



Explainable Artificial Intelligence for species identification

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Identification in biology

Definition :

- Matching a **living specimen** to its **taxonomic group**.
- Mostly based on **morphological (visual) characteristics** of the group.



Identification in biology



Identification in biology

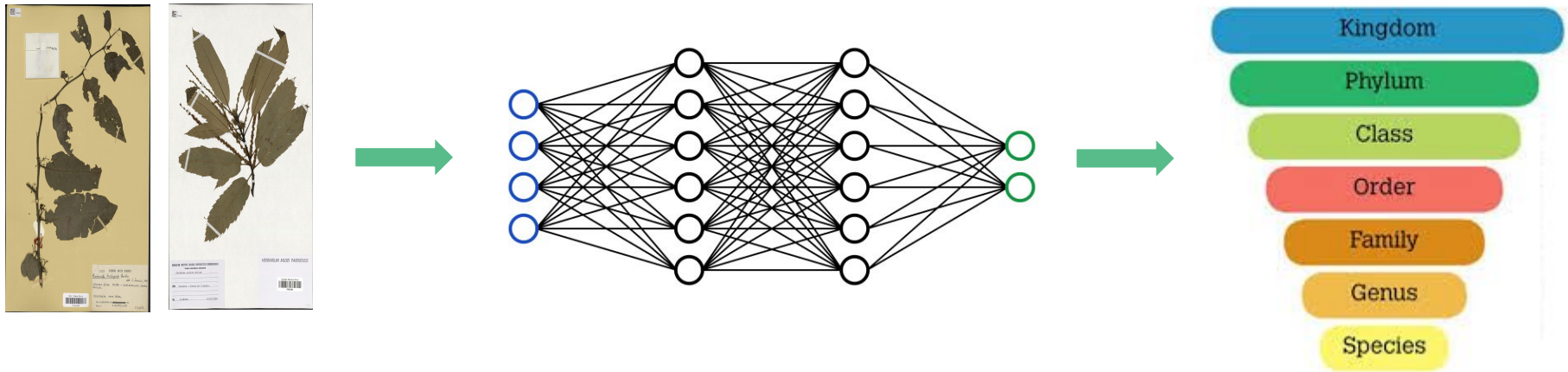
Muséum Herbarium



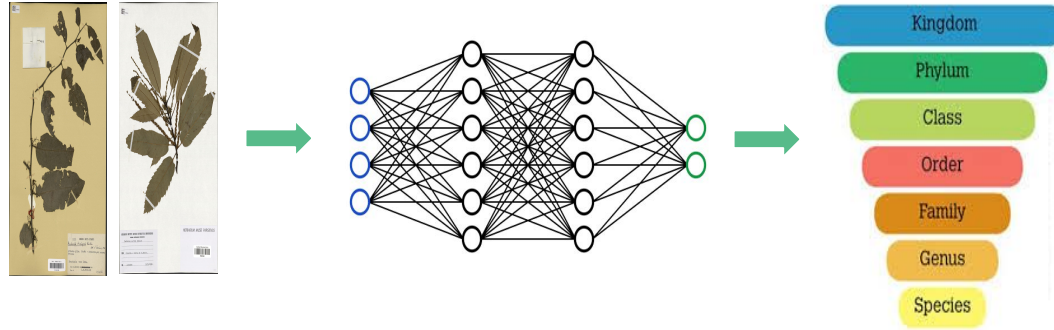
Flora corpora



How to automate this task ?



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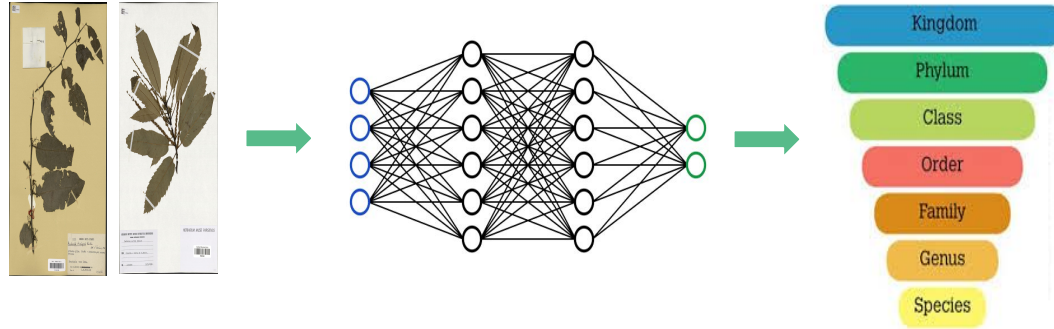


- Fully supervised
- Data is available (Herbarium of the National Museum of Natural History)



5 millions numerized specimen

How to automate this task ?

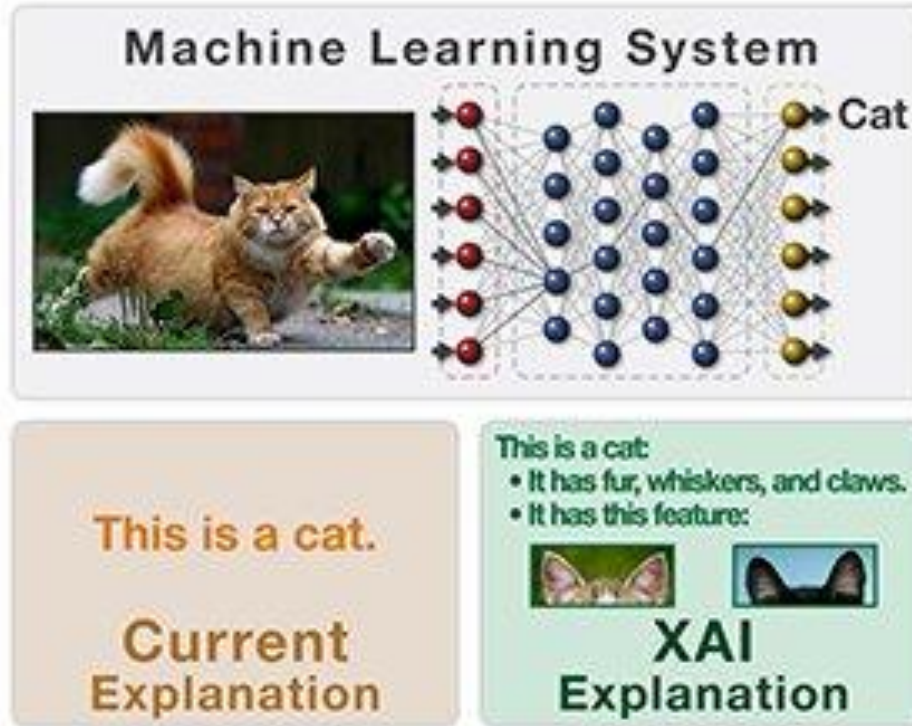


- What if the model gets it wrong ?
- What makes the model identify a specimen to a specific species ?
- Can the model explain its decision ?

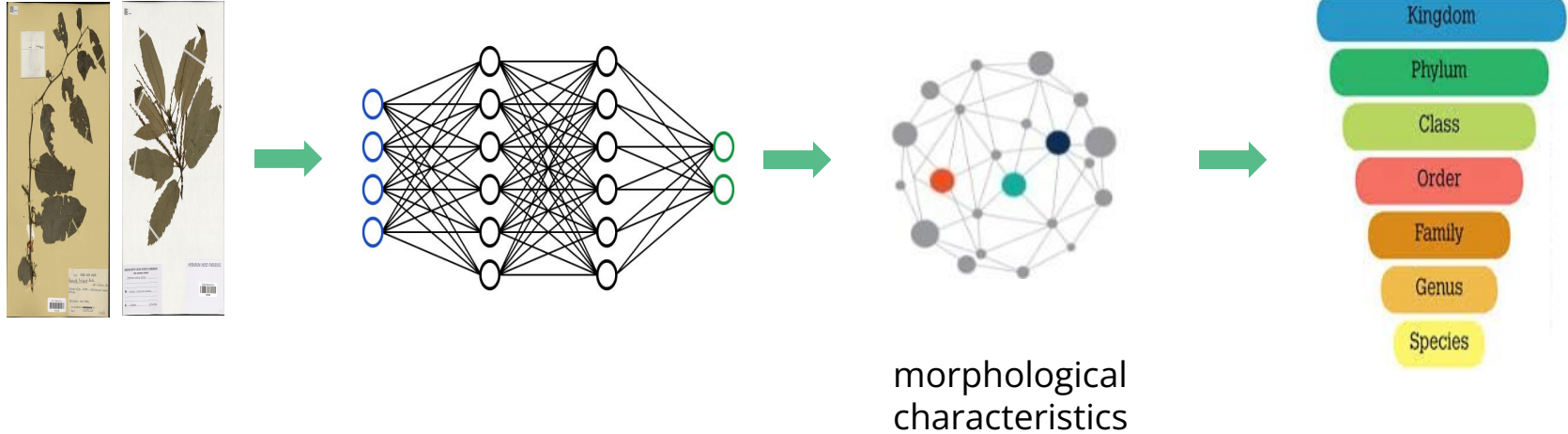


Black box

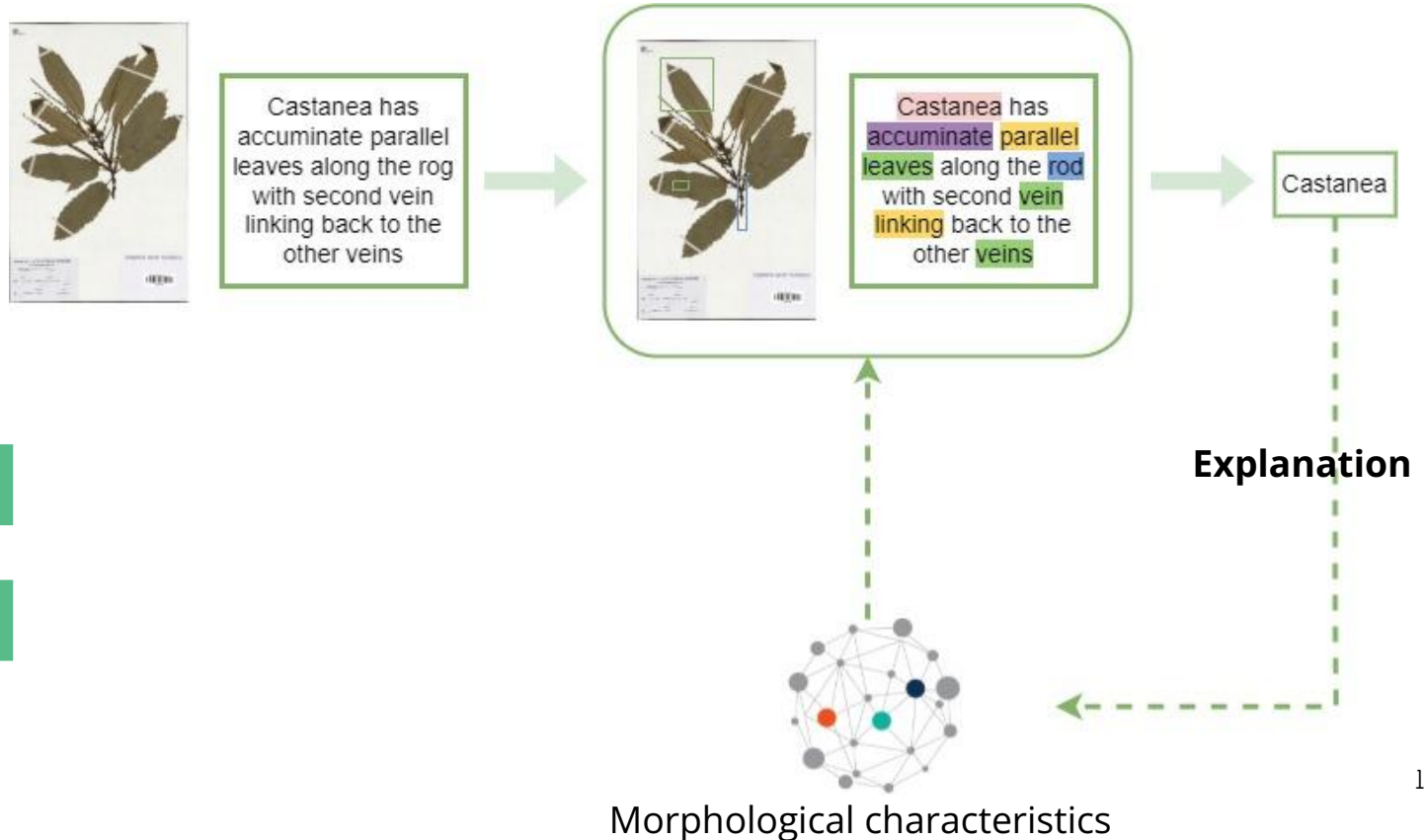
We need explainability !



What if we make use of the species descriptions ?



Proposed method



Proposed method

Text processing

Image processing

Extracting morphological characteristics from the texts.

bracts 7-10, chartaceous, ovate, sometimes marginally ciliolate;
lamina sometimes succulent, ovate or elliptic basally cruneate.

- (bracts, form, ovate)
- (bracts, form, Ciliolate)
- (lamina, surface, succulent)
- (lamina, form, ovate)
- (lamina, form, elliptic)
- (lamina, form, cruneate)

Proposed method

Text processing

Image processing

Verifying the presence of the characteristics in images



- (bracts, form, ovate)
- (bracts, form, Ciliolate)
- (lamina, surface, succulent)
- (lamina, form, ovate)
- (lamina, form, elliptic)
- (lamina, form, cruneate)

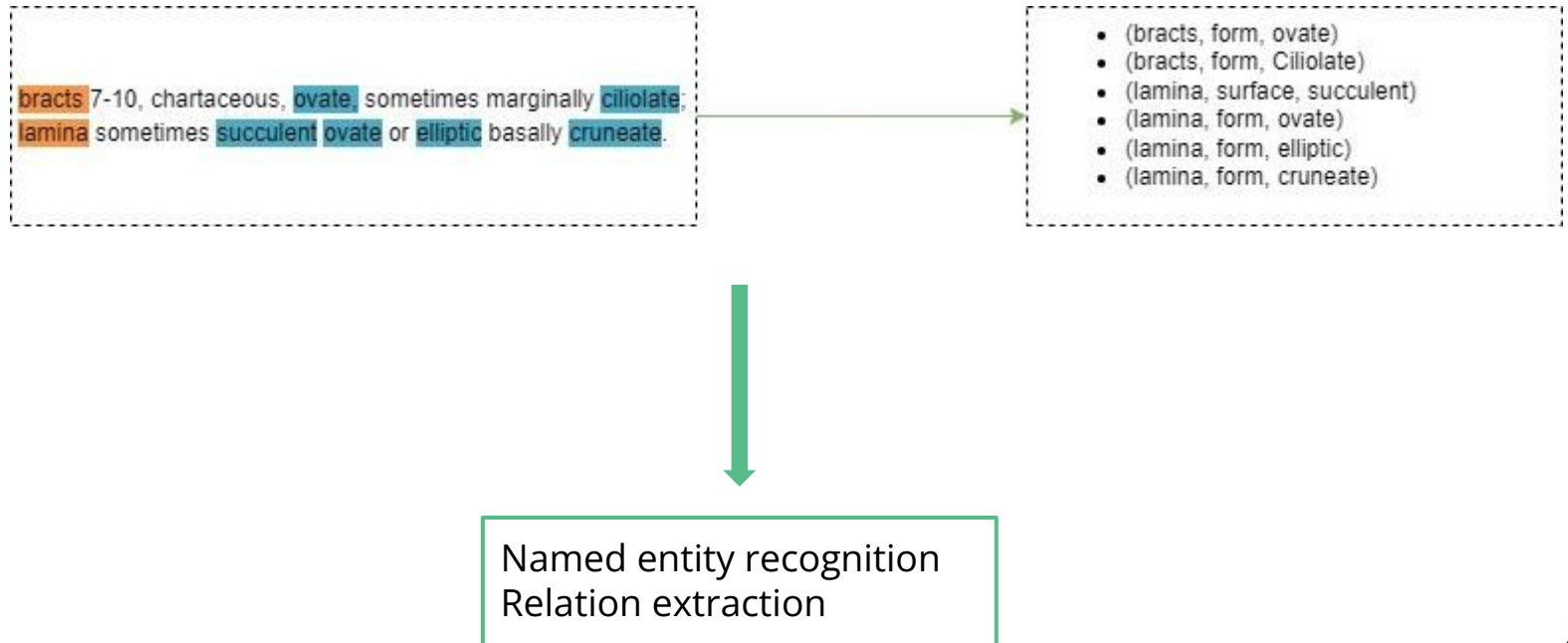




Text processing

Image processing

Identify the task

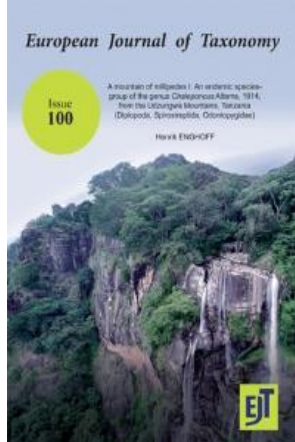


Identify the task

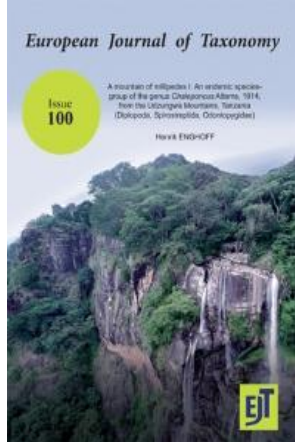
- Historical task.
- Entities detection and classification.
- Measure of performance for **detection** and **classification**.

When **Sebastian Thrun PERSON** started working on self - driving cars at **Google ORG** in **2007 DATE** , few people outside of the company took him seriously . “ I can tell you very senior CEOs of major **American NORP** car companies would shake my hand and turn away because I was n’t worth talking to , ” said **Thrun PERSON** , in an interview with **Recode ORG** earlier this week **DATED** .

Check the data



Check the data



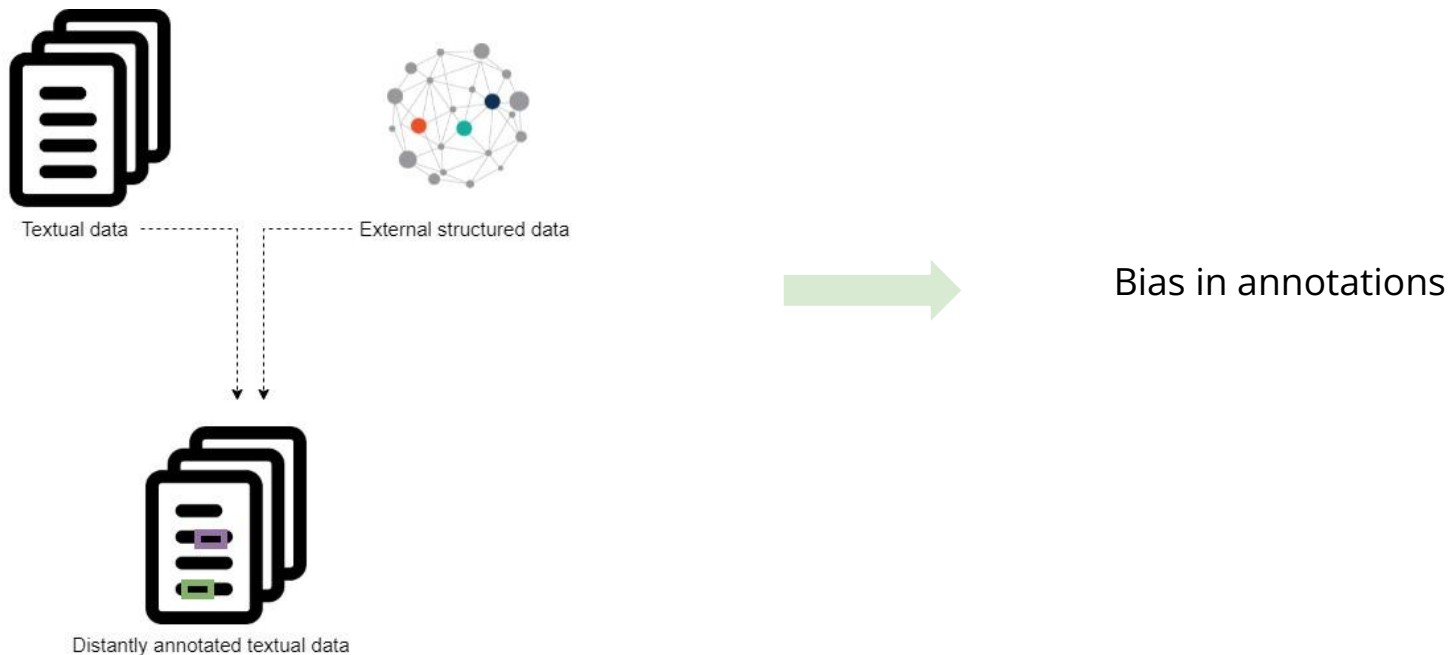
No text-to-triplet matching



Distant supervision

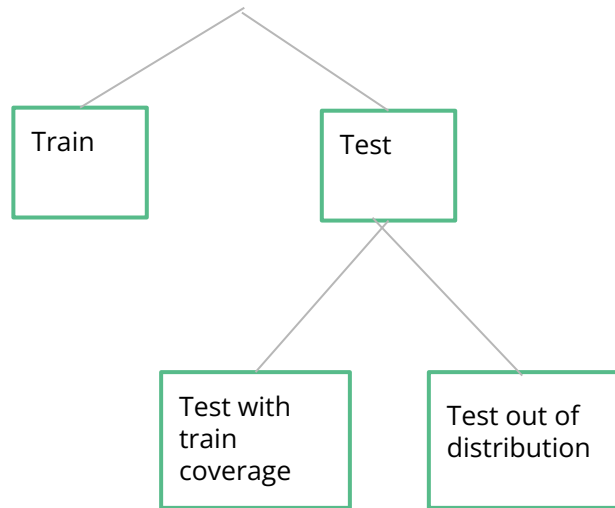
Check the data

What's distant supervision ?

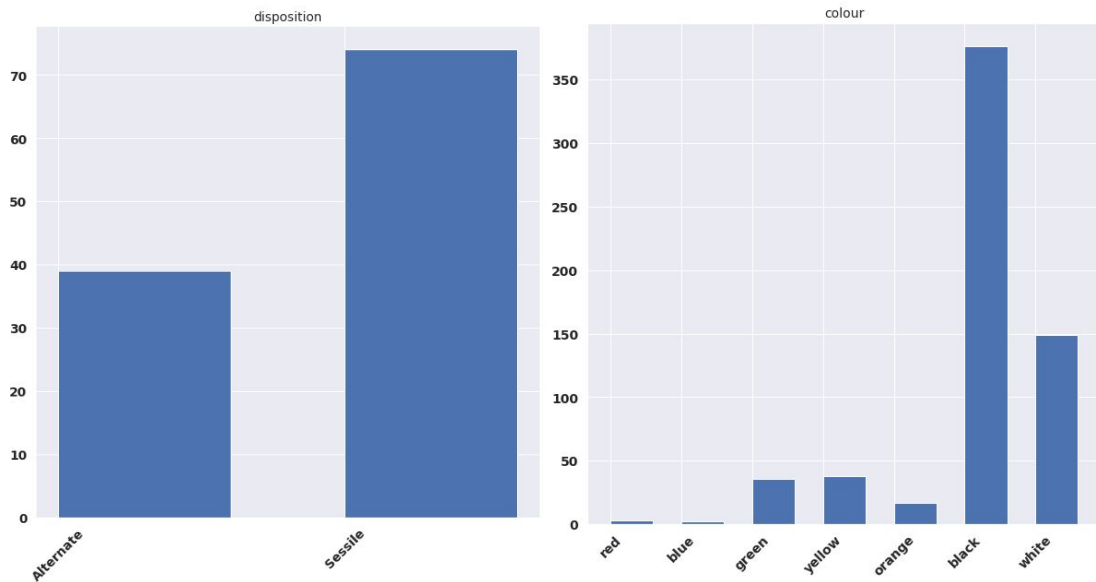


Create the dataset

Ensemble of all sentences

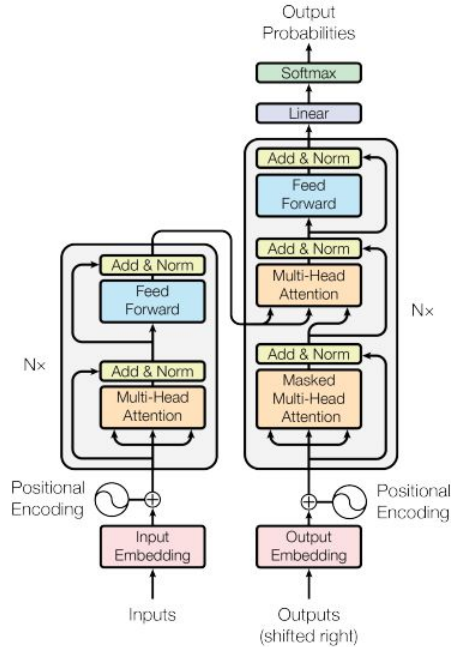


Check the histograms



Model architecture

Transformers



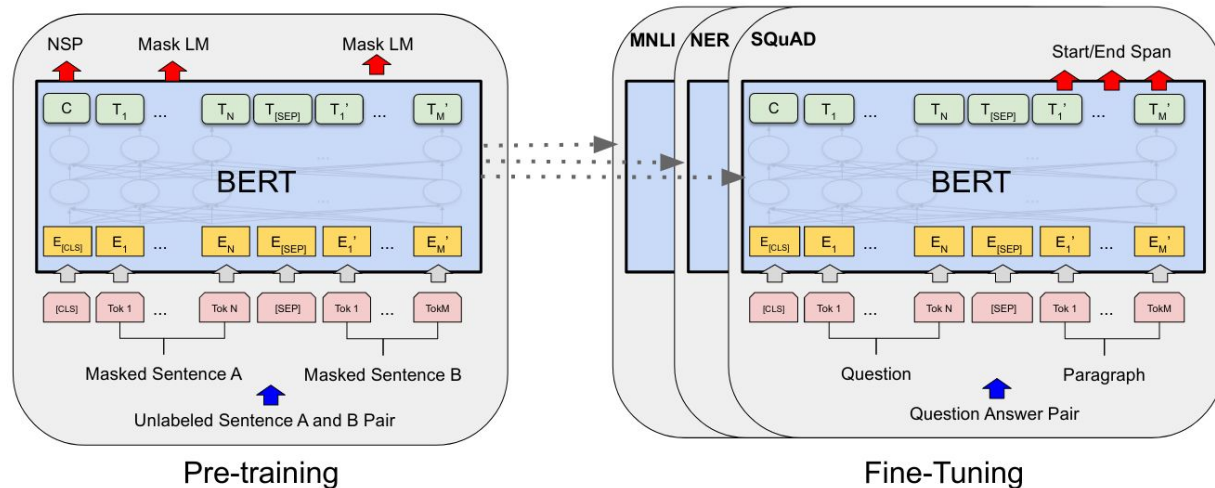
Attention mechanism

	the	European	economic	zone
la	0.80	0.00	0.00	0.20
zone	0.00	0.00	0.00	1.00
économique	0.00	0.00	1.00	0.00
européenne	0.00	0.80	0.00	0.20

Transformers : Attention Is All You Need
(Ashish Vaswani et al, 2017)

Model architecture

Transformers

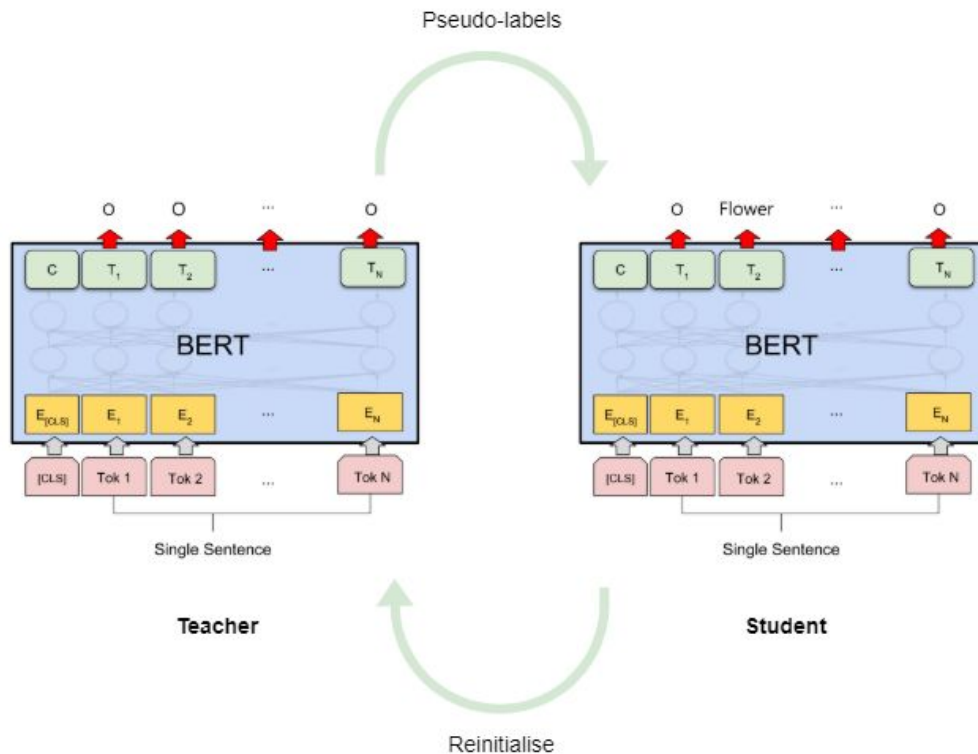


Bert : Transformer encoder.

- Next sentence prediction
- Masked word prediction

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Model architecture



Results

Detection

	X (New sentences)			Xc (new sentences without "O")			Xt (New sentences + new words)		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Baseline w/ distant supervision	95.46	95.64	95.50	100	72.36	83.97	100	60.82	75.64
Baseline w/ distant supervision + Im	96.29	96.41	96.23	100	72.54	84.08	100	59.02	74.23
Baseline w/ distant supervision + knowledge dist.	91.64	85.36	87.40	100	82.16	90.21	100	78.46	87.93
Baseline w/ co-occurrence prior	94.93	94.84	94.88	100	77.09	87.06	92.35	92.61	92.19

Results

Classification

	X (New sentences)			Xc (new sentences without “O”)			Xt (New sentences + new terms)		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Baseline w/ distant supervision	94.4	94.8	94.5	61.5	72.4	65.3	87.4	56.9	68.4
Baseline w/ distant supervision + lm	95.8	96.0	95.6	85.2	64.9	75.05	93.5	58.3	71.0
Baseline w/ distant supervision + knowledge dist.	91.9	85.1	87.5	41.2	67.1	54.15	86.9	68.4	74.6
Baseline w/ prior on co-occurences	94.1	93.9	93.8	68.9	62.5	63.8	88.34	61.9	71.9

Results

Baseline

Inflorescences: terminal, few- or much-branched, few- or many-flowered[Auteur in1] , elongated, paniculate cymes with spirally arranged paracladia, peduncles of main florescences (4—)8.4—12 cm long and those of coflorescense (1.5—)7—8.5 cm, bracts elliptic, 5-8 mm long, margins with knob shaped, stipitate. glands: glabrous or pubescent on both surfaces; pedicels 1.8-2 mm long. Capsules: ellipsoid, 1-1.1 \times 0.8-1 cm, surface glabrous, pubescent, or pilose, often with some red coloration. Seeds: creamy white with red-brown mottling, oval, 7-8 \times 4-4.5 mm, caruncle large and conspicuously lobed.

Knowledge distillation

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colour
development
disposition
ecology-geography
flower
form
fruit
leaf
margin leaf
Taxon
part of
plant
position
structure
surface

Qualitative results over two texts of two variants of the model, the underlined tokens are the named entities present in the test set as a ground truth