



# 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

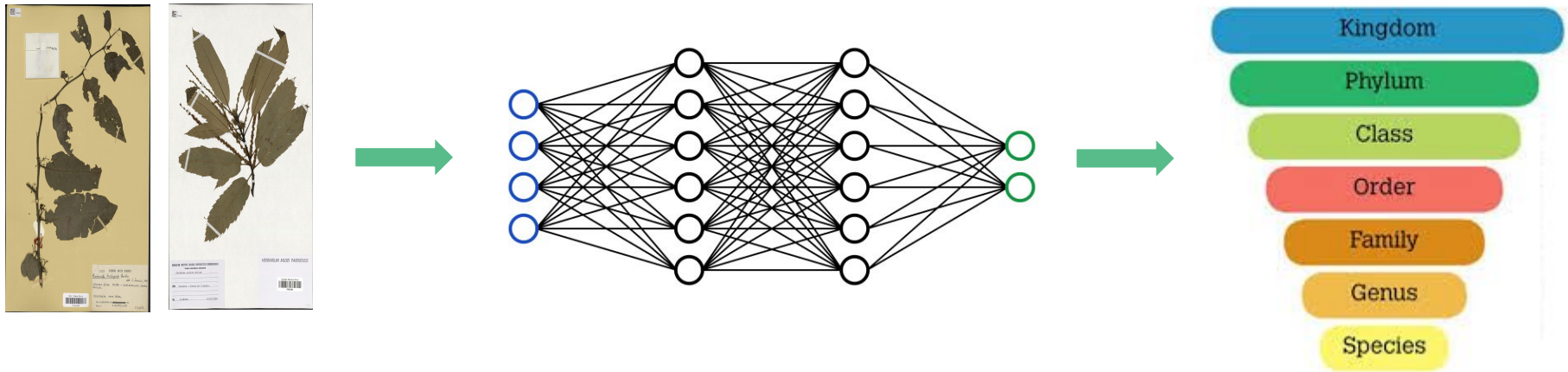
Muséum Herbarium



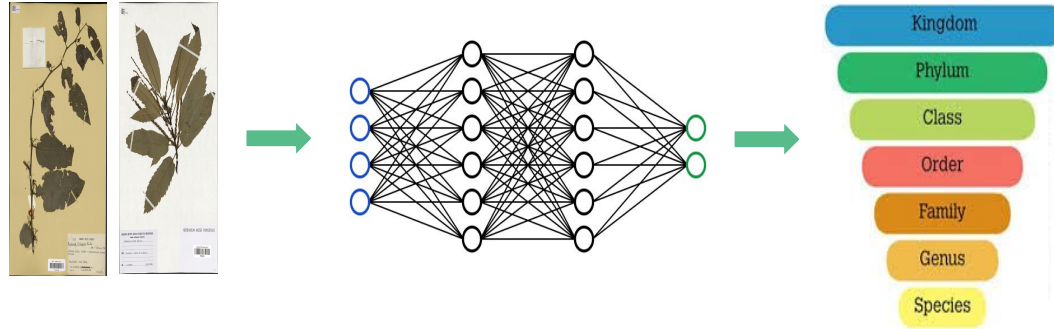
Flora corpora



# How to automate this task ?



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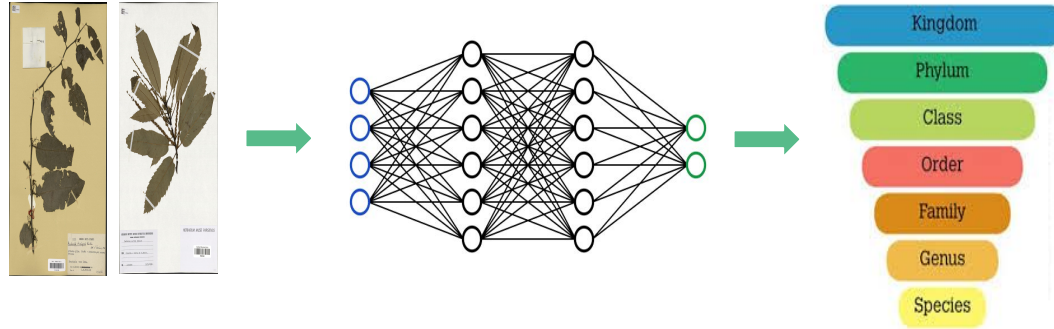


- Fully supervised
- Data is available ( Herbarium of the National Museum of Natural History)



**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 ?

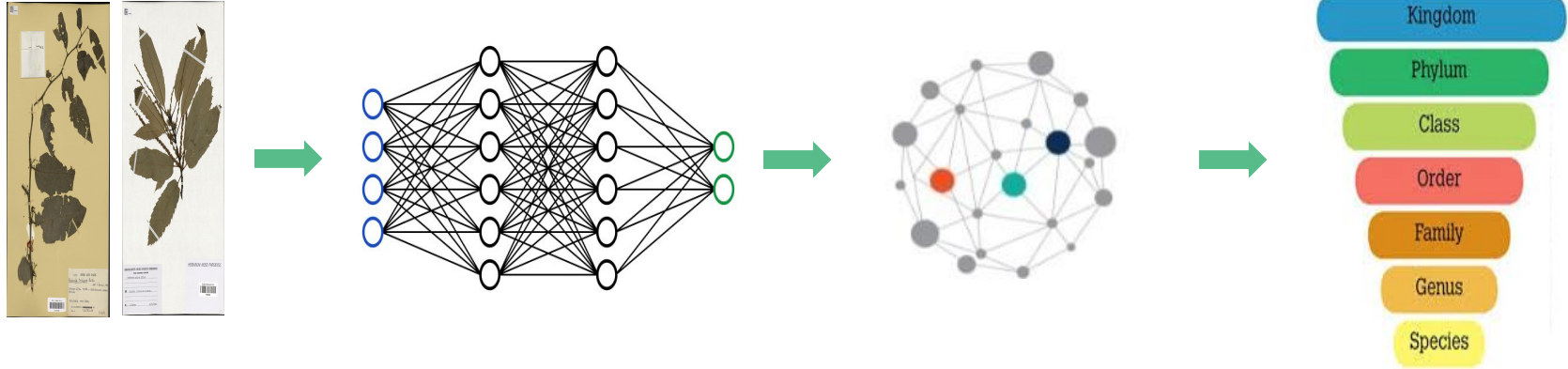


**Black box**

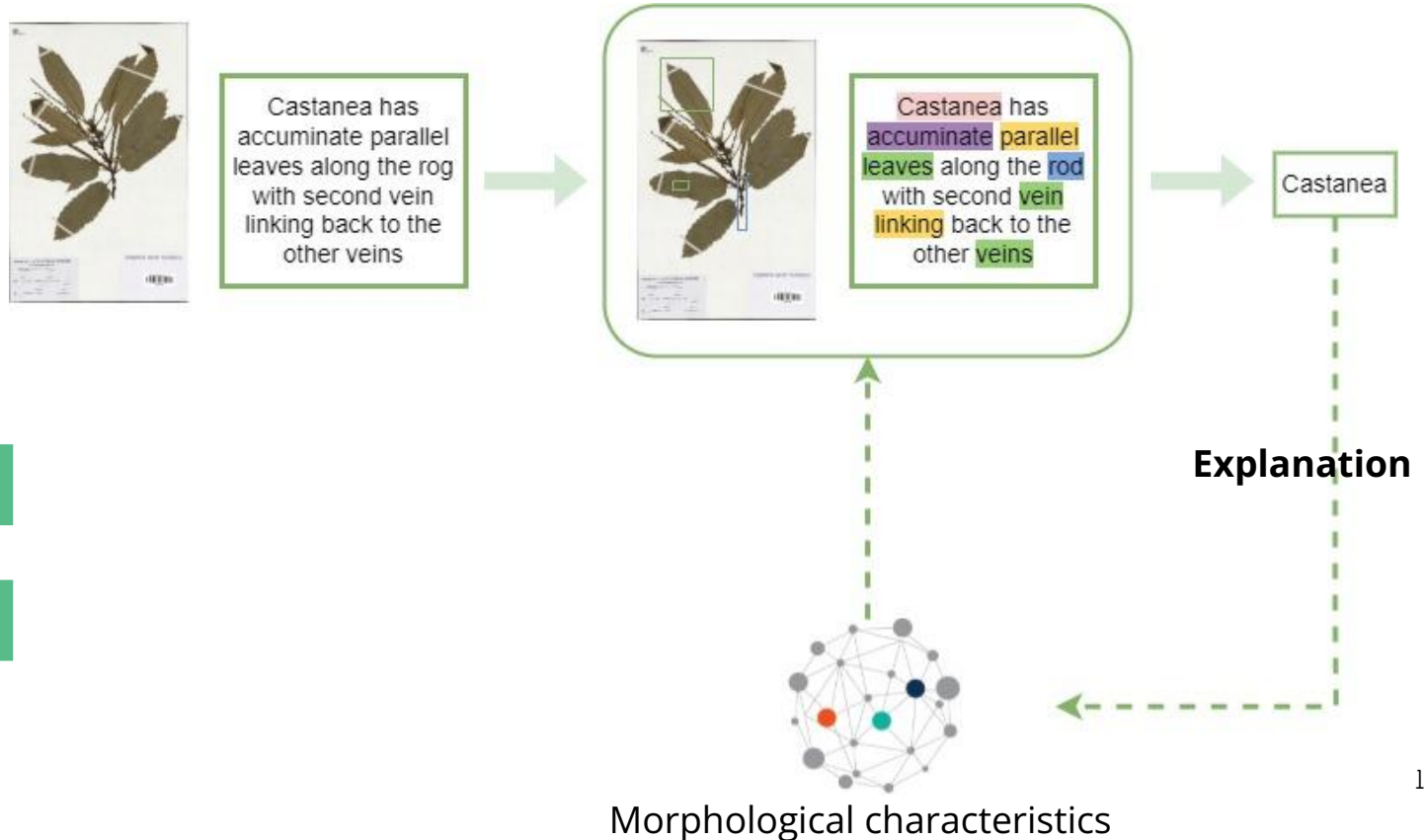
We need explainability !



# 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 ciliate;  
lamina sometimes succulent, ovate or elliptic basally cruminate.

- (bracts, form, ovate)
- (bracts, form, Ciliate)
- (lamina, surface, succulent)
- (lamina, form, ovate)
- (lamina, form, elliptic)
- (lamina, form, cruminate)

# 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)

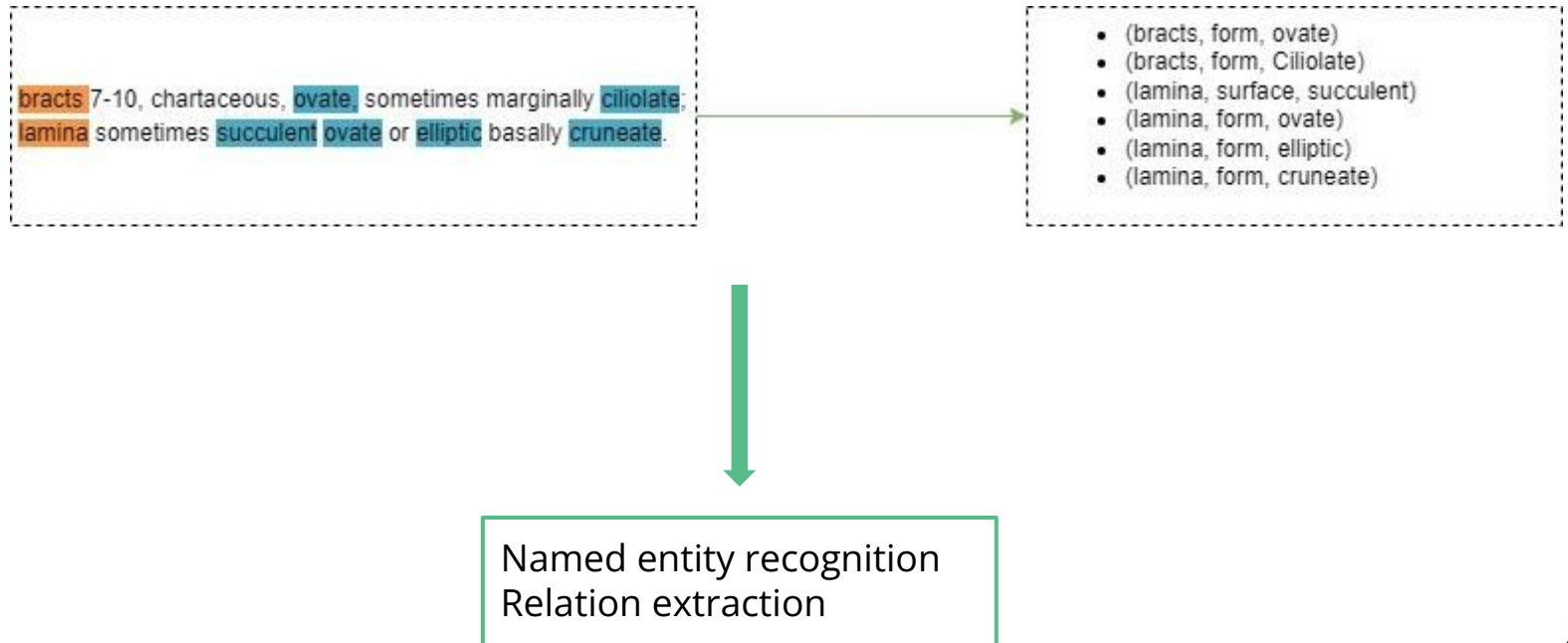




**Text processing**

**Image processing**

# Identify the task

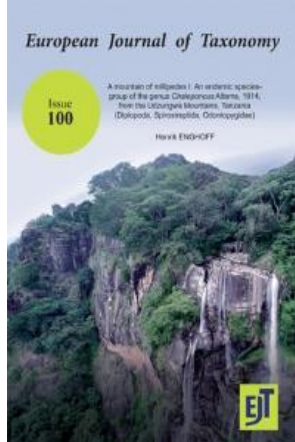


# Identify the task

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

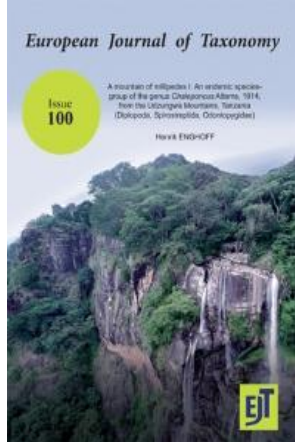
When Sebastian Thrun PERSON started working on self - driving cars at Google ORG in 2007 DATE , few people outside of the company took him seriously . “ I can tell you very senior CEOs of major American NORP car companies would shake my hand and turn away because I was n’t worth talking to , ” said Thrun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

# Check the data





# Check the data



No text-to-graph direct matching



**Distant supervision**

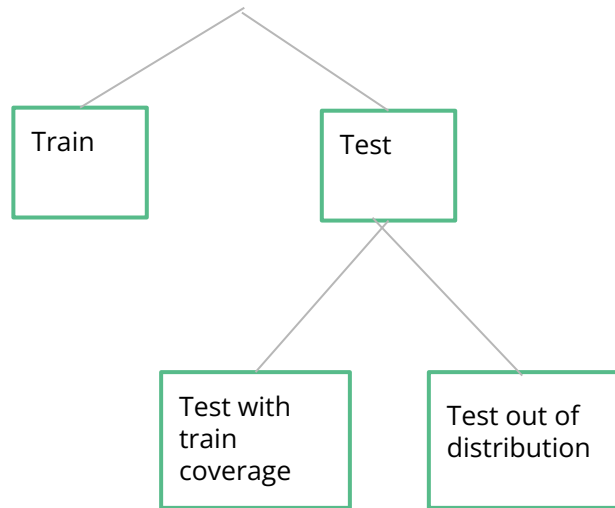
# Check the data

What's distant supervision ?

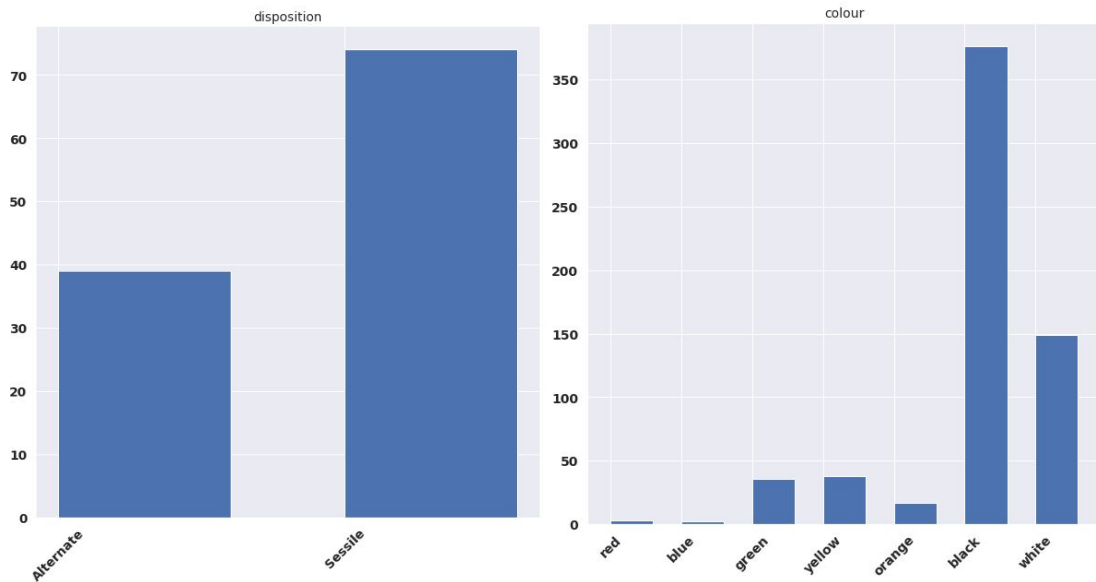


# Create the dataset

## Ensemble of all sentences

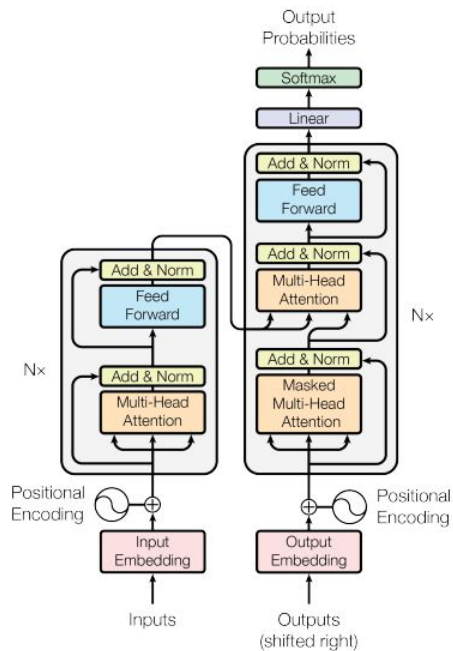


## Check the histograms



# Model architecture

## Transofrmers



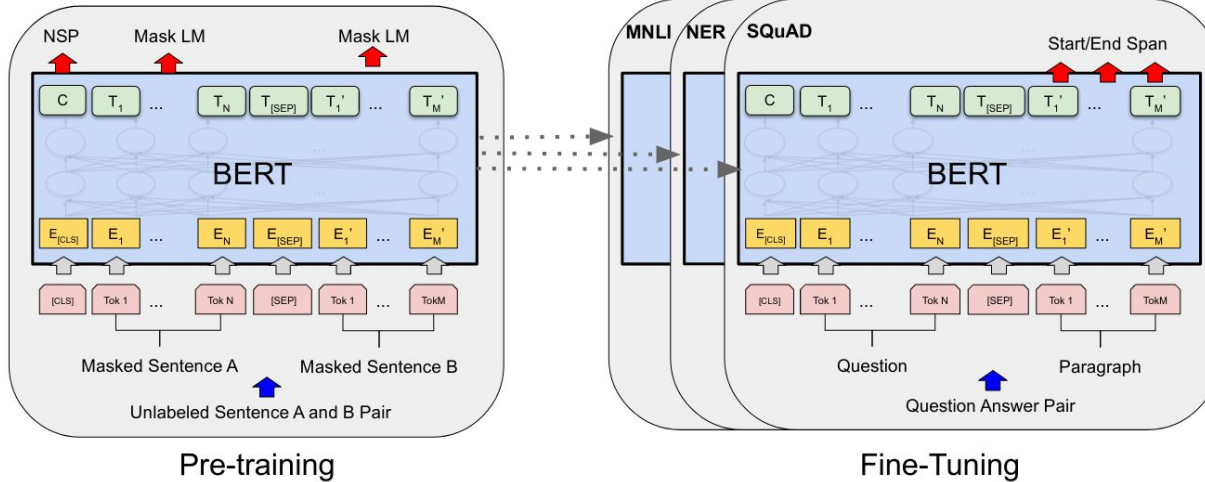
## Attention mechanism

	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

# Results

## Détection

	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	<b>96.29</b>	<b>96.41</b>	<b>96.23</b>	100	72.54	84.08	100	59.02	74.23
Baseline w/ distant supervision + knowledge dist.	91.64	85.36	87.40	100	<b>82.16</b>	<b>90.21</b>	100	78.46	87.93
Baseline w/ co-occurrence prior	94.93	94.84	94.88	100	77.09	87.06	92.35	<b>92.61</b>	<b>92.19</b>

# 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	<b>72.4</b>	65.3	87.4	56.9	68.4
Baseline w/ distant supervision + lm	<b>95.8</b>	<b>96.0</b>	<b>95.6</b>	<b>85.2</b>	64.9	<b>75.05</b>	<b>93.5</b>	58.3	71.0
Baseline w/ distant supervision + knowledge dist.	91.9	85.1	87.5	41.2	67.1	54.15	86.9	<b>68.4</b>	<b>74.6</b>
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

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 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.

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