Artificial Intelligence and/for the Social Sciences

Active Tigger tutorial

Today's program

- Methodological choices in an age of textual abundance
- An Introduction to the interface ActiveTigger
- Going further
- Q&A

Active Tigger

An Interface to speed up Annotation with LLMs

CRESTER
CENTER FOR RESEARCH
IN ECONOMICS AND STATISTICS

Introduction

Textual data overload

How can we make the most of analyzing massive datasets without sacrificing nuance?

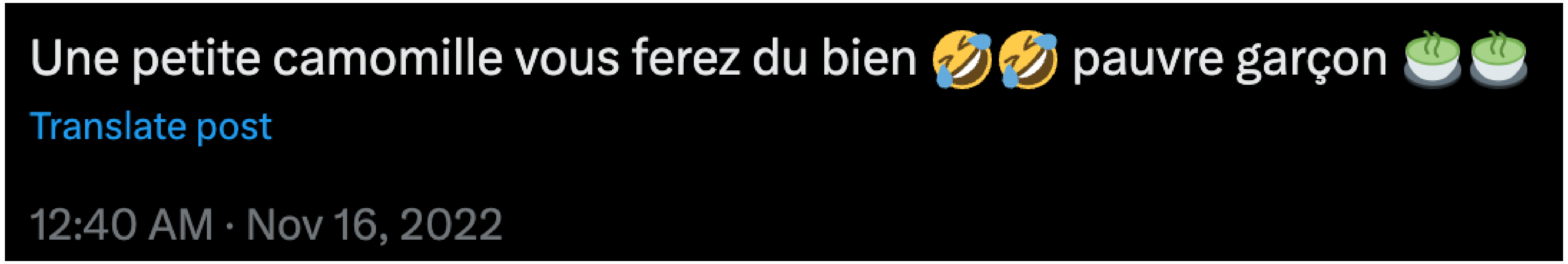
- Possible with qualitative methods
- But always human limits on scale

Introduction

Example

Objective: quantify online abuse targeting French politicians

Pre-trained models exist, but they do not necessarily reflect types of expression used in French Twittersphere, nor the types of nuance that I wanted to capture

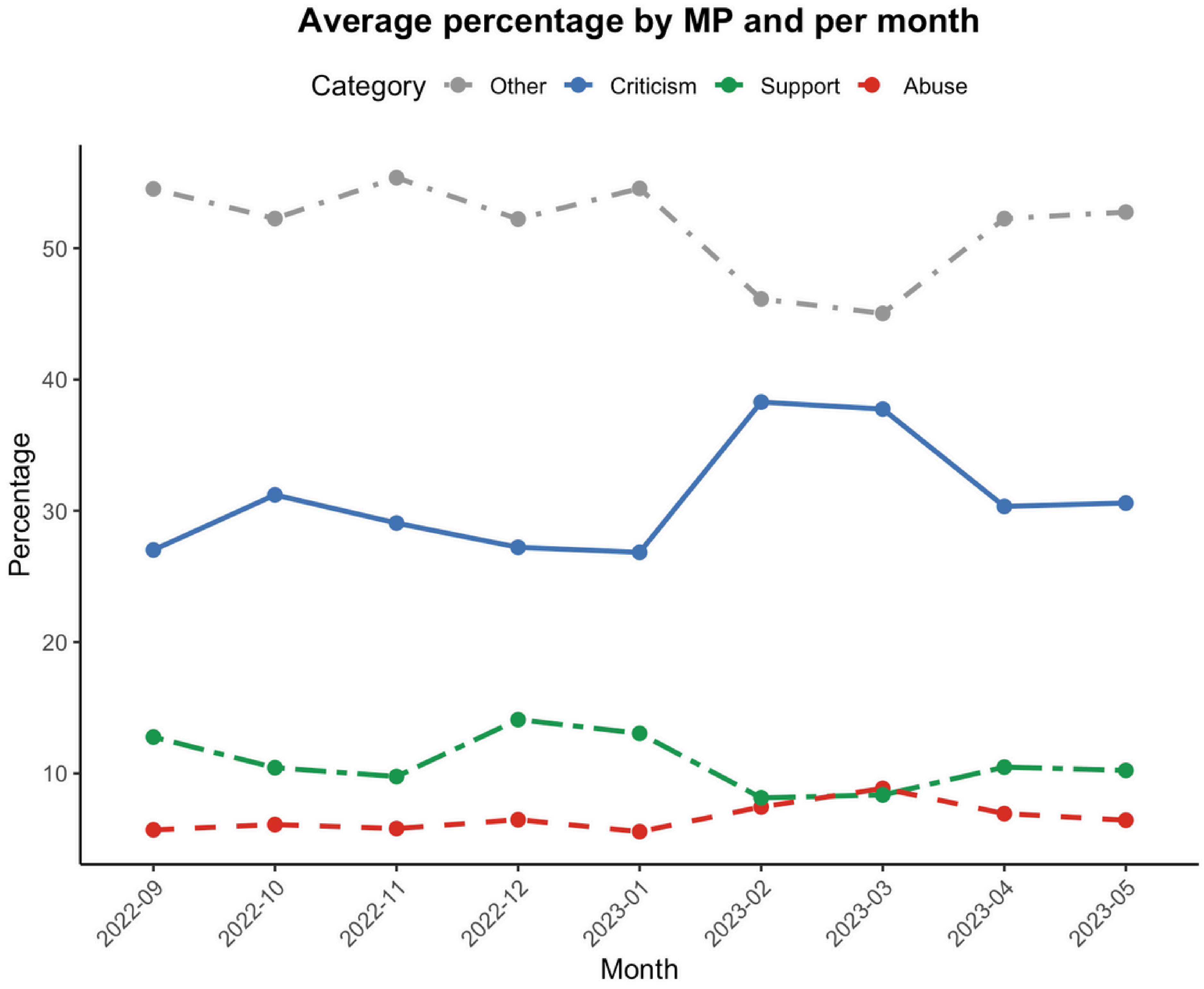

Une petite camomille vous ferez du bien 🤣🤣 pauvre garçon 🍵🍵
Translate post
12:40 AM · Nov 16, 2022

Introduction

Example

Solution: train a bespoke classifier to identify online abuse according to my own coding scheme

3000 manual annotation =>
30+ million of classified tweets



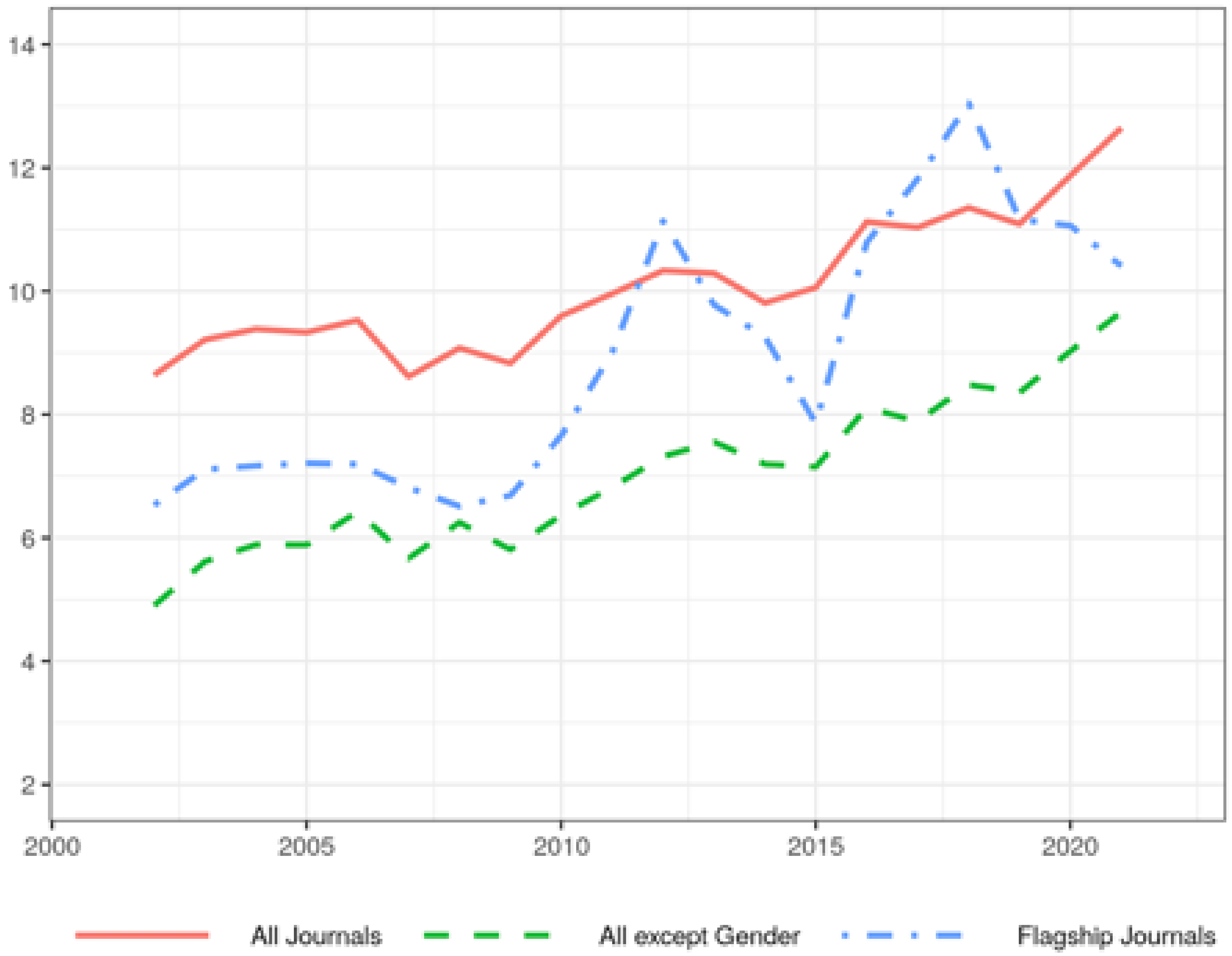
Introduction

Example

Is a gender perspective becoming more common in French social science?

Boelaert, Coavoux, Gollac, Ollion

Recognizing gender-related terms in article abstracts (50 000+)



Machine learning

Annotating data

- A standalone method
- Or a step to apply a coding scheme on a larger corpus (via a model)

Machine learning

Supervised learning

= training a model to recognize your coding scheme (through annotations) to then extend it to a larger dataset

Machine learning

Supervised learning

Recently, ***large language models*** (LLMs) have become powerful tools for classification, including in social sciences

It is, for example, possible to ask ChatGPT to perform such tasks (benefits & limitations)

Balance between function, time, and cost => encoder models (**BERT**).

Machine learning

Supervised learning

BERT: A language model based on neural networks + Transformers architecture
Bidirectional Encoder Representations from Transformers

Pros:

- Takes into account the context surrounding a given word or sphrase
- Allows us to categorize texts on precise criteria

Machine learning

(Augmented) classification

So what are the steps?

1. Defining categories (what are you looking for?)
2. Patient annotation of a smaller corpus
3. Traning and validating model
4. Extension(“inferring”) on total dataset

Do, S., Ollion, É., and Shen, R (2024) The augmented social scientist

Machine learning

(Augmented) classification

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Machine learning

(Augmented) classification

Annotation requires:

1. a deep understanding of your data
2. a codebook
3. patience and iterations

ActiveTigger

ActiveTigger

= an interface simplifying the annotation process

- A user-friendly, non-coding interface
- Offers ways to accelerate the annotation process
- Provides quality indicators
- Trains and applies model on data

ActiveTigger

Key Functions

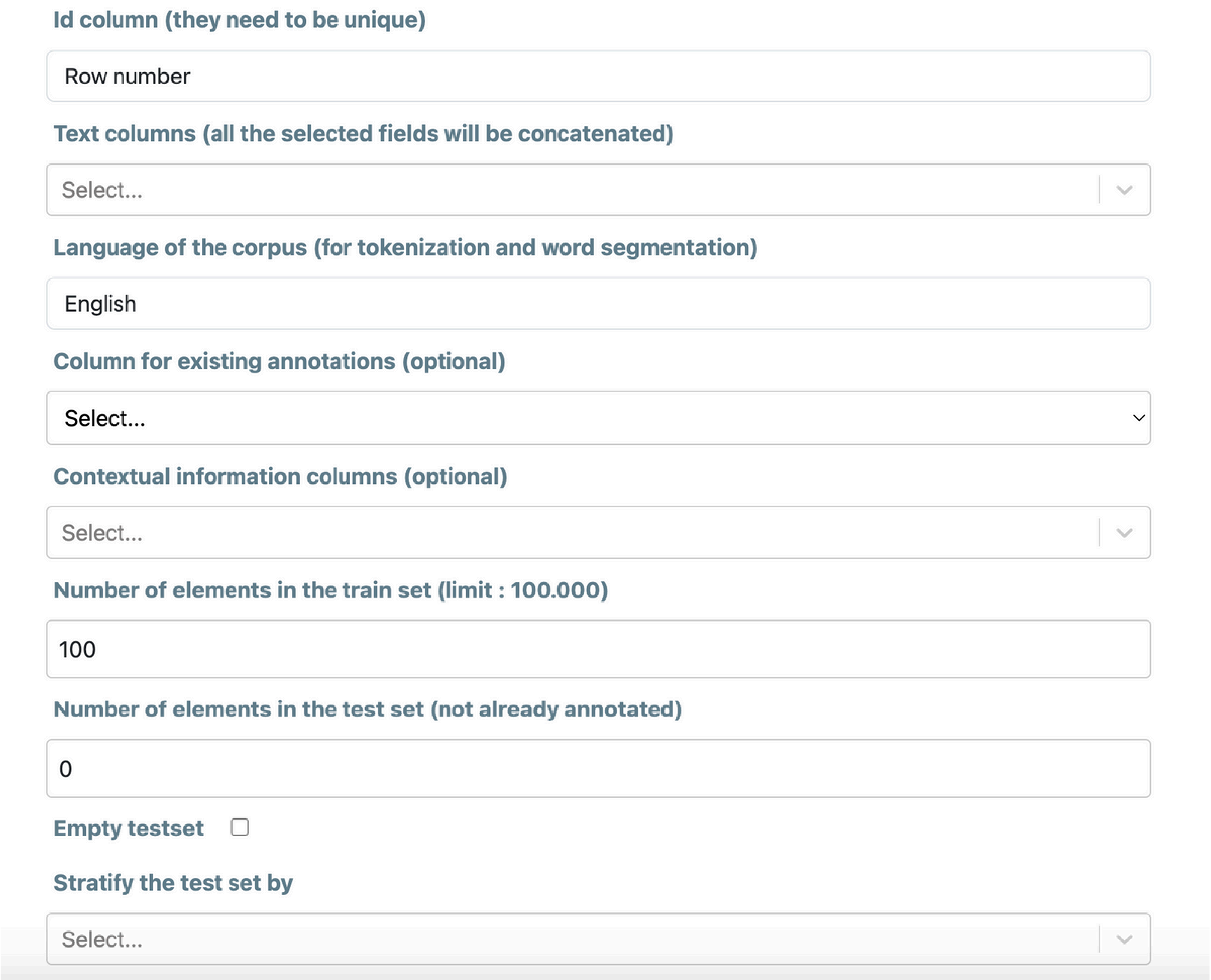
1. Load
2. Annotate
3. Validate
4. Predict and Export

ActiveTigger

Create a Project

You will (only) need a file **(csv, xlsx or parquet)** containing the texts of interest (unit can vary), with unique identifiers

If you want, you can separate your data into a training dataset and a test dataset (best practice)



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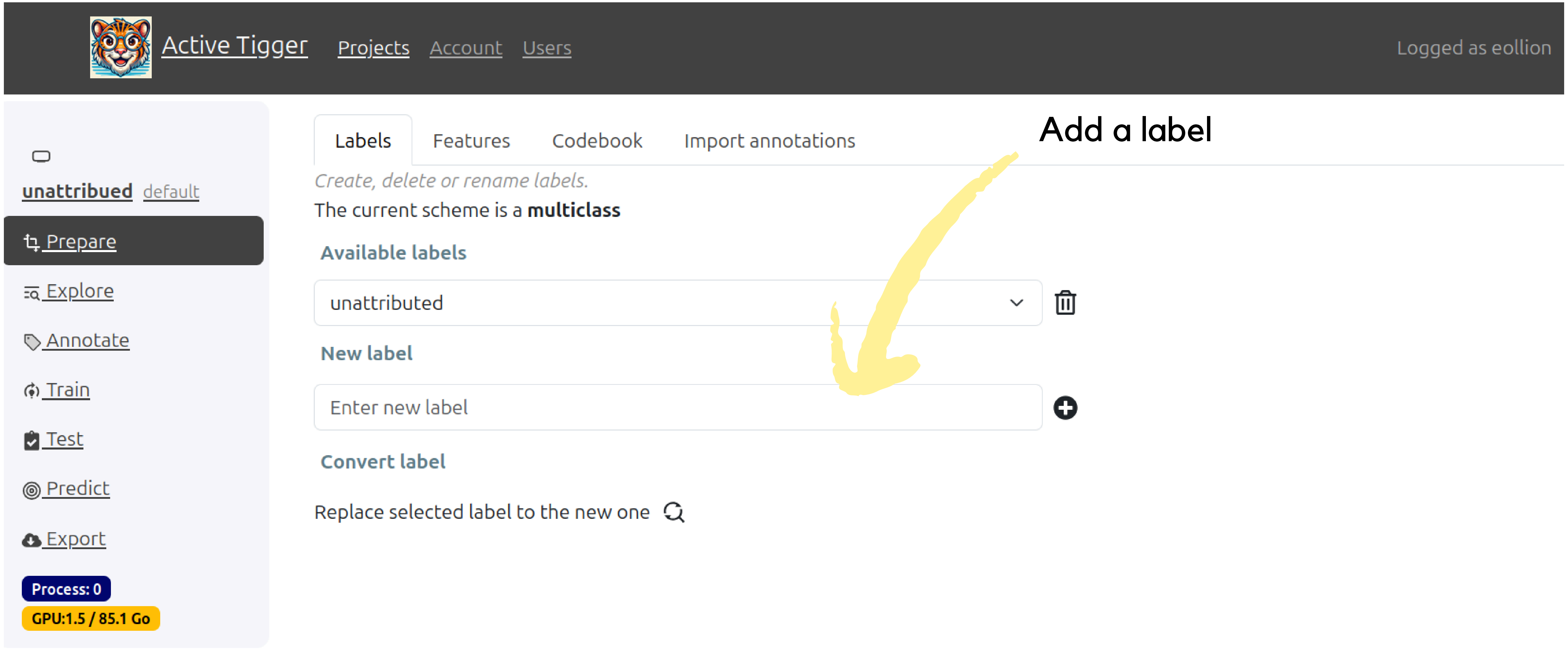
Prepare: Devise an Annotation Scheme



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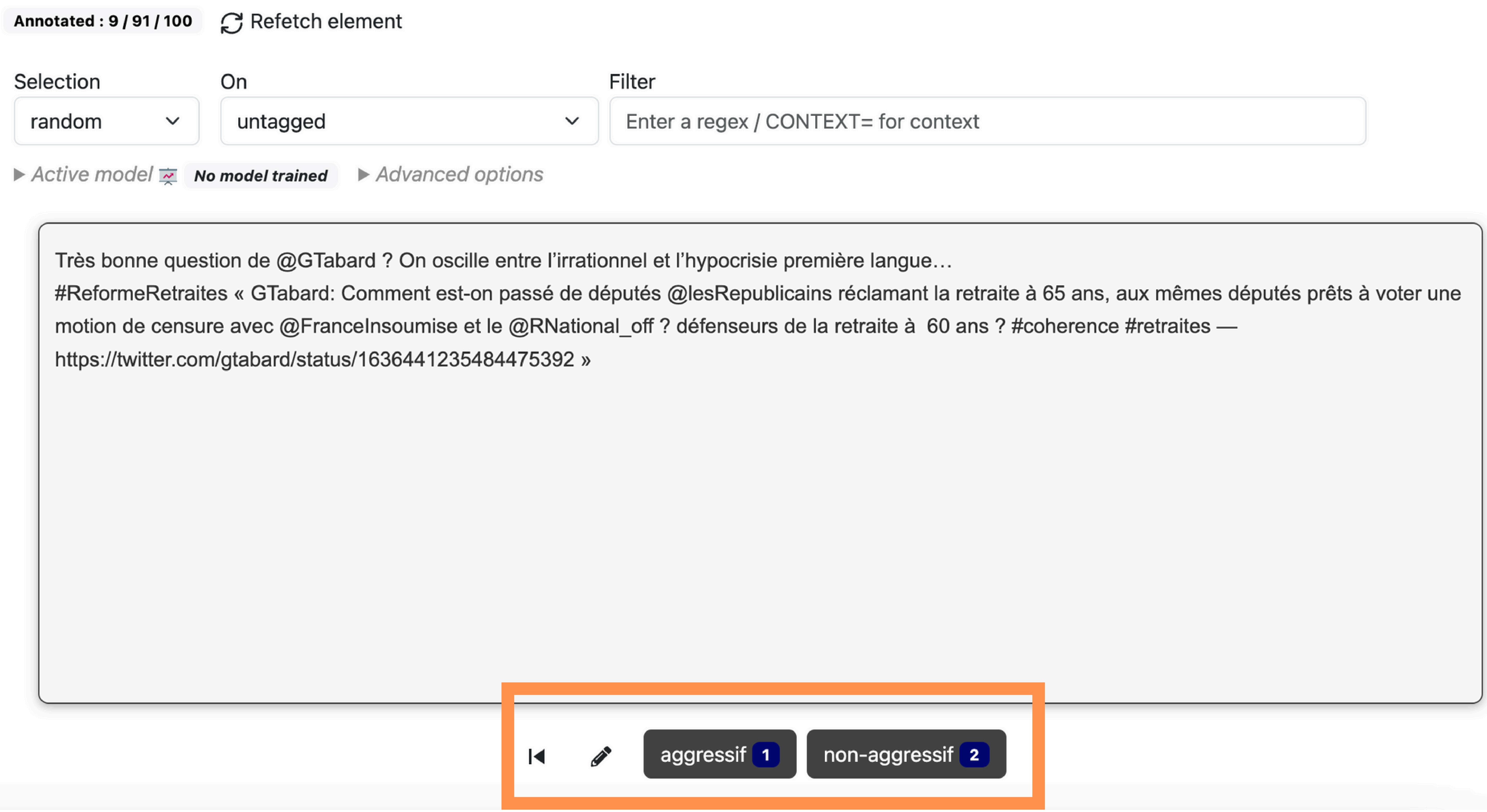
Annotate



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Validate

To monitor your progress, you have several options.

You can train “quick models” as you go through the annotation process to monitor your progress. This will also help you speed up annotation through **active learning.**

You can then train full BERT models (iteratively) until you are happy with the result.

ActiveTigger

http://activetigger2.eschultz.fr/

Download data and see
logins in shared Drive folder

https://emilienschultz.github.io/activetigger/docs/quickstart/

To go further

Advanced options & Tricks

1. Active learning
2. Coding Scheme
3. Validation Scores
4. Tips

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Validate

A quick model

1) Select Features under Prepare (sbert)
2) Train quick model (using training data) under Tag

10-CV : 10-fold cross-validation

Evaluates the performance of a model by testing it on 10 different samples.

Efficient, but to be taken with a grain of salt

To go further

Active learning

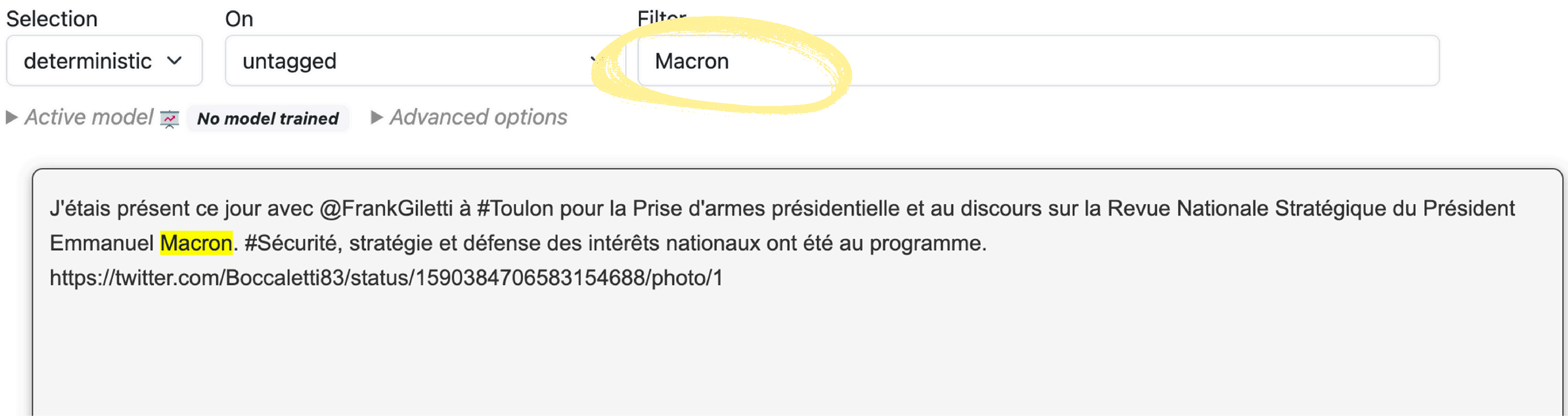
Rare cases can take forever to annotate if you pick them out at random

But it is possible to speed up the process

To go further

Active learning

a) Look for words / ideas (regular expression)



To go further

Active learning

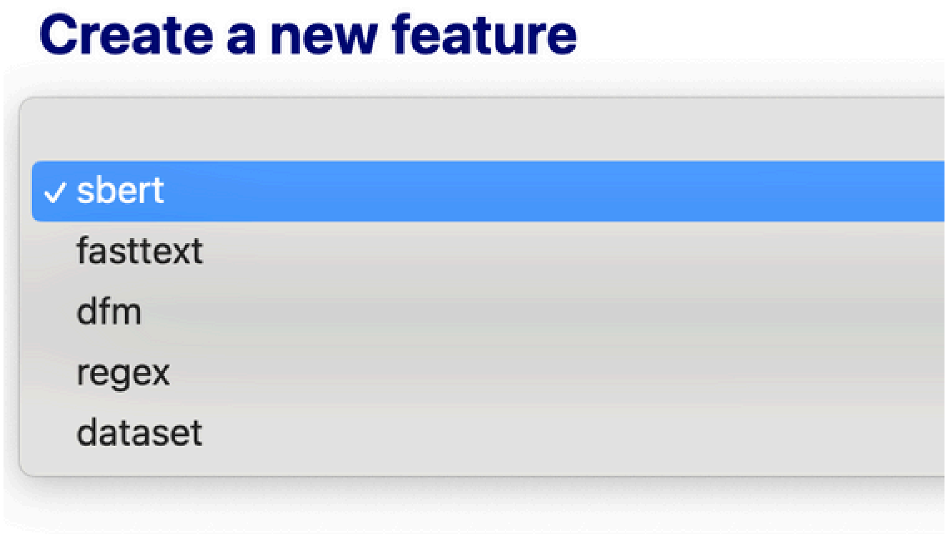
b) Active learning

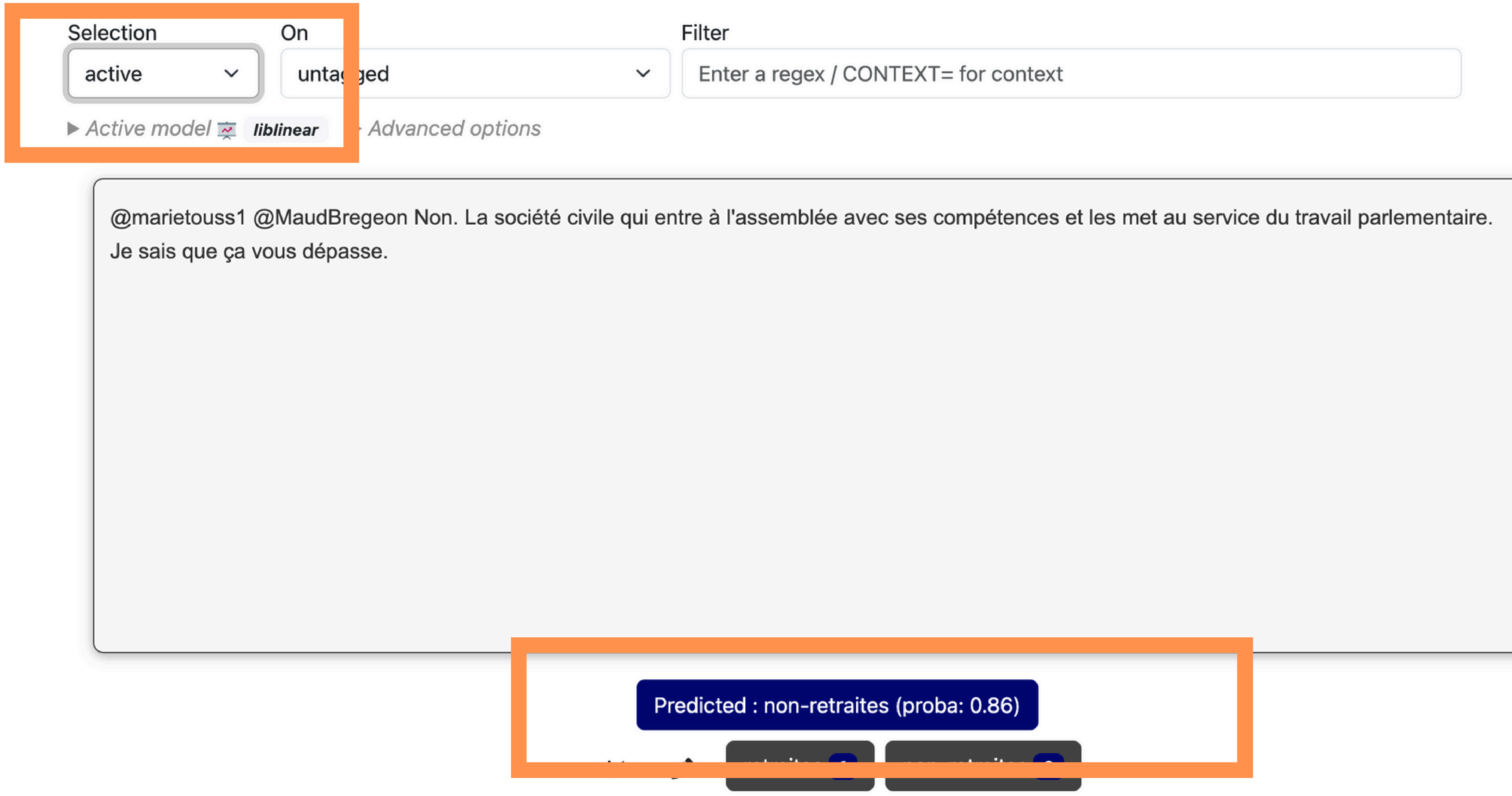
After a quick model is trained, we can look at **least certain predictions**

By classifying these cases specifically, we help the model improve faster

To go further

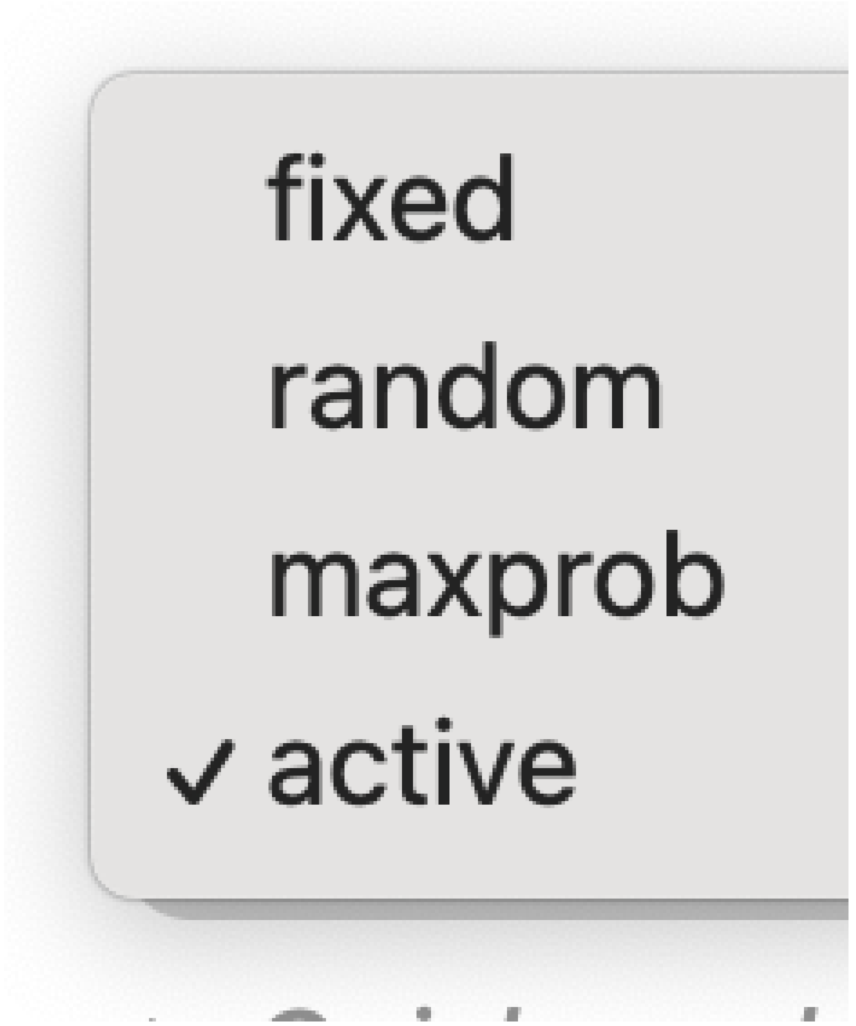
Active learning





To go further

Choose annotation strategy

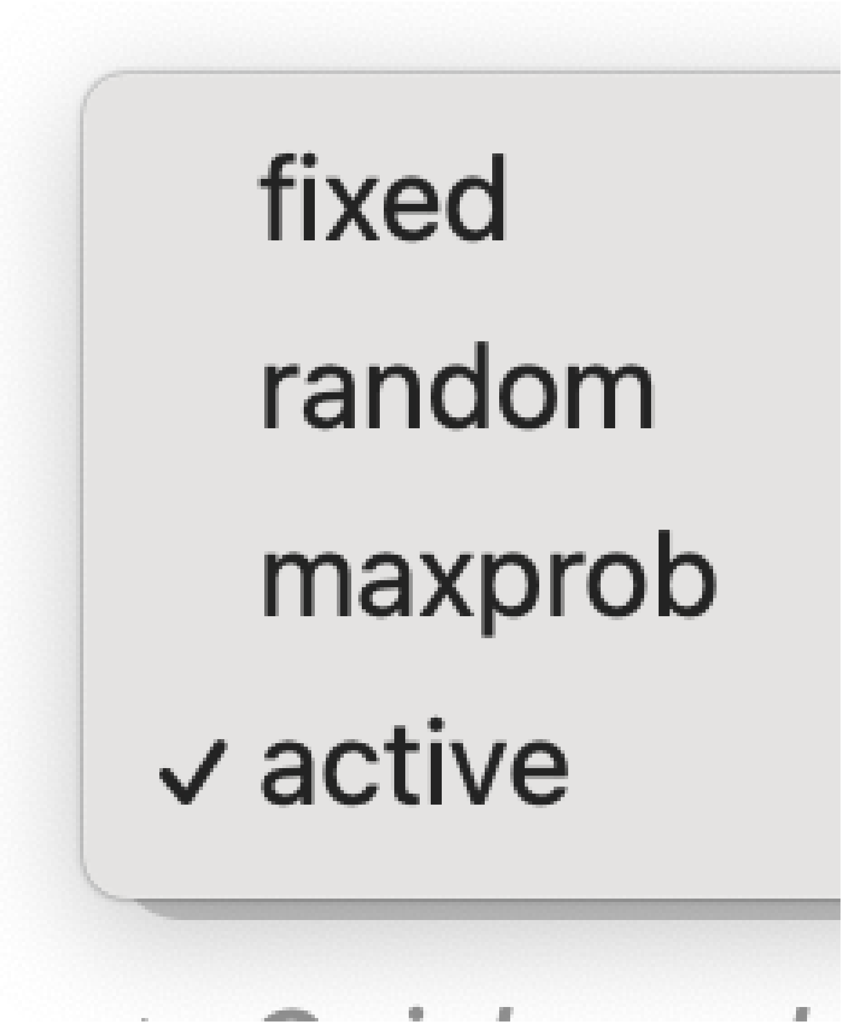


Fixed: order of the dataset

Random: random draw
→ to see a diversity of cases
[start with & go back to this often]

To go further

Choose annotation strategy



Active: most ambiguous phrases
→ helps to refine model

MaxProb: Most certain sentences
→ helps to consolidate a category

To go further

Validation Metrics

▾ Scores

Key	Value
F1 micro	0.926
F1 macro	0.926
F1 weighted	0.926
F1	{"Pas_Politique":0.928,"Politique":0.925}
Precision	{"Pas_Politique":0.973,"Politique":0.883}
Recall	{"Pas_Politique":0.887,"Politique":0.972}
Accuracy	0.926

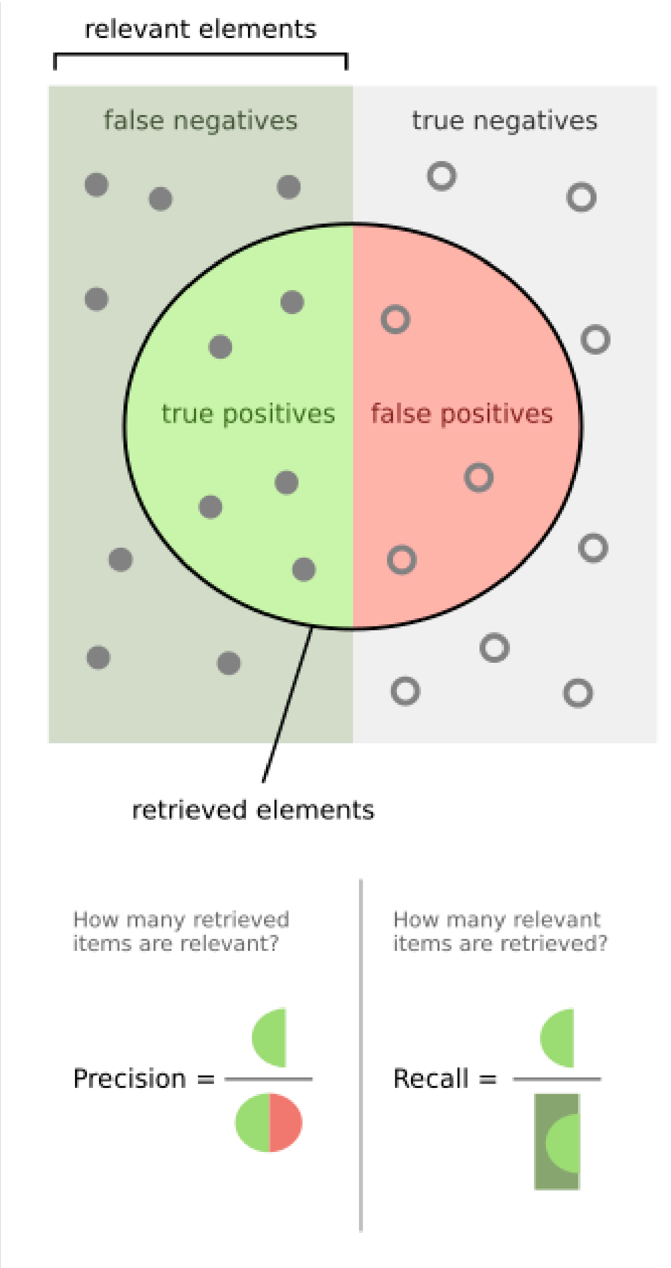
To go further

Validation Metrics

Precision = Out of all the predicted positives, how many were actually correct?

The model marks 10 emails as spam.
If 8 of those really are spam, precision is 80%.

👉 Low Precision = Model is a bit trigger happy in labeling cases



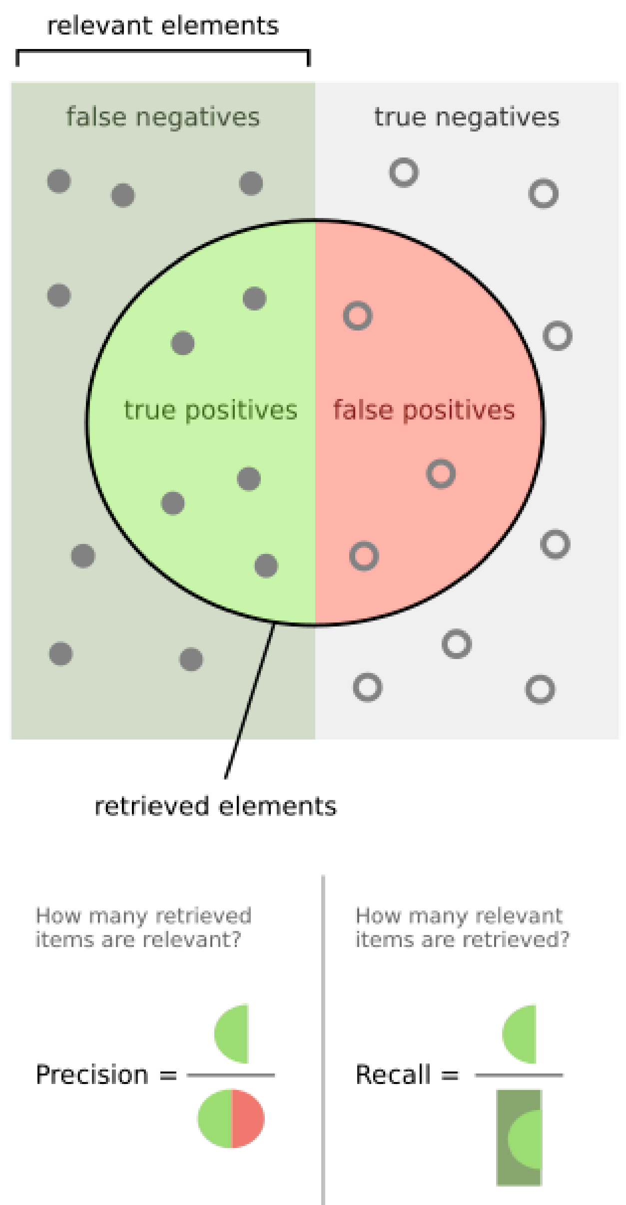
To go further

Validation Metrics

Recall = Out of all the actual positives,
how many did the model correctly identify?

There are 20 actual spam emails.
The model correctly finds 15. Recall is 75%.

👉 Low Recall means the model misses real positive cases



To go further

Validation Metrics

F1 = Harmonic Mean between Precision and Recall.

No clear threshold, as quality depends on the difficulty of the task (and on how confident you are with the error rate)

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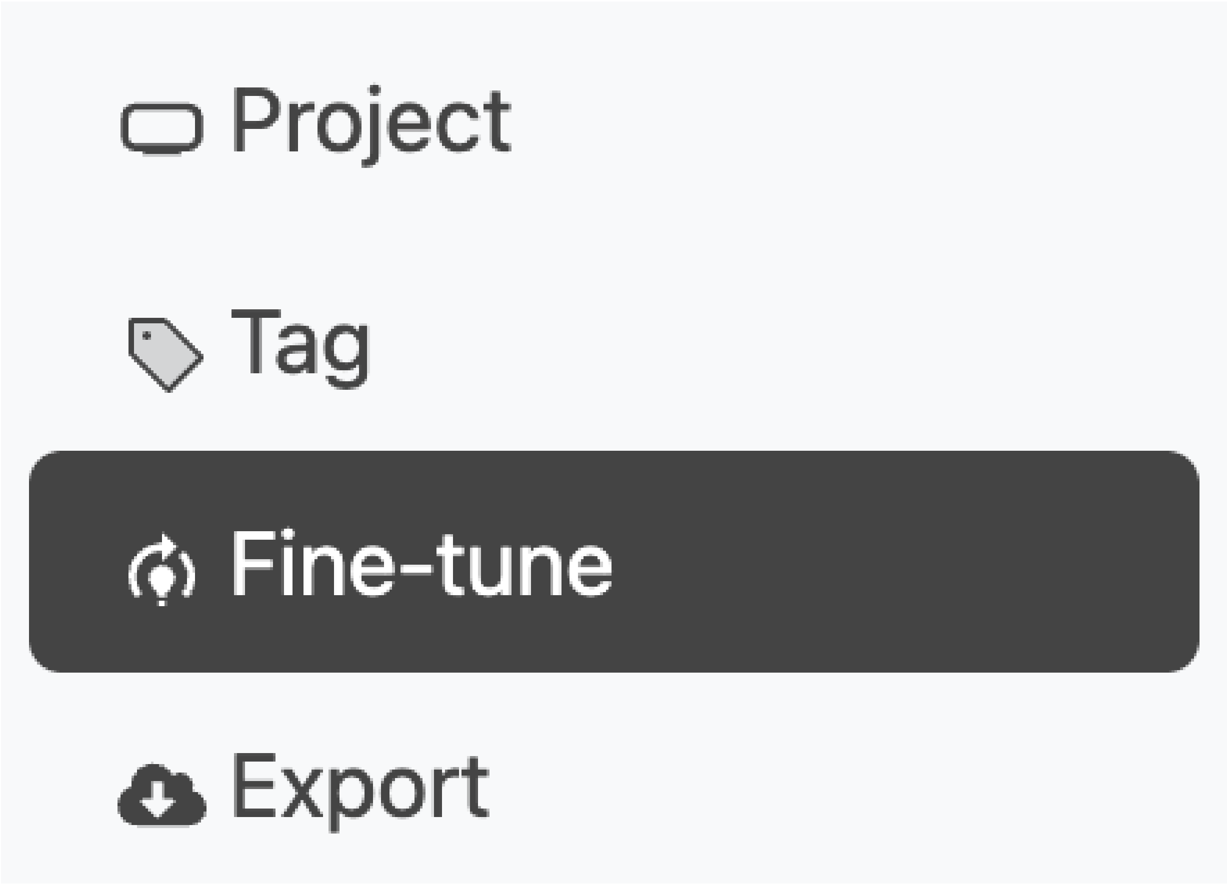
Predict

If you are happy with your test results, you can use the model to predict on the entire corpus, and export them



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Export

Download data (annotations, features, predictions) and fine-tuned models

Select a format

csv

Annotations

Export training data

To go further

Tips

How many categories?

- Overall, binary classifiers (“political”/”not political”) are easier to train than multiclass.

Minimum size for a category?

- **A few %...** otherwise might take some time to train
- A **few hundred annotations** is probably necessary for any classifier to work

To go further

Tips

What if my results are not good?

- Add more data to the training set
- Is your test set separate?
- Does your category make sense? Do you hesitate a lot?
- How do the training data parameters look like?

How to define a category

- Depends, but
  - Can you explain it easily?
  - Does it take a long time for an expert (you) to annotate it?

Feedback

We are still working on the interface

Something unclear? Something buggy? A suggestion? Join the beta testers!

We have a Discord for discussion & troubleshooting