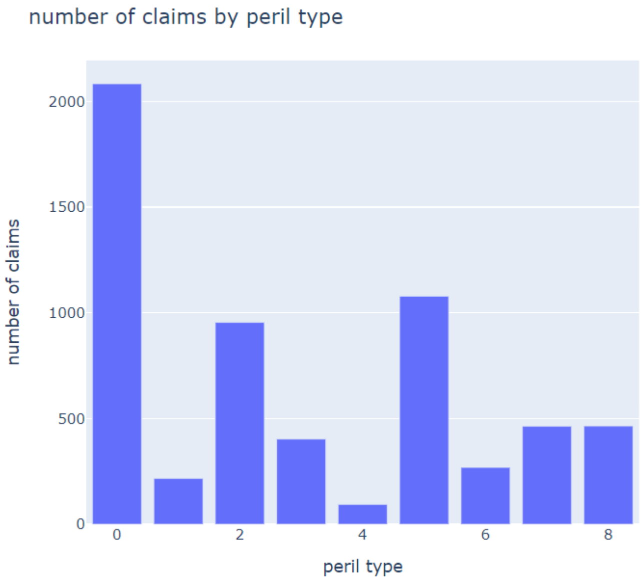
Data (1/4): Wisconsin Local Government Property Insurance Fund (LGPIF)

- The data consists of **6’030 records** (4’991 in the training set, 1’039 in the test set) which include a claim amount, a short English claim description and a hazard type with 9 different levels: Fire, Lightning, Hail, Wind, WaterW (weather related water claims), WaterNW (other weather claims), Vehicle, Vandalism and Misc (any other).
- The following exhibit shows an example

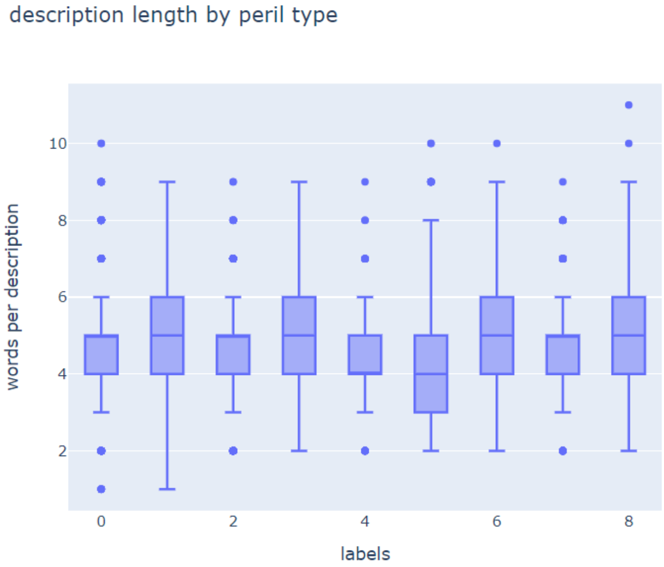
row	Vandalism	Fire	Lightning	Wind	Hail	Vehicle	WaterNW	WaterW	Misc	Loss	Description
1	0	0	1	0	0	0	0	0	0	6838.87	lightning damage
2	0	0	1	0	0	0	0	0	0	2085	lightning damage at Comm. Center
6	1	0	0	0	0	0	0	0	0	8775	surveillance equipment stolen
7	0	0	0	1	0	0	0	0	0	34610.27	wind blew stack off and damaged roof
9	0	0	0	0	0	1	0	0	0	9711.28	forklift hit building damaging wall and door frame
11	0	0	0	0	0	0	0	1	0	1942.67	water damage at courthouse
30	0	0	0	0	0	1	0	0	0	3469.79	light pole damaged

https://github.com/OpenActTexts/Loss-Data-Analytics/tree/master/Data

Data (2/4): Wisconsin Local Government Property Insurance Fund (LGPIF)



	peril	train	valid
0	Vandalism	1774	310
1	Fire	171	46
2	Lightning	832	123
3	Wind	296	107
4	Hail	76	18
5	Vehicle	852	227
6	WaterNW	202	67
7	WaterW	426	38
8	Misc	362	103
9	Total	4991	1039



Overall number of words by claim description:
min 1, average 5, max 11

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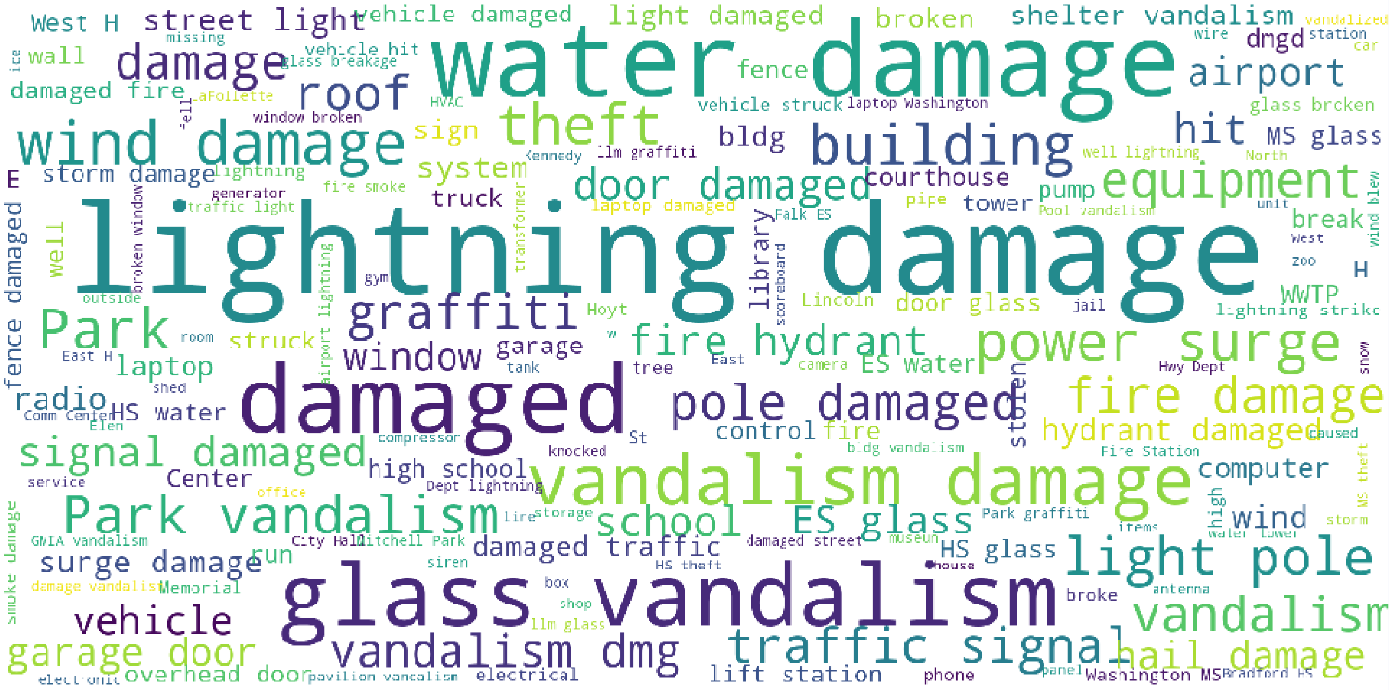
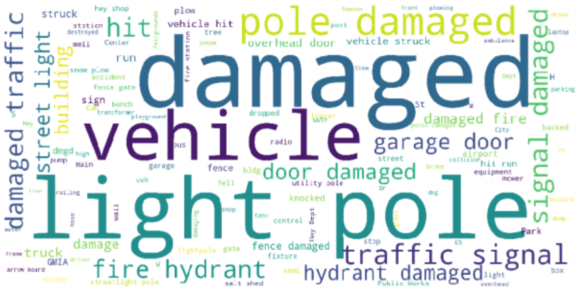
Data (3/4): Wisconsin Local Government Property Insurance Fund (LGPIF)



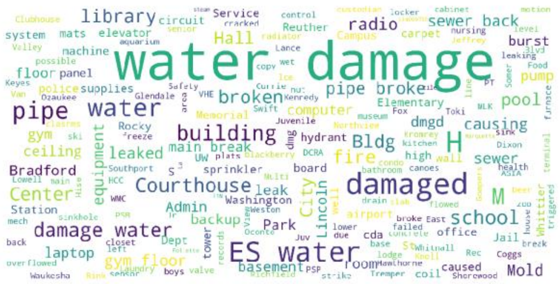
Data (4/4): Wisconsin Local Government Property Insurance Fund (LGPIF)

Vandalism

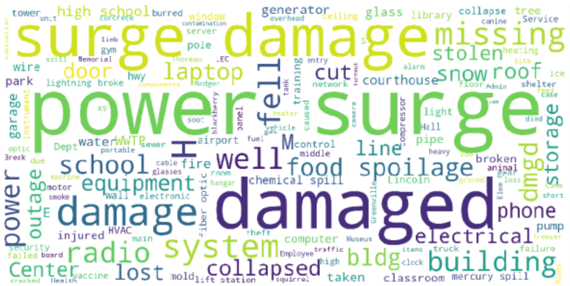
Vehicle



WaterNW



Misc



Framing the Business and Analytics Problem

- Business Problem: Classify the claims into the 8 categories based on the claims description.
- Analytics Problem: short property insurance claim description which we aim to classify by peril type.

- Classify by peril type in a supervised setting
  - We apply standard NLP supervised learning techniques to the dataset.
- Zero-shot classification
  - This technique assigns each text sample to one element of a pre-defined list of candidate expressions. This allows classification without any task-specific training and without using the labels. This fully unsupervised approach is useful in situations with no labels.
- Unsupervised classification using similarity
  - This technique encodes each *input sentence* and each *candidate expression* into en embedding vector. Then, pairwise similarity scores between each input sequence and each candiate expression are calculated. The candidate expression with the highest similarity score is selected. This fully unsupervised approach is useful in situations with no labels.
- Unsupervised topic modeling by clustering of document embeddings
  - This approach extracts clusters of similar text samples and proposes verbal representations of these clusters. The labels are not required, but may be used in the process if available. This technique does not require prior knowledge of candidate expressions.

Classify by peril type in a supervised setting

High-level approach

Label (Y)	Description (X)
Lightning	lightning damage
Vandalism	surveillance equipment stolen
Wind	wind blew stack off and damaged roof

How to fit a supervised model, when the feature space are words?

➔ First idea: Encode the words with one-hot-encoding like categorical features. This results in a very high-dimensional, sparse matrix X.

Y	Lignhtning	Damage	Center	Surveillanc e	Equipment	stolen	…
Lightning	1	1	0	0	0	0	…
Vandalism	0	0	0	1	1	1	…
Wind	0	1	0	0	0	0	…

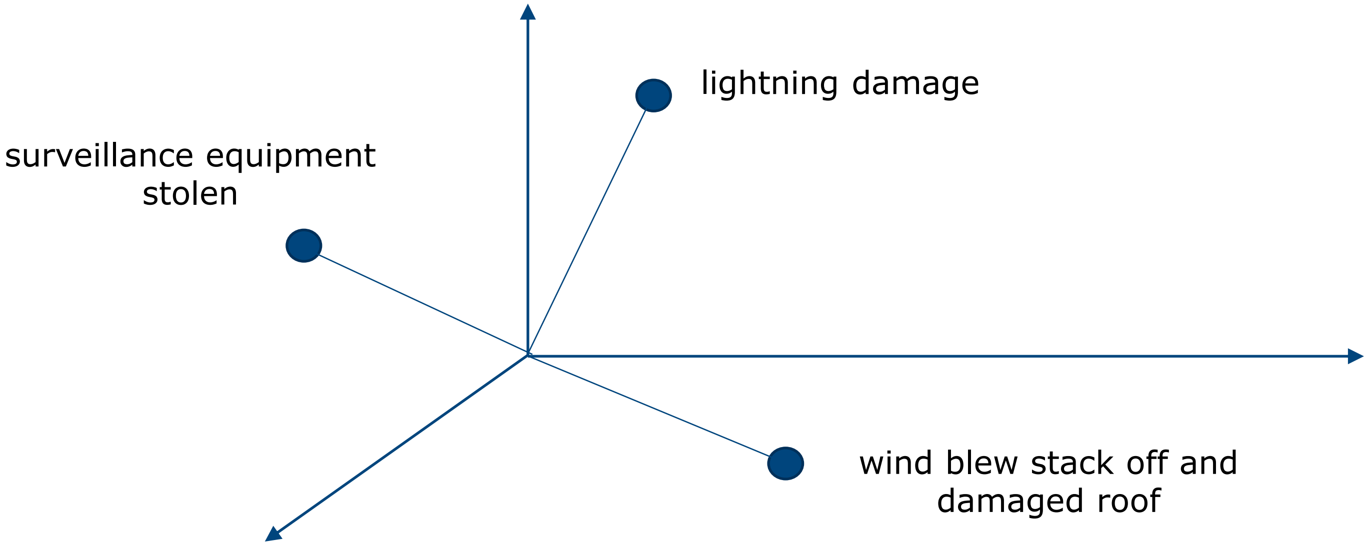
High-level approach

How to fit a supervised model, when the feature space are words?

➔ Second idea: Embed the sentences in a low-dimensional space, such that there is some logic when vectors are close to each other

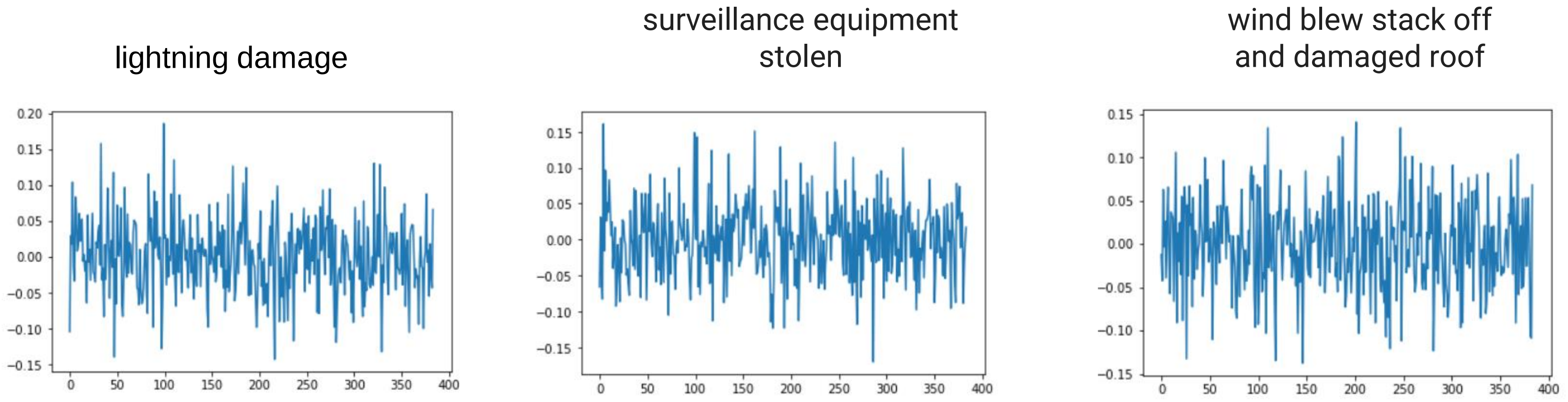
➔ **Transformers** are models that do that embedding. And recently, it has been shown that those embedings are really good, compared to older models some years ago.

➔ We do not go into details about transformers at this stage

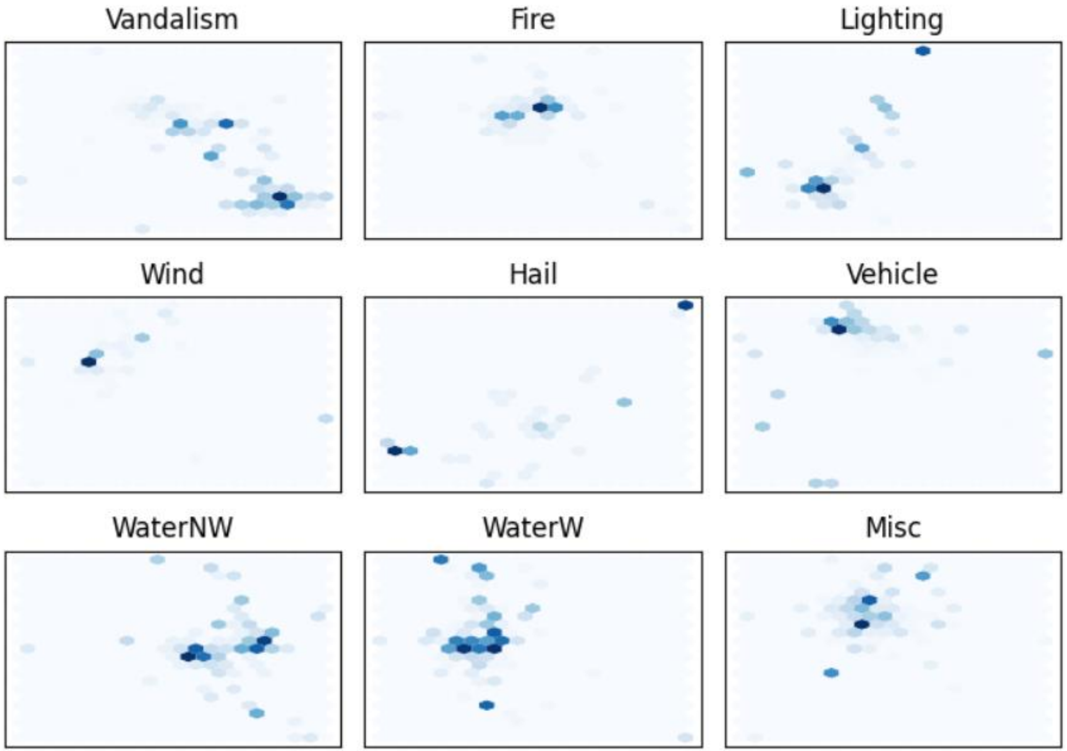


Features (1/2)

- x: 384 dimensional feature vector, all vectors of unit length
- Y: peril types (labels)



Features (2/2)



- **Project the 384 dimensions to 2D** using Uniform Manifold Approximation and Projection (UMAP).
- The perils occupy different regions with different varying distributions.
- The charts indicate that a good separation of the perils might be feasable.
- Upcoming challenges separating WaterNW and WaterW are not visible.
- UMAP has a random component, so the seed needs to be set

Results

Dummy classifier

actual class \ predicted class	Vandalism	Fire	Lightning	Wind	Hail	Vehicle	WaterNW	WaterW	Misc
Vandalism	310	0	0	0	0	0	0	0	0
Fire	46	0	0	0	0	0	0	0	0
Lightning	123	0	0	0	0	0	0	0	0
Wind	107	0	0	0	0	0	0	0	0
Hail	18	0	0	0	0	0	0	0	0
Vehicle	227	0	0	0	0	0	0	0	0
WaterNW	67	0	0	0	0	0	0	0	0
WaterW	38	0	0	0	0	0	0	0	0
Misc	103	0	0	0	0	0	0	0	0

Logistic Regression classifier

actual class \ predicted class	Vandalism	Fire	Lightning	Wind	Hail	Vehicle	WaterNW	WaterW	Misc
Vandalism	296	1	0	1	0	6	0	0	6
Fire	3	32	3	0	0	2	0	1	5
Lightning	1	0	114	1	0	1	0	1	5
Wind	5	0	5	93	1	1	0	1	1
Hail	1	0	0	2	14	1	0	0	0
Vehicle	12	0	0	2	0	209	3	1	0
WaterNW	10	0	1	0	0	0	23	29	4
WaterW	1	0	0	2	0	1	5	29	0
Misc	20	1	4	1	0	12	1	2	62

Python Code: Using google Colab providing the infrastructure

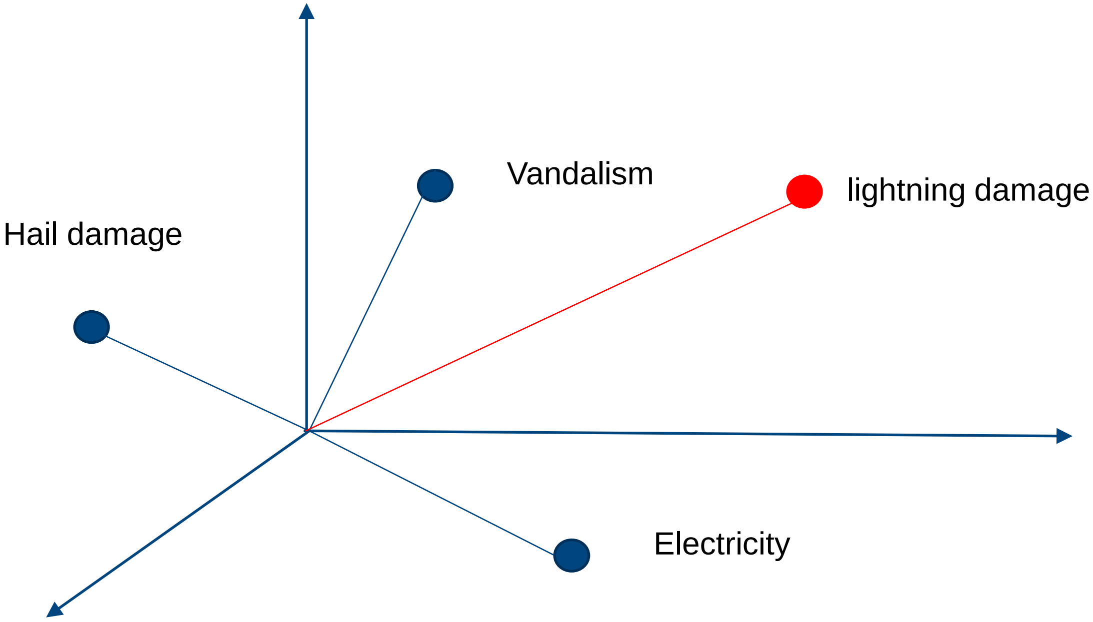
Given the infrastructure,
just a few lines of code are needed!

```
# load the model and the tokenizer
model_name = "distilbert-base-uncased«
tokenizer = AutoTokenizer.from_pretrained(model_name)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = AutoModel.from_pretrained(model_name).to(device)
# define a function to tokenize a batch
def tokenize(batch):
 return tokenizer(batch["Description"], truncation=True, padding=True, max_length=12)
# apply the function to the whole dataset
ds = ds.map(tokenize, batched=True)
ds = ds.map(extract_sequence_encoding, fn_kwargs={"model": model}, batched=True, batch_si
ze=16)
x_train, y_train, x_test, y_test = get_xy(ds, "mean_hidden_state", "labels")
# fit a logarithmic regression classifier to the encoded texts
clf = logistic_regression_classifier(x_train, y_train, c=0.2)
```

Unsupervised classification using similarity

High-level approach

- Every claims description is translated into a 384-dimensional vector with unit length
- Cosine similarity, which is the dot product of two embedding vectors, each normalized to unit length
- The peril type with the highest score is selected.



Results

Peril Type	Candidate expressions
Vandalism	Vandalism, Glass, Theft
Fire	Fire damage
Lightening	Lightning damage
Wind	Wind damage
Hail	Hail damage
Vehicle	Damage cause by a vehicle
WaterNW	Water damage
WaterW	Weather damage, Ice
Misc	Electricity, power surge

Similarity

actual class \ predicted class	Vandalism	Fire	Lightning	Wind	Hail	Vehicle	WaterNW	WaterW	Misc
Vandalism	249	8	4	3	3	6	7	26	4
Fire	1	38	3	1	0	0	1	1	1
Lightning	0	0	117	0	0	1	1	1	3
Wind	3	0	2	90	2	0	0	10	0
Hail	0	0	0	0	18	0	0	0	0
Vehicle	5	9	17	3	3	162	13	14	1
WaterNW	3	0	1	0	0	0	59	3	1
WaterW	0	0	0	0	0	0	28	10	0
Misc	17	4	3	2	1	15	15	15	31

Conclusions

Conclusions

- Transformers
  - Useful in situations of small data
  - Useful in situations with no labels
  - Transformer models are relatively new
  - Results are good due to progress in the language models used
  - Business problems which could not be solved 5 years ago are nowadays feasable
  - Few lines of codes
  - Computationally intensive. Platform with GPU support recommended.
- Tutorial available here, and corresponding Python notebooks here.
- www.actuarialdatascience.org

Appendix

Transformers

- Neural network architecture developed by Google researchers in 2017.
- Uses word embeddings and self-attention layers to understand words in their context.
- Quickly became dominant for achieving state-of-the art results on many NLP tasks.

- BERT (Bidirectional Encoder Representations from Transformers) is a Transformer encoder architecture, introduced in 2019
- Multilingual DistilBERT, derived from BERT: 134 million parameters, pre-trained on Wikipedia in 104 different languages
- Multilingual alternatives: XLM, XLM-RoBERTa, …

- Easy-to use Python library and model hub provided by Huggingface (https://huggingface.co/)

References

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Fragen

- Im Oktober 2022 wusste ich, was grosse Sprachmodelle sind. → Ja/Nein
- Im April 2023 wusste ich was ChatGPT ist →Ja/Nein
- Mein Wissen über die Funktionsweise von ChatGPT etc ist auf einer Skala von 1-5 → 1: niedrig, 5: hoch
- Wo stehe ich im Vortrag → kann überhaupt nicht folgen, etwa folgen, gut folgen, langweilig
- Ich habe schon mit Sprachmodellen wie ChatGPT codiert → Ja/Nein
- Der Vortrag war auf einer Skala von 1-5 → 1: sehr schlecht, 5: sehr gut