A practical workshop on automatic morpho-syntactic annotation of large language corpora using the Universal Dependencies framework

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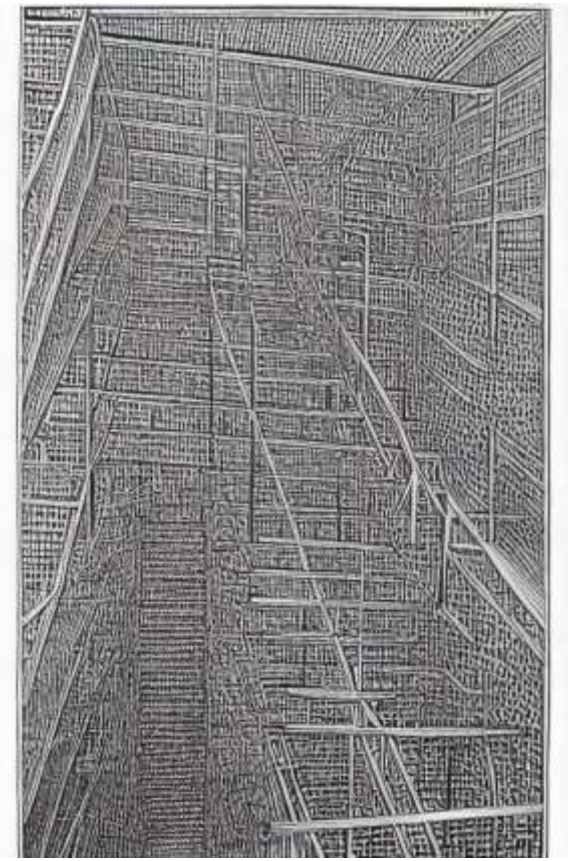
Workshop Day 5

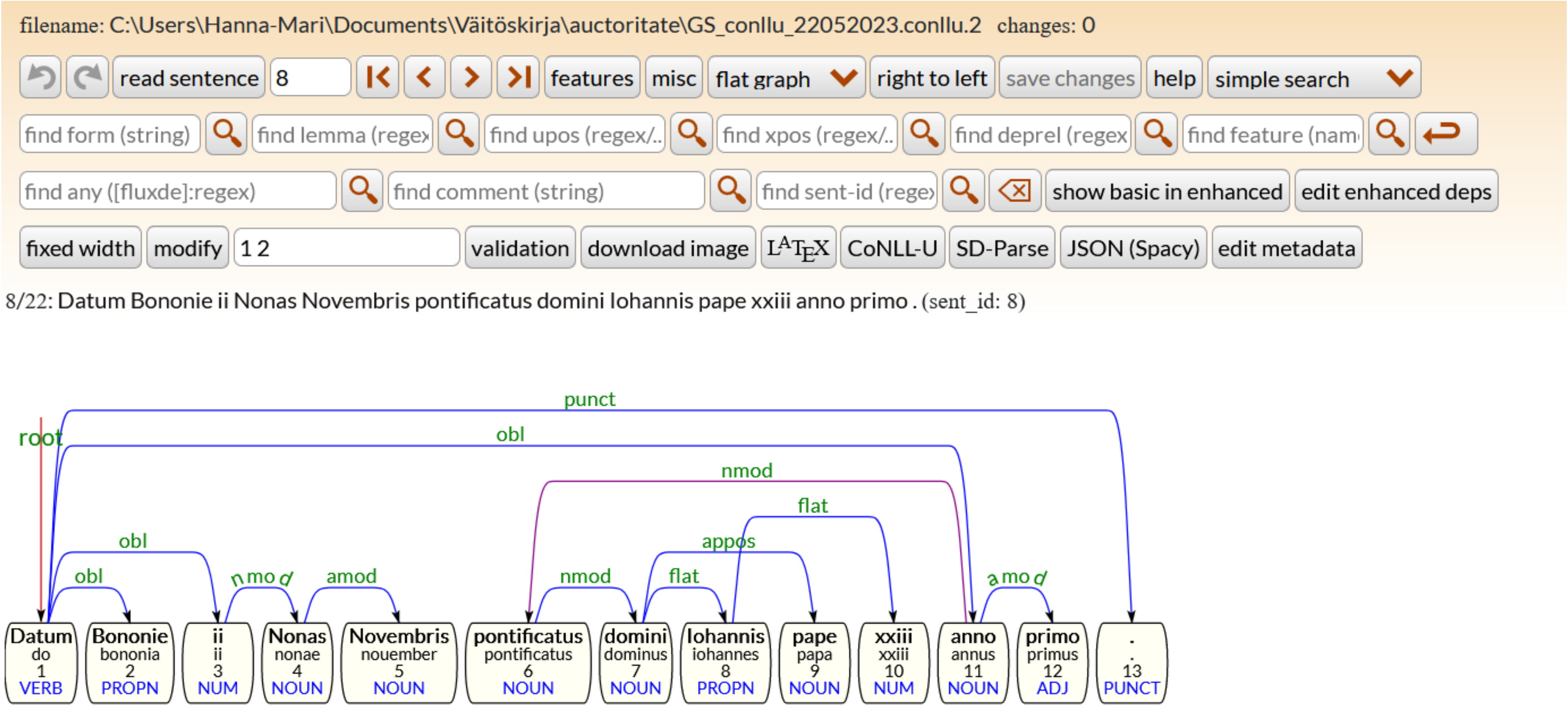
- Recap of ConlluEditor
- Overview of next possible directions
- A short presentation of my own work
- Personal projects help



Deep AI

ConlluEditor for creating a Gold Standard treebank:

- Install Conllu-editor

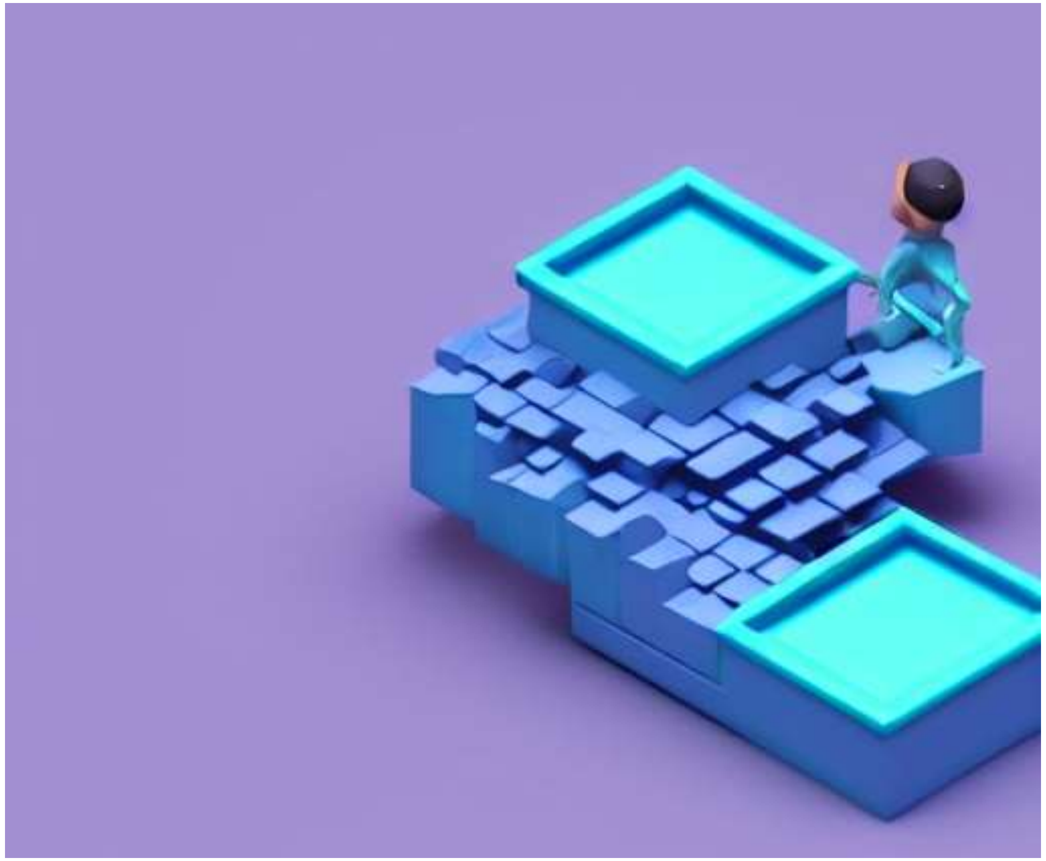


Detailed instructions to follow

- https://github.com/HannaKoo/ParsersTartu/blob/main/ConlluEditor_use.md
- clicking on a word and then clicking on the head-word creates a dependency relation. An edit window opens to enter the relation a name
- Existing relations can be renamed by clicking on their name
- Clicking twice on a word deletes its eventual dependency relation and makes it root
- https://github.com/Orange-OpenSource/conllueditor

Hungry for more?

DeepAI

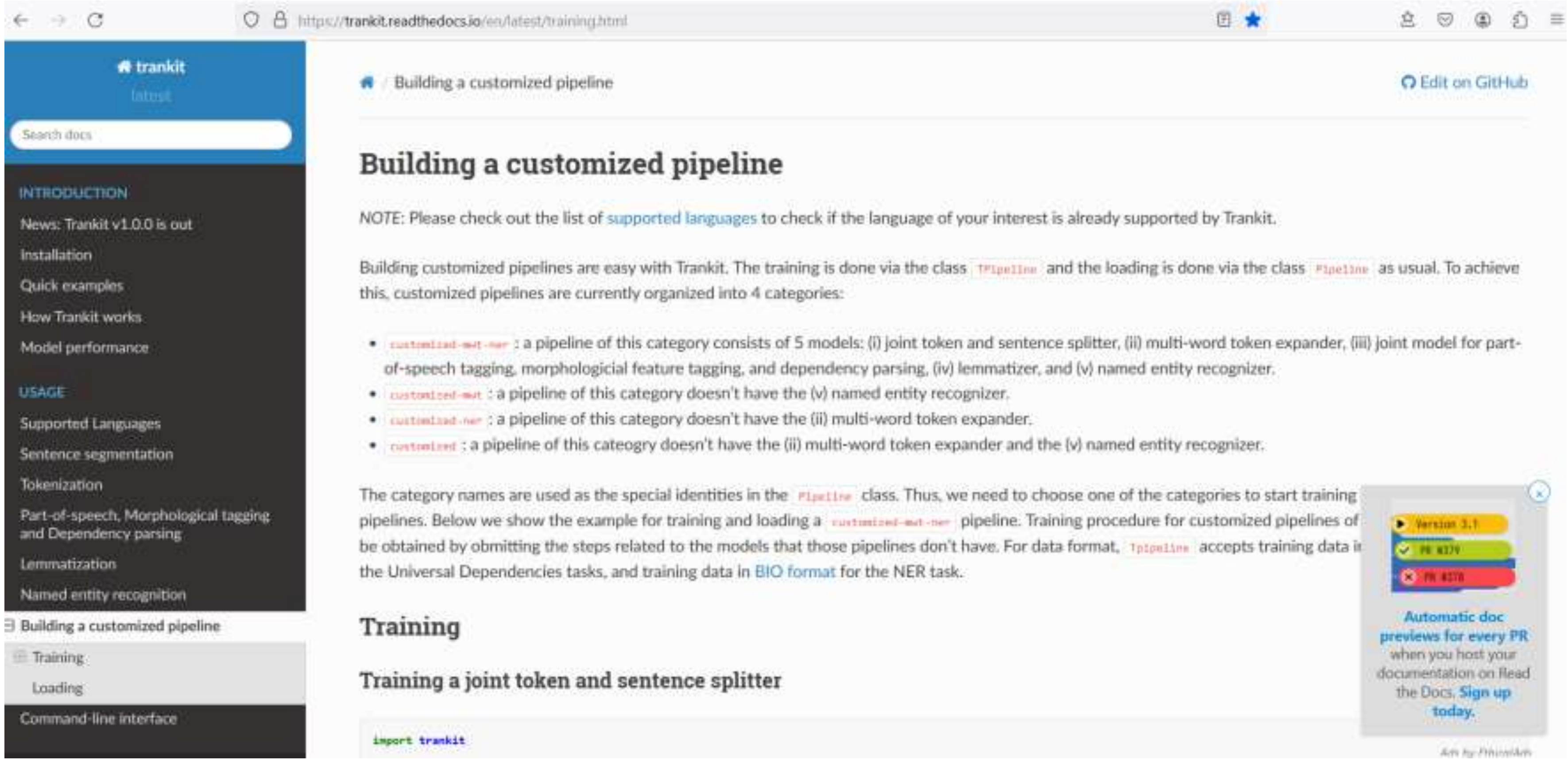


- Developing your own model
- Improving your results with a voting system
- Reporting your results
- Programming skills for working better with tabular data
- Looking into machine learning

Developing your own model

- Needs 3 things
  - A suitable dataset
  - A suitable GPU (supercomputer)
  - Some programming skills
- Trankit detailed instructions
- https://trankit.readthedocs.io/en/latest/training.html
- The basis is the XML-RoBERTa Large
- Finetuned with your own treebank model

Trankit training


https://trankit.readthedocs.io/en/latest/training.html

trankit
latest
Search docs

INTRODUCTION
- News: Trankit v1.0.0 is out
- Installation
- Quick examples
- How Trankit works
- Model performance

USAGE
- Supported Languages
- Sentence segmentation
- Tokenization
- Part-of-speech, Morphological tagging and Dependency parsing
- Lemmatization
- Named entity recognition
- Building a customized pipeline
  - Training
  - Loading
- Command-line interface

Building a customized pipeline

Edit on GitHub

Building a customized pipeline

NOTE: Please check out the list of supported languages to check if the language of your interest is already supported by Trankit.

Building customized pipelines are easy with Trankit. The training is done via the class `TPipeline` and the loading is done via the class `Pipeline` as usual. To achieve this, customized pipelines are currently organized into 4 categories:

- `customized-mwt-ner` : a pipeline of this category consists of 5 models: (i) joint token and sentence splitter, (ii) multi-word token expander, (iii) joint model for part-of-speech tagging, morphologicial feature tagging, and dependency parsing, (iv) lemmatizer, and (v) named entity recognizer.
- `customized-mwt` : a pipeline of this category doesn't have the (v) named entity recognizer.
- `customized-ner` : a pipeline of this category doesn't have the (ii) multi-word token expander.
- `customized` : a pipeline of this cateogry doesn't have the (ii) multi-word token expander and the (v) named entity recognizer.

The category names are used as the special identities in the `Pipeline` class. Thus, we need to choose one of the categories to start training pipelines. Below we show the example for training and loading a `customized-mwt-ner` pipeline. Training procedure for customized pipelines of be obtained by obmitting the steps related to the models that those pipelines don't have. For data format, `TPipeline` accepts training data i the Universal Dependencies tasks, and training data in BIO format for the NER task.

Training

Training a joint token and sentence splitter

```
import trankit
```

Requirements for finetuning

- All data must be in CoNLL-U format
- A requirement of training and development data
  - `.train`
  - `.dev`
- Typically, you also have a `.test` dataset to compare the predicted results to a Gold Standard
- Training datasets are in essence Gold Standard annotated
  - This can be split into 3 parts, e.g. 80 % for train, 10 % dev and 10 % test

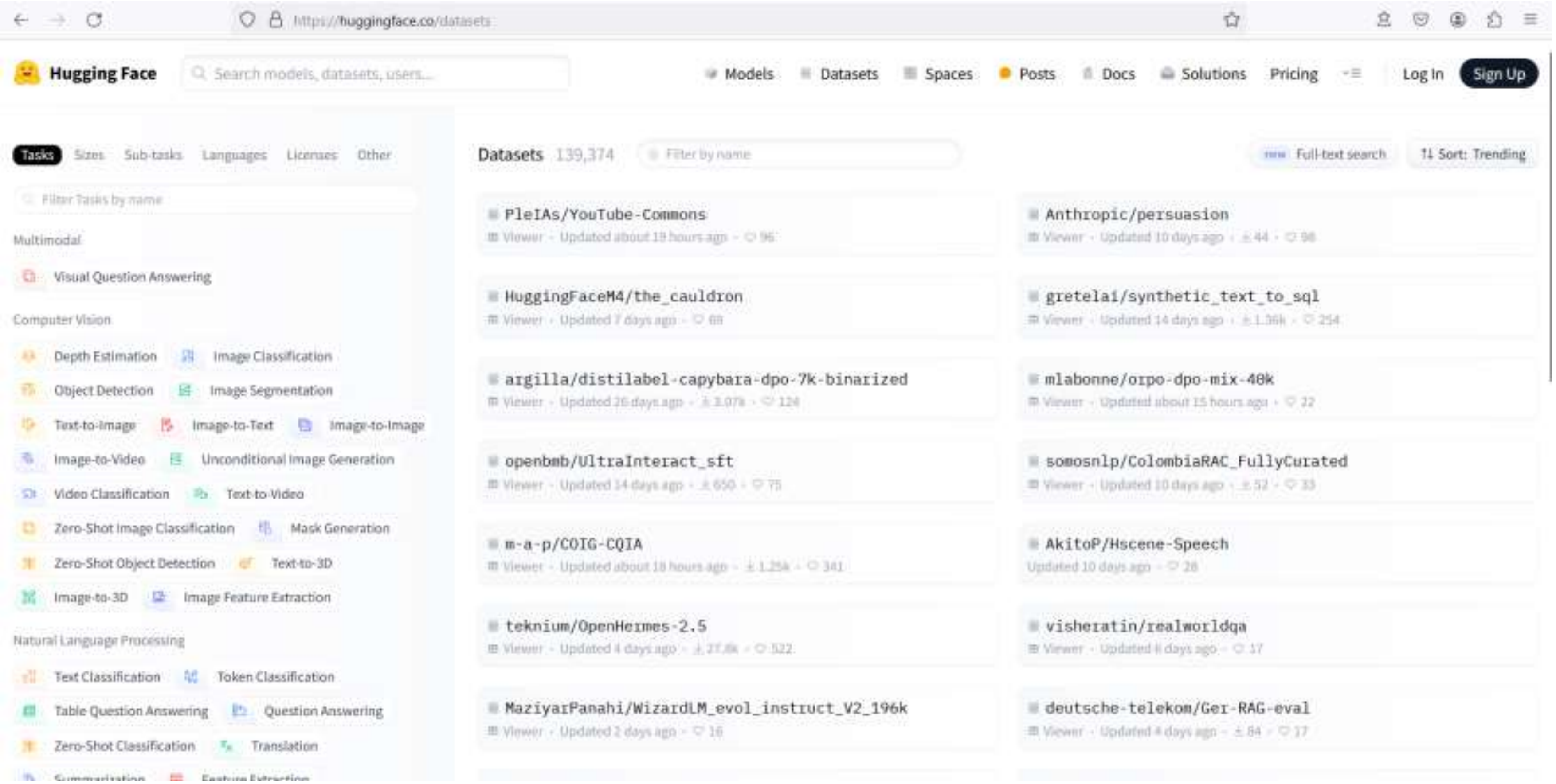
What to consider in training?

- Find the biggest amount of data that is suitable for your own needs
- Think about the characteristics of your own corpus regarding the training data (genre, time period)
- Expect some noise
- If you don't take into consideration the computational resources, the more the better (impact on cost, environmental burden)

Nvidia's greenhouse gas emissions in 2023 amounted to **73,017 metric tons of CO2 equivalent**

Huggingface resources

- https://huggingface.co/datasets



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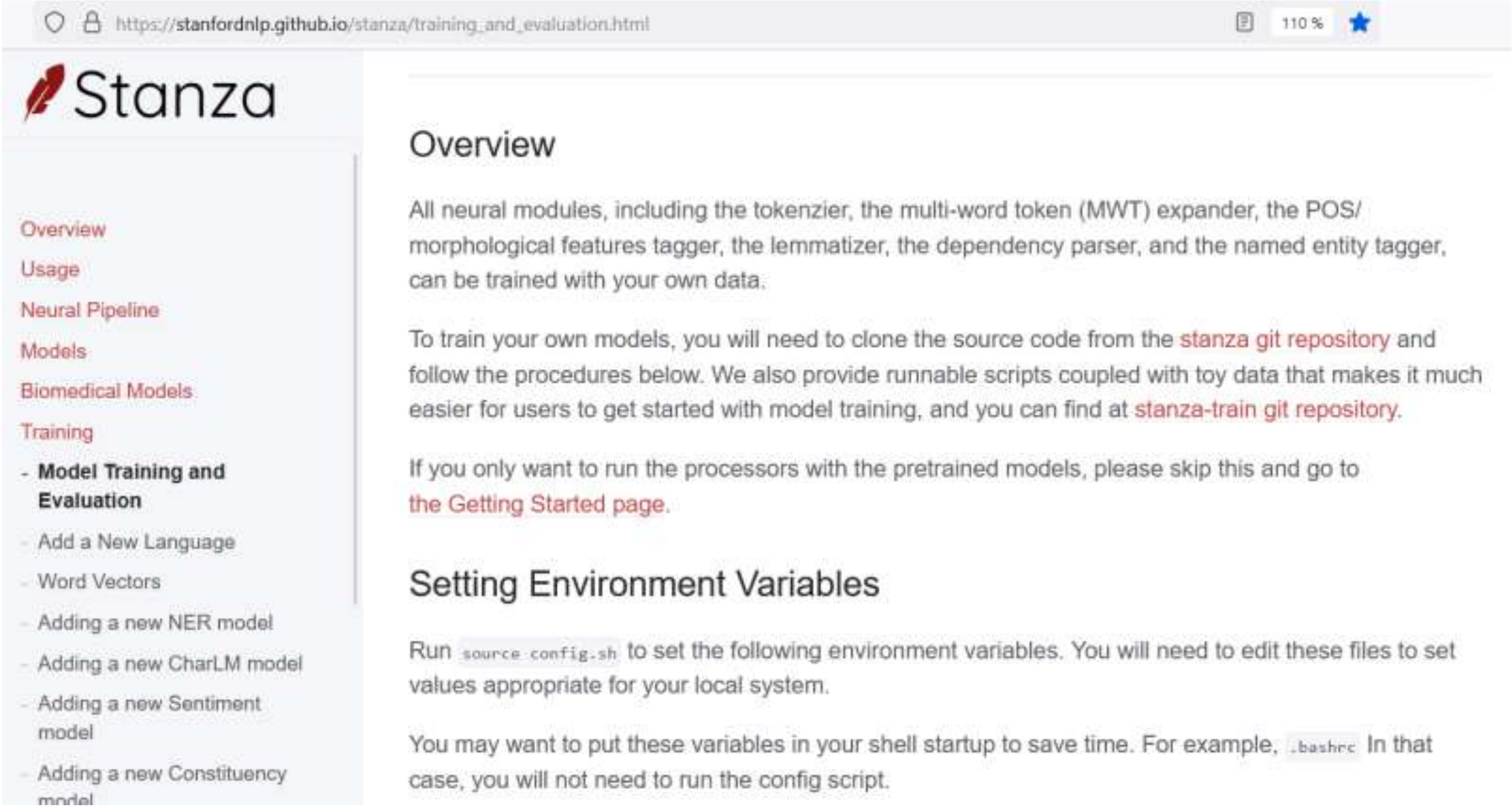
What to consider in training?

- Experiment with several options
- Continue with the most accurate one and create your own treebanks by correcting manually some output
- Use this Gold Standard to develop a new model (save some of course for .dev and .test)

Stanza can also be trained



https://stanfordnlp.github.io/stanza/training_and_evaluation.html

Stanza

Overview

All neural modules, including the tokenzier, the multi-word token (MWT) expander, the POS/morphological features tagger, the lemmatizer, the dependency parser, and the named entity tagger, can be trained with your own data.

To train your own models, you will need to clone the source code from the stanza git repository and follow the procedures below. We also provide runnable scripts coupled with toy data that makes it much easier for users to get started with model training, and you can find at stanza-train git repository.

If you only want to run the processors with the pretrained models, please skip this and go to the Getting Started page.

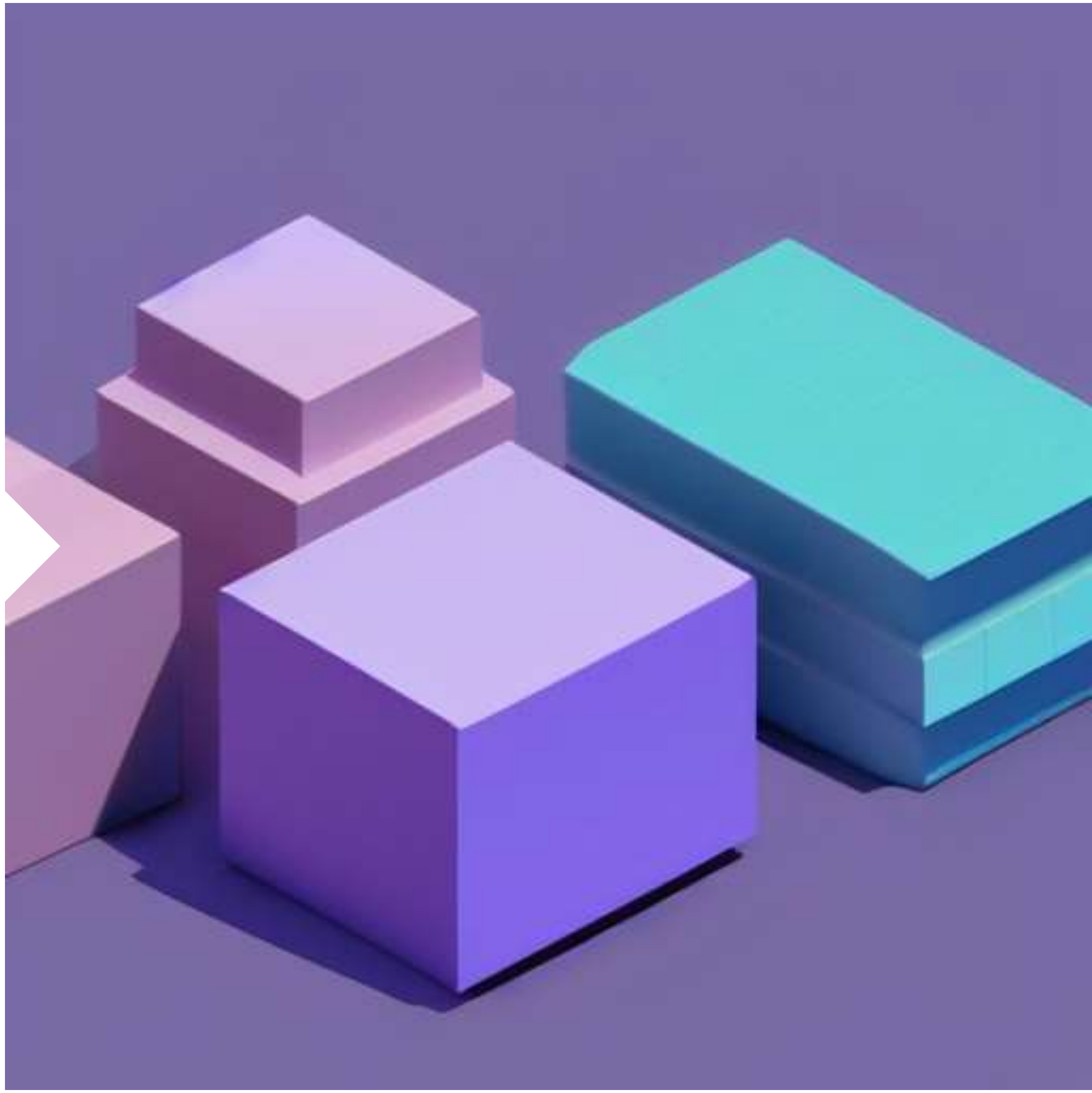
Setting Environment Variables

Run `source config.sh` to set the following environment variables. You will need to edit these files to set values appropriate for your local system.

You may want to put these variables in your shell startup to save time. For example, `.bashrc` In that case, you will not need to run the config script.

Take home message of training

- Read the documentation
- Don’t be frustrated when the documentation is poor
- Make high quality notes
- Consider sharing your models and training data



Improve your results with voting

- Use 3 models or more
- Take the most common result
- https://aclanthology.org/W05-1518.pdf
- Improving Parsing Accuracy by Combining Diverse Dependency Parsers, Zeman et al, 2005

Report your results

- Publish all numbers in a GitHub repo
- Take your most important numbers up in the paper
- Think about the reader of the paper

	ittb.udp		llct.udp		perseus.udp		proiel.udp		udante.udp	
	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS
ITTB	**84.51%**	**86.23%**	44.25%	52.16%	29.54%	40.56%	30.54%	45.43%	59.93%	65.77%
LLCT	44.22%	50.16%	**93.02%**	**93.85%**	28.92%	37.44%	40.37%	52.10%	45.57%	53.42%
Perseus	33.28%	44.21%	39.85%	48.71%	**61.80%**	**67.18%**	38.93%	55.16%	35.64%	45.79%
PROIEL	39.10%	50.86%	43.16%	53.08%	41.52%	52.36%	**73.51%**	**77.45%**	39.43%	48.62%
UDante	50.78%	58.51%	36.95%	45.78%	22.44%	32.41%	26.72%	40.41%	**50.81%**	**57.32%**

Table 3: UDPipe scores before treebank alignment. Columns correspond to trained models, rows to test data.

	ittb.udp		llct.udp		perseus.udp		proiel.udp		udante.udp	
	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS
ITTB	**83.83%**	**85.51%**	43.80%	51.45%	43.17%	53.12%	40.46%	51.33%	61.68%	67.39%
LLCT	43.12%	48.55%	**93.11%**	**93.88%**	47.31%	54.13%	46.69%	55.23%	41.56%	49.05%
Perseus	42.73%	53.54%	48.69%	55.24%	**63.80%**	**68.38%**	49.98%	59.25%	43.59%	54.23%
PROIEL	46.77%	55.39%	50.37%	57.48%	53.11%	59.88%	**75.78%**	**78.87%**	46.13%	55.15%
UDante	53.06%	59.95%	38.51%	46.69%	35.59%	45.64%	30.72%	44.11%	**54.50%**	**61.02%**

Table 4: UDPipe scores after treebank alignment. Columns correspond to trained models, rows to test data.

https://aclanthology.org/2023.udw-1.2.pdf Gamba et Zeman, 2023

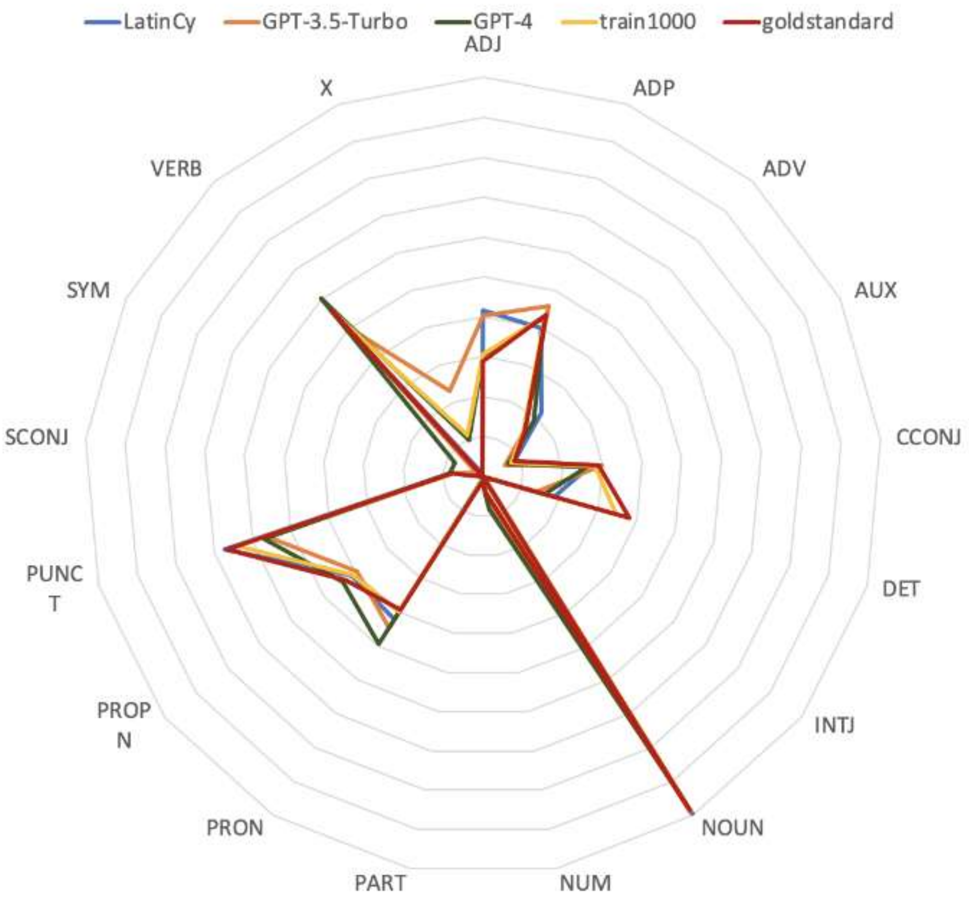


Figure 6: POS tag distribution in the LLCT test set.

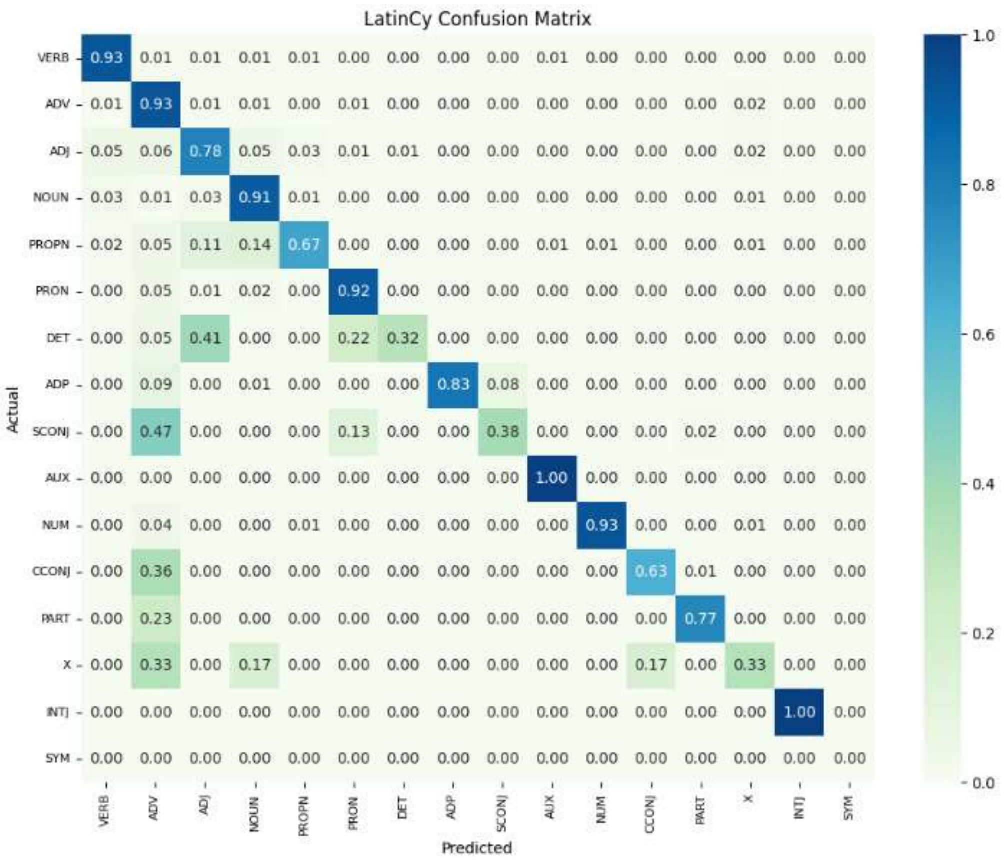


Figure 7: Confusion matrix for LatinCy on the Bullinger sample.

https://aclanthology.org/2024.latechclfl-1.18.pdf Stüss et al, 2024

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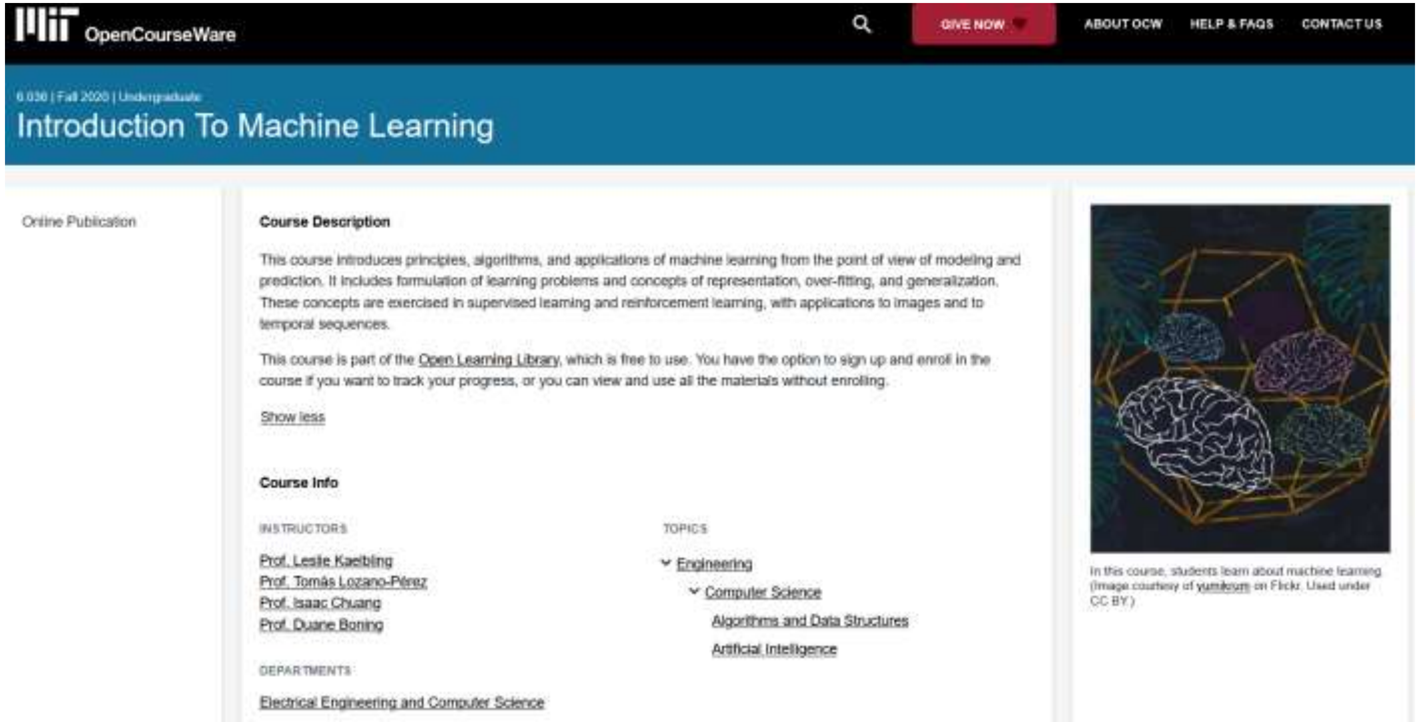
Most important programming skills

- Basic Python
- Skills to work with tabulator separated values
- Some insight into ML
- Folgert Karsdorp:
- http://www.karsdorp.io/python-course/



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My own use of parsing tools

- To analyze a large amount of texts
- We have countless studies on differences between Classical and Medieval Latin
- Usually these discuss one feature of language or are based in the heuristic understanding of the researcher
- What can we say quantitatively that makes medieval Latin medieval?

Penitentiary documents provide us an insight to the communicative means of persuasive language use

The situation – e.g. violent assault

description

+
Linguistic features

Thanks to University of Tartu

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Kieli- ja käännöstieteiden laitos 2024