

AI and ML

Cover photo by Conny Schneider https://unsplash.com/@choys_

- ML Introduction
- ML Best Practices
- Model Quantization
- SpaCy GPU
- SpaCy CoRef
- Core Scientific Concepts (CoreSC)
- Stratified Sampling in Pandas
- From Crowd Ratings to Predictive Models of Newsworthiness to Support Science Journalism
- Stable Diffusion
- AI Causing Chaos
- Tasks
 - Question Answering
 - Coreference Resolution
 - Keyword Extraction
 - Relationship Extraction
 - Federated Learning
 - Large Scale Multi-Label Learning
- Machine Learning with Limited Data
 - Pattern Exploitative Training
 - Learning with Limited Data
- DeBERTa Zero Shot
- Explainability and Model Analysis
 - Explainability

- Model Confidence Scores

- Argilla

ML Introduction

Welcome to my Machine Learning and AI notebook.

▣▣ AI and ML Fundamentals

- [AI Best Practices](#) - some thoughts and principles that I've built up during my career building data projects.
- [Learning with Limited Data](#) - thinking around
- [AI Causing Chaos](#) - a compilation of examples of AI cautionary tales.

▣▣ Data Collection and Annotation

- Working with Argilla

▣▣ LLMs

- [Local LLMs](#)
- Reproducibility

ML Best Practices

Machine learning is a complex and multifaceted activity that requires the combination of a number of success factors in order to work. In order to execute machine learning well, it is important to have a good understanding of the processes and variables that frequently come into play together. Here I document and lay out some of the best practices and ML processes that I have learned and continue to learn during my career.

A personal bugbear of mine is when people refer to machine learning as "an art rather than a science". It is true that machine learning involves random-seeming aspects that could be conflated with magic or wizardry. [There are a lot of ways that poorly thought-through or executed machine learning projects can go wrong](#). However, there are well established protocols and principles that can guide a project towards success and we can execute projects in a risk-averse, incremental way allowing us to fail fast before a large amount of time and energy has been spent on a project.

Key Principles

Garbage In; Garbage Out

Machine learning is all about trying to infer statistical relationships between data. There are a lot of reasons why this might not work well which we will explore in depth. It's always important to remember that if you have bad data or a flawed hypothesis, your model is not going to perform well. Conversely, if your model is performing really well (perhaps *"too good to be true" levels of well*) this can be a red flag that something is wrong with your data or your process which leads into...

Professional Pessimism

I love this phrase that I picked up during my career stint as a QA Engineer. If something appears to be too good to be true, it probably is. Always question your results and double check your working. Typically if a machine learning model is achieving high-90% in appropriate performance metrics, it is worth your time to investigate whether something weird is happening. You may have training data in your test set (i.e. your model got hold of the exam answer sheet) or your model may have found a short cut. For example, if all the positive examples of fractured ribs come from x-rays of women and all the negative examples come from x-rays of men then the model may have just learned to separate male and female anatomy rather than what a fractured rib looks like.

Keep it Simple, Stupid (KISS)

As tempting as it might be to want to use the latest and greatest ML models, always start with the simplest approach possible and disqualify these approaches based on sound theoretical rationale or empirical experimentation:

- The more complex a modelling approach, the more uncertainty we invite into the process.
- Complex models are significantly more expensive to train and run and scaling them to run quickly on a large amount of data is a challenge.

Keep Receipts

Machine Learning is usually an iterative process. As you move through this process it is important to understand where you came from and why at all times and to be able to refer back to earlier results and hypotheses. Furthermore, in a business setting, you will likely be asked questions about how work that you did days or weeks ago compares to your current iteration of thinking.

Keeping receipts is about using simple tools (good note taking and ticket hygiene) in combination with more specific purpose-built AI and ML tooling to ensure that you can answer these questions at all times.

Deep Learning Best Practices

For deep learning I like to work with torch. My opinion on how torch code should be written aligns quite closely with [this styleguide](#)

Model Quantization

Deploying models that are performant (obviously statistically but in this context I primarily mean **computationally**) is challenging when you are working with large models such as BERT etc.

Quantization involves compressing model weights into smaller, more efficient representations. Weights are normally stored as 32 bit floating point numbers but they can be compressed into 8 bit integers with a very small amount of performance loss.

This article talks about how to do [quantization](#) effectively ([mirror](#)).

Quantization with Optimum and OpenVino

Openvino is an open source framework from Intel that provides quantization and x86 CPU support for torch and huggingface transformers.

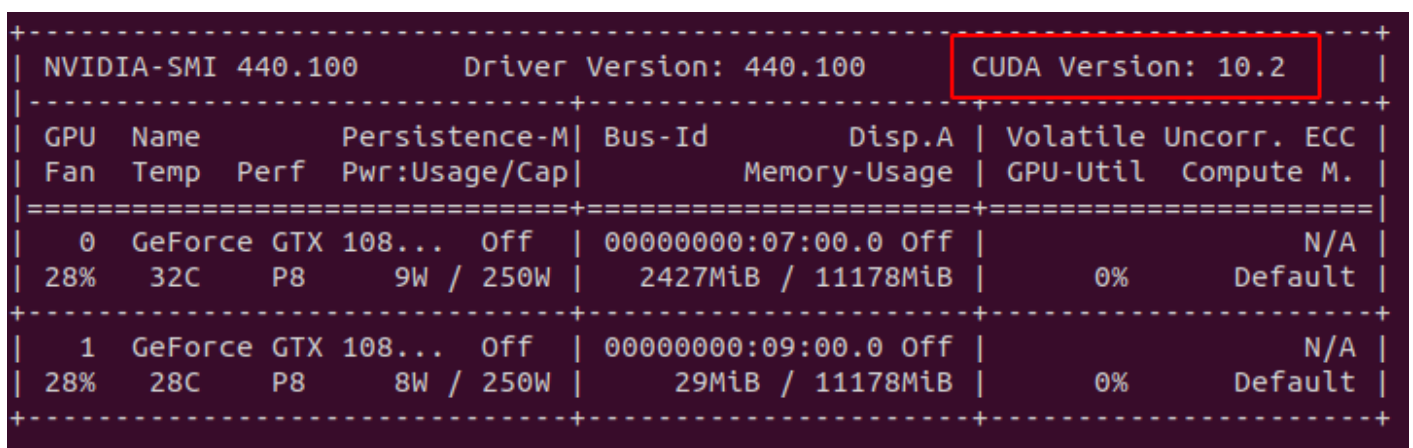
SpaCy GPU

Set Up Environment

It's relatively easy to use SpaCy with a GPU these days.

First set up your conda environment and install cudatoolkit (use nvidia-smi to match versions of the toolkit with the drivers):

Run `nvidia-smi`:



```
+-----+
| NVIDIA-SMI 440.100      Driver Version: 440.100      CUDA Version: 10.2  |
+-----+-----+
| GPU   Name               Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf    Pwr:Usage/Cap|      Memory-Usage | GPU-Util  Compute M. |
+-----+-----+
|  0  GeForce GTX 108...    Off   | 00000000:07:00.0 Off |             N/A     |
| 28%   32C   P8      9W / 250W | 2427MiB / 11178MiB |      0%      Default |
+-----+-----+
|  1  GeForce GTX 108...    Off   | 00000000:09:00.0 Off |             N/A     |
| 28%   28C   P8      8W / 250W | 29MiB / 11178MiB |      0%      Default |
+-----+-----+
```

Create conda env:

```
conda create -n test python=3.8
conda activate test
conda install pytorch cudatoolkit=10.2 -c pytorch
```

Installing SpaCy

Now install spacy - depending on how you like to manage your python environments either carry on using conda for everything or switch to your preferred package manager at this point.

```
conda install -c conda-forge spacy cupy
```

or

```
pdm add 'spacy[cuda-autodetect]'
```

Download Models

Download a spacy transformer model to make use of your GPU/CUDA setup:

```
python -m spacy download en_core_web_trf
```

Using GPU

As soon as your code loads you should use the `prefer_gpu()` or `require_gpu()` functions to tell spacy to load cupy then load your model:

```
import spacy

spacy.require_gpu()

nlp = spacy.load('en_core_web_trf')
```

Now you can use the model to do some stuff

```
doc = nlp("My name is Wolfgang and I live in Berlin")

for ent in doc.ents:
    print(ent.text, ent.label_)
```

You can check that the GPU is actually in use with `nvidia-smi`:

Thu Oct 20 09:14:26 2022

NVIDIA-SMI 440.100				Driver Version: 440.100				CUDA Version: 10.2			
GPU	Name	Persistence-M	Bus-Id	Disp.A	Volatile	Uncorr.	ECC				
Fan	Temp	Perf	Pwr:Usage/Cap	Memory-Usage	GPU-Util	Compute	M.				
0	GeForce GTX 108...	Off	00000000:07:00.0	Off			N/A				
28%	31C	P8	8W / 250W	1149MiB / 11178MiB	0%		Default				
1	GeForce GTX 108...	Off	00000000:09:00.0	Off			N/A				
28%	27C	P8	8W / 250W	29MiB / 11178MiB	0%		Default				

Processes:						GPU Memory
GPU	PID	Type	Process name	Usage		
0	9770	C	...scroft/miniconda3/envs/lbner/bin/python	1137MiB		
1	2752	G	/usr/lib/xorg/Xorg	9MiB		
1	2852	G	/usr/bin/gnome-shell	6MiB		

(base) iravenscroft@shockwave:~/lbner test\$

Also if you try to use transformer models without a GPU it will hang for AGES and max out your CPUs - another tell that something's not quite right.

SpaCy CoRef

Spacy Coref is an experimental coreference resolution model in spacy

The project repository is [here](#).

There is currently a hard dependency on the [LDC OntoNotes dataset](#) which makes it difficult to use without spending money. Hopefully they will release a pre-trained model soon

Core Scientific Concepts (CoreSC)

Core Scientific Concepts (CoreSC) is an annotation scheme used to delineate different parts of scientific discourse in a scientific paper.

There are 11 categories:

- Background
- Conclusion
- Experiment
- Goal
- Hypothesis
- Method
- Model
- Motivation
- Object
- Observation
- Result

Classification Methods

- The original model used for automatic classification of sentences in scientific papers into CoreSCs is [SAPIENTA](#)
- Subsequent work by [Brack et al](#) incorporates multi-task learning and their models are available [here](#)

References

- [Guidelines for the Multi-Annotation of Core Scientific Concepts \(CoreSC\)](#)

Stratified Sampling in Pandas

- Use `groupby` on the label column to create sub-frames for each label and then use the `sample()` function.
- Passing an integer gives an exact sample (e.g. `sample(5)` gives 5 rows).
- Passing `frac=0.1` gives a percentage (i.e. 10%)
- Remember to set `random_state` for reproducible results

```
df = pd.read_csv("path/to/data.csv")
```

```
df.groupby('Category', group_keys=False).apply(lambda x: x.sample(frac=0.1, random_state=42))
```

From Crowd Ratings to Predictive Models of Newsworthiness to Support Science Journalism

[Paper Link](#)

Authors:

- Sachita Nishal
 - Nicholas Diakopoulos
-

Notes

- Their work comes at the problem from the scientific paper - essentially they are trying to predict whether or not a scientific article might make an interesting news article (as opposed to our work which analyses the news article to attempt to understand which part of the scientific paper is worth mentioning)
- Their definition of newsworthiness is broad and incorporates scientific and social impact but also factors in stuff that we would probably consider less helpful for understanding impact like how controversial the work is.
- They use computer science pre-prints gathered from ArXiv via their API (filtered by category/subject area).
- Their data set is 50 papers in 'train' set, 55 in validation set
- Scientific journalists were paid as experts. Non-specialists were recruited for crowd-sourcing at larger scale (MTurk)
- Crowd-source workers asked to score papers based on the abstract (full text was optionally available but only for gathering additional context/if necessary).
- Workers asked to score along 4 dimensions: actuality, surprise, impact magnitude, impact valence
- They use Likert scales for crowd-rating of newsworthiness
- Crowd source workers achieve moderate associations with the "expert" annotators.

- They train an extra trees random forest classifier with Sentence-BERT feature input (single 768 dim vector used for each article abstract). Additional features include binary indicator if article makes code or data available (hypothesis is that this could increase impact)
- They rank outputs based on likelihood score from the classifier (Extra Trees classifier) and achieve reasonable results

Stable Diffusion

Web UI API

Run the web UI with:

```
./webui.sh --api
```

Example Python Script

```
import webuiapi

# create API client
api = webuiapi.WebUIApi()

# create API client with custom host, port
#api = webuiapi.WebUIApi(host='127.0.0.1', port=7860)

# create API client with custom host, port and https
#api = webuiapi.WebUIApi(host='webui.example.com', port=443, use_https=True)

# create API client with default sampler, steps.
#api = webuiapi.WebUIApi(sampler='Euler a', steps=20)

# optionally set username, password when --api-auth=username:password is set on webui.
# username, password are not protected and can be derived easily if the communication channel is not
# encrypted.
# you can also pass username, password to the WebUIApi constructor.

result1 = api.txt2img(width=512,height=768,
    prompt="Morgan Freeman in star wars jedi robe",
    negative_prompt="ugly, out of frame",
    seed=1003,
    styles=["anime"],
```

```
cfg_scale=7,
steps=30,
# sampler_index='DDIM',
# steps=30,
# enable_hr=True,
# hr_scale=2,
# hr_upscaler=webuiapi.HiResUpscaler.Latent,
# hr_second_pass_steps=20,
# hr_resize_x=1536,
# hr_resize_y=1024,
# denoising_strength=0.4,
alwayson_scripts = {
    "ADetailer": {
        "args": [
            {
                "ad_model": "face_yolov8n.pt"
            }
        ]
    }
}

result1.image.save("out.png")
```


AI Causing Chaos

“So much AI turns out to be low-waged people in a call center in the Global South pretending to be robots that Indian techies have a joke about it: “AI stands for ‘absent Indian’” - [Cory Doctorow](#)

I am collecting examples of AI fails by people who either deliberately or naively mislead about the capabilities of AI.

2024

- **11/02/24** - System set up to detect cheating students found 97% of students were cheating and UK officials just accepted this
- **09/02/24** - Gemini LLM conflates unsafe in the C# memory management context with unsafe as in unethical.
- **05/02/24** - Using neural networks to generate images of fake ids for online verification
- **04/02/24** - via [Yoav Goldberg](#) - GEM using models to predict protected characteristics of job applicants when such information is not supplied
- **28/01/24** Dudesy Podcast claimed that they trained an AI to impersonate the late comedian [George Carlin](#) but [Cory Doctorow](#) and [Simon Willison](#) both call bullshit. IT stinks of the "We made an AI watch 100 hours of X..." meme that went round a few years ago.
- **20/1/24** DPD introduce a ChatGPT-powered bot which users jailbreak and get to swear and call DPD 'useless'

2023

- **20/12/23** [Chevrolet integrated a ChatGPT-powered bot into their site](#) but because there is no such thing as input sanitization for [LLMS](#) people used prompt injection attacks to make the bot agree to sell users cars for \$1.
- **24/10/23** [Cruise robo-taxi dragged a person 20ft along the floor](#) and had their license to operate in San Francisco suspended.

- **17/01/23** it emerged that [a 2016 demo of Tesla's self-driving capabilities was completely staged](#)
-

Tasks

Tasks within ML and NLP

Question Answering

Approaches

Fine-Tuning Sentence-BERT for Question Answering

CapitalOne [produced a tutorial](#) ([mirror](#)) about using sentence-transformers for Question Answering.

- They use SBERT because it is optimised for fast compute on individual sentence and has good general performance on a number of NLP tasks. They are most interested in the STS capability of SBERT
 - They fine-tuned the model on 7k utterances and saw a huge improvement in performance:
 - 52% match rate on 200 test Q-A pairs with no fine tuning
 - 79% match rate on the 200 sample dataset after fine tuning
 - They use triplet loss (minimise distance between alike sentences, maximise distance between different sentences)
 - This is a nice simple approach where you want to present the answer, as-written, back to the user but its not appropriate for factoid type use cases where we want to highlight the exact word or phrase in the answer text.
-

Haystack

[Haystack](#) is an open source NLP framework for use cases involving large collections of documents. It could be used for searching and ranking type use cases and question answering type use cases.

Haystack works flexibly with existing document stores including DB systems and ElasticSearch.

Coreference Resolution

Co-reference Resolution (CR) is the task of deciding whether two entity mentions refer to the same instance or not.

For example in:

“ Joe Biden appeared at the event at 8pm. The president was wearing a Louis Vuitton Tuxedo.

The objective is to identify that Joe Biden and The president are the same entity.

Coreference Detection is related to [Relationship Extraction \(RE\)](#) - in fact you could even say that CR is a special case of RE in the sense that we are interested in the special relationship between entity mentions when they both refer to the same entity.

In-Document Coreference Resolution

This is the "normal" CR case in which you're trying to resolve mentions of entities within the same document e.g. a single news article.

Approaches

- **2022-10-23** [A recent blog post](#) from explosion / spaCy shows how they have implemented end-to-end CR in their excellent NLP pipeline but as of writing they do not provide a trained model and they require you to have a copy of the Ontonotes dataset.

Cross-Document Coreference Resolution

Cross-Document Coreference Resolution (CDCR) is when you try to link named entity references across multiple input documents. A use case might be identifying that a number of news articles do actually refer to the same person (e.g. "Joe Biden", "The President").

CDCR is challenging because there are so many possible entities and thus $O(n^2)$ comparisons to make between candidates.

Approaches

- In 2021 [we proposed CD²CR](#) - a CDCR approach across documents and domains that allows us to match mentions of people, places, technologies etc across scientific papers and news articles that discuss them.

Keyword Extraction

Graph-Based Keyword Extraction

Graph-based approaches like TextRank allows the extraction of keywords + phrases based on their centrality to the semantics of the other words in the document.

- <https://github.com/SkBlaz/rakun2> - RaKUn 2.0, a very fast keyphrase extraction algorithm suitable for large-scale keyphrase retrieval. It has an [associated preprint](#).

Relationship Extraction

Relationship Extraction (RE) is a task that is related to [Coreference Resolution](#) but with a focus on identifying relationships between entities.

In the following example:

“James, the CTO at Filament AI, lives in the South of England.”

We want to identify the following relationships:

(James, isCTOof, Filament AI)

(James, livesIn, England)

Approaches

- [FewRel](#) by the NLP group at Tsinghua University propose a few-shot model which takes 2 entity mentions, in context, and N possible relationship types - it predicts which of the relationships is most likely to apply. It can also predict when none of the relationships are applicable.

Federated Learning

- [Flower](#) is a federated learning framework with compatibility with Torch, Tensorflow and others

Large Scale Multi-Label Learning

The Keras website has a tutorial on how to do multi-label learning with a large number of labels:

- https://keras.io/examples/nlp/multi_label_classification/ (mirror)

Machine Learning with Limited Data

Machine Learning with Limited Data

Pattern Exploitative Training

PET or [Pattern Exploitative Training](#)

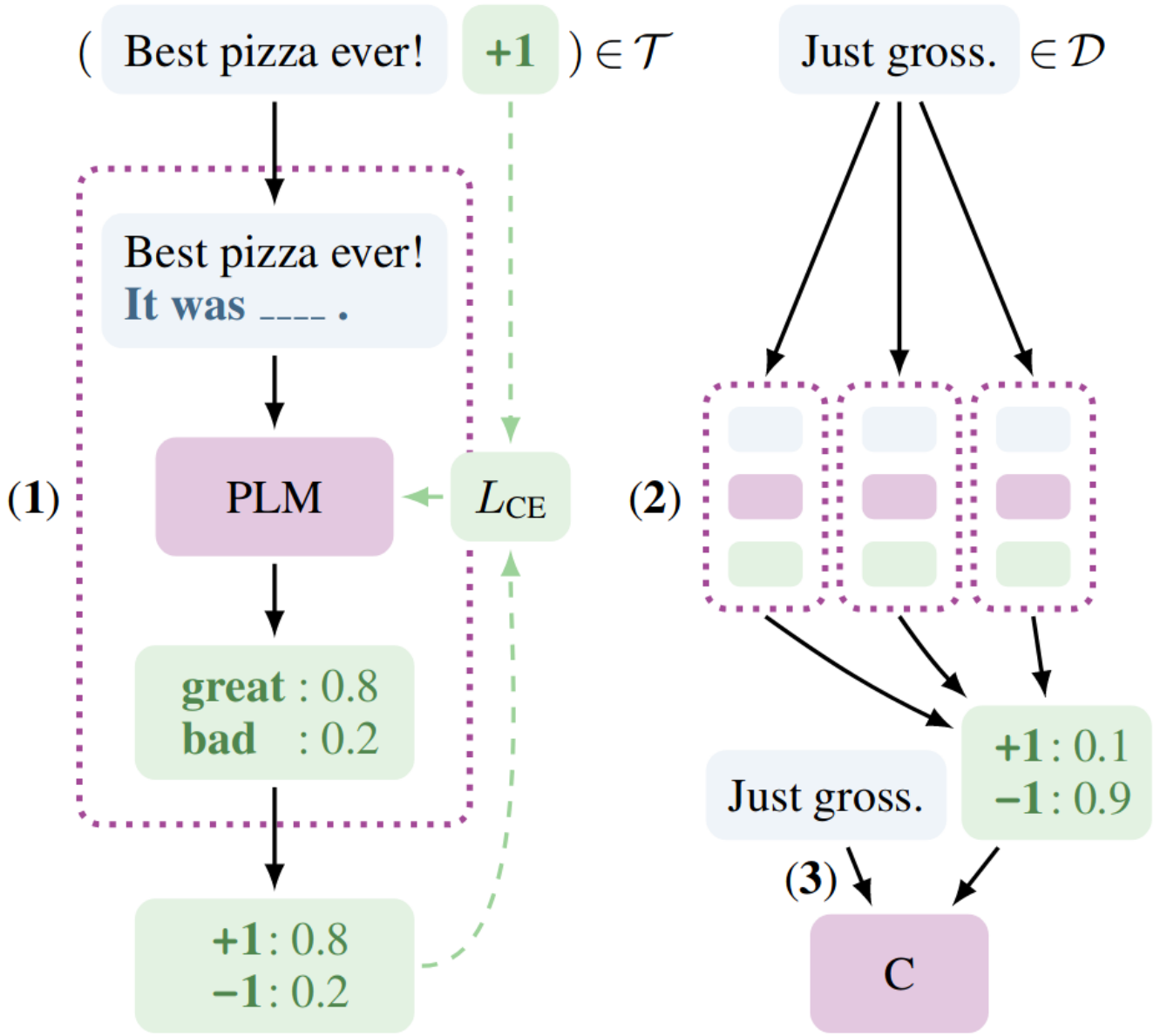


Figure 1: PET for sentiment classification. **(1)** A number of patterns encoding some form of task description are created to convert training examples to cloze questions; for each pattern, a pretrained language model is finetuned. **(2)** The ensemble of trained models annotates unlabeled data. **(3)** A classifier is trained on the resulting soft-labeled dataset.

```
journal={Computing Research Repository},  
volume={arXiv:2001.07676},  
url={http://arxiv.org/abs/2001.07676},  
year={2020}  
}
```

```
@article{schick2020small,  
  title={It's Not Just Size That Matters: Small Language Models Are Also Few-Shot Learners},  
  author={Timo Schick and Hinrich Schütze},  
  journal={Computing Research Repository},  
  volume={arXiv:2009.07118},  
  url={http://arxiv.org/abs/2009.07118},  
  year={2020}  
}
```

Learning with Limited Data

Good machine learning is heavily dependent on good data. [A few more good data-points is likely to be worth billions of model parameters.](#)

However, sometimes we need to train models when data is limited. There are a number of strategies that we can try.

Zero-Shot and Few-Shot Learning

- [Pattern Exploitative Training](#) is a way to use a small number of examples to train text classifiers. It is technically an example of synthetic data generation.

In Context Learning (ICL)

Synthetic Data Generation and Augmentation

DeBERTa Zero Shot

The DeBERTa [zero-shot](#) model is an NLP zero-shot classifier trained by Moritz Laurer and [made publically available on HuggingFace](#)

Explainability and Model Analysis

Explainability

Explainability is a big challenge in machine learning.

I wrote a [blog post about the ELI5 library](#) and how it can be applied to NLP models.

Introducing ML customers to explainability early on can be a great way to build trust. A colleague suggests using [Streamlit](#) tools to allow customers to play with models and understand the contribution different features have had to a particular decision.

Model Confidence Scores

Many ML classification models can provide a confidence score which tells the user how confident the model is that it has made the correct choice.

The values of these confidence scores and what constitutes a "good" or "bad" score can vary a lot depending on the type and behaviour of the model. We often get asked why a particular model only ever seems to be 20% confident when a different model gives 99% confidence. Here's why that happens.

Confidence vs Certainty

Confidence and certainty are related but distinct concepts. We want models to be confident that they are correct (a high score is allocated to one of the labels and a low score allocated to the remaining labels) but also we want it to be certain it is correct (we want it to rely on features/cues that lead to the actual correct outcome).

Neural networks are known to often be over-confident in their results but still incorrect due to the way that modern deep learning learns. The paper [On Calibration of Neural Networks](#) dives into this further.

In order for us to be able to trust confidence scores, models must also be well calibrated.

Confidence in Random Forest Models

Random Forest Models are made up of an ensemble of **decision tree models** which are trained based on randomly selected sub-samples of the full training set - allowing the trees to learn different feature priorities based on the variance in the data that they are "assigned".

A single decision tree model cannot easily tell you how confident it is - the data is passed in and the algorithm traverses the branches in the tree until it reaches a decision. Within the random forest, confidence is calculated by assigning each tree a "vote" on the outcome class and then working out the distributions of votes across the possible outcome classes as a percentage.

In scikit-learn decision trees[do have confidence scores](https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html#sklearn.tree.DecisionTreeClassifier.predict_proba) calculated as the proportion of each class that ended on

Say we train a random forest model containing 100 trees on a company sector/industry classification problem with 5 classes. In theory, some of the trees will learn to prioritise the most important features in the dataset. Likewise, we can assume that some of the trees will be trained on less representative sub-samples of the training data and will prioritise less discriminative features.

When we predict on an unseen data sample we might get an output like this:

“ We specialise in using AI to improve user experience for customers of high end grocery stores

35 Trees votes for "Consumer Goods"
25 Trees voted for "IT & Technology"
22 Trees voted for "Health & Beauty"
12 Trees voted for "Retail"
6 Trees voted for "Automotive Manufacturing"

I used 100 random trees in my model for easy maths, so we would say in this case that the model is 35% confident that this description is from a company in consumer goods.

Can We Calibrate Confidence in Random Forest Models?

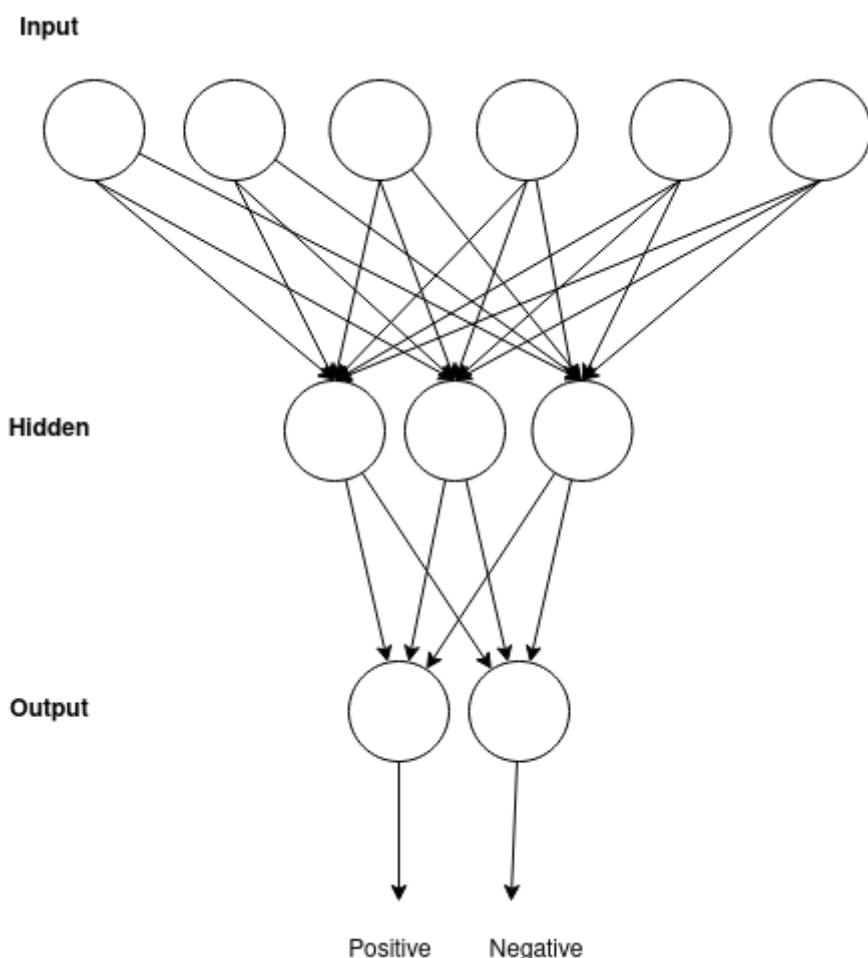
Confidence calibration is a technique that allows us to more closely map the confidence of an ML model (via its decision function) onto the real life probability that a sample belongs to a particular class.

- [Some work has been done on calibration of random forests for probability](#)
- Scikit-Learn provide an out of the box class for providing this functionality

[CalibratedClassifierCV](#)

Confidence in Neural Networks

Neural classification models can have many different internal structures but tend to have a set of inputs that correspond to the feature vector of the task being learned (e.g. a sparse bag-of-words, a set of RGB pixel values or numerical sensor readings) and a set of outputs equal to the number of classes being predicted.



Activation functions in hidden layers can produce wildly different and un-normalised values depending on the inputs, random initialisations and what is learned (although we can use normalisation constraints in our learning to prevent individual weights from going too far).

The output of the model is therefore typically normalised using [SoftMax](#) which essentially takes a weighted average of the results - its a bit like saying "which output received a higher percentage of the overall signal propagated through the network?"

Can We Calibrate Confidence in Neural Networks?

- [Some research has been done on this subject](#)

Argilla

Argilla is a data annotation tool with an API that allows you to use external models to automatically suggest labels and carry out active learning.

Resources

- [Argilla Few Shot Learning Tutorial](#) - warning some of the code in this notebook is wrong