Catégorisez automatiquement des questions

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Mars 2023

OpenClassrooms

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Programme

1. Rappel **mission**
2. Pre-processing + exploration
3. **Modélisation** + évaluation + choix de modèle
4. Développement **API**
5. **Conclusions**

1

Mission

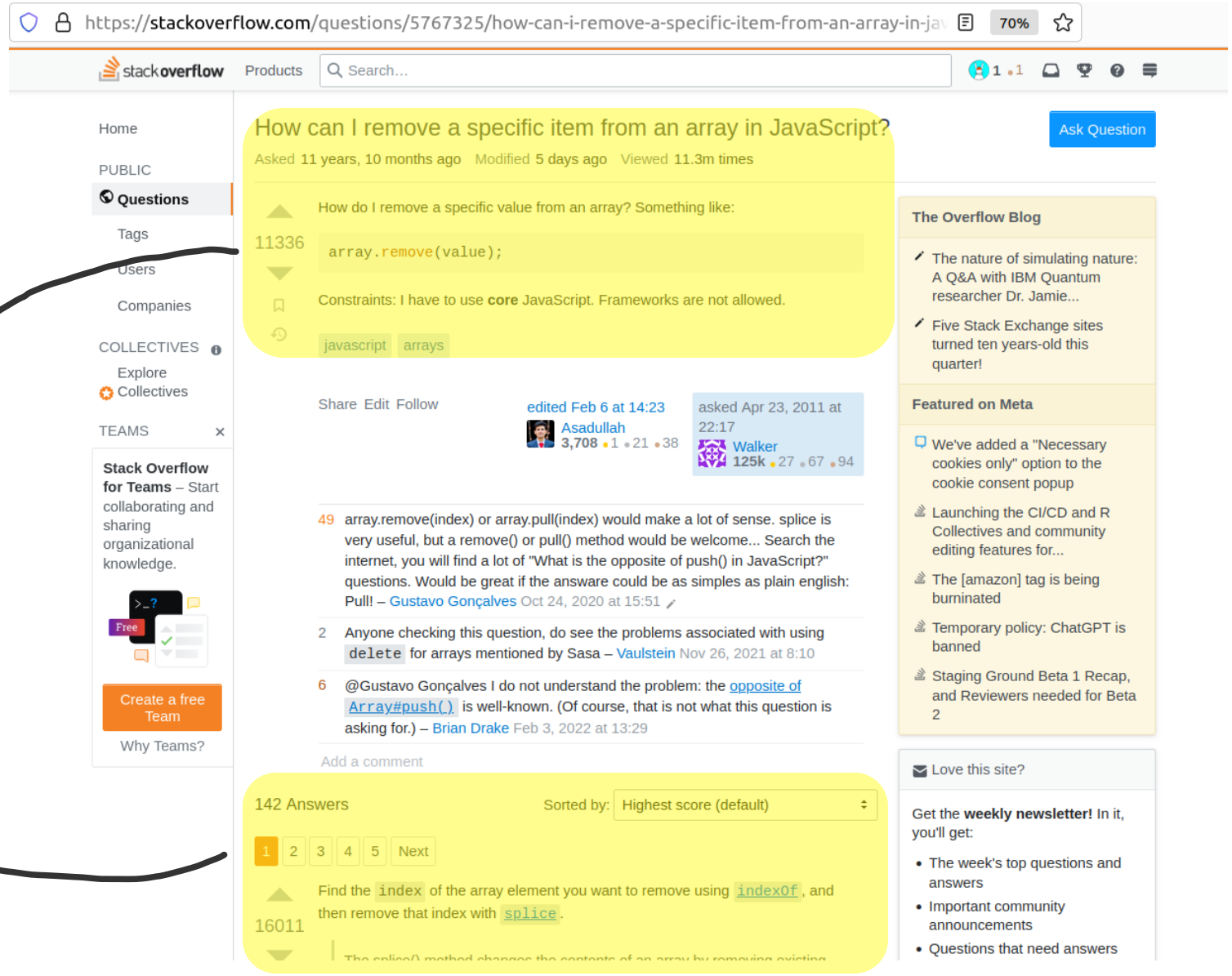
Mission

À propos de

stackoverflow

question

réponses



Mission

À propos de

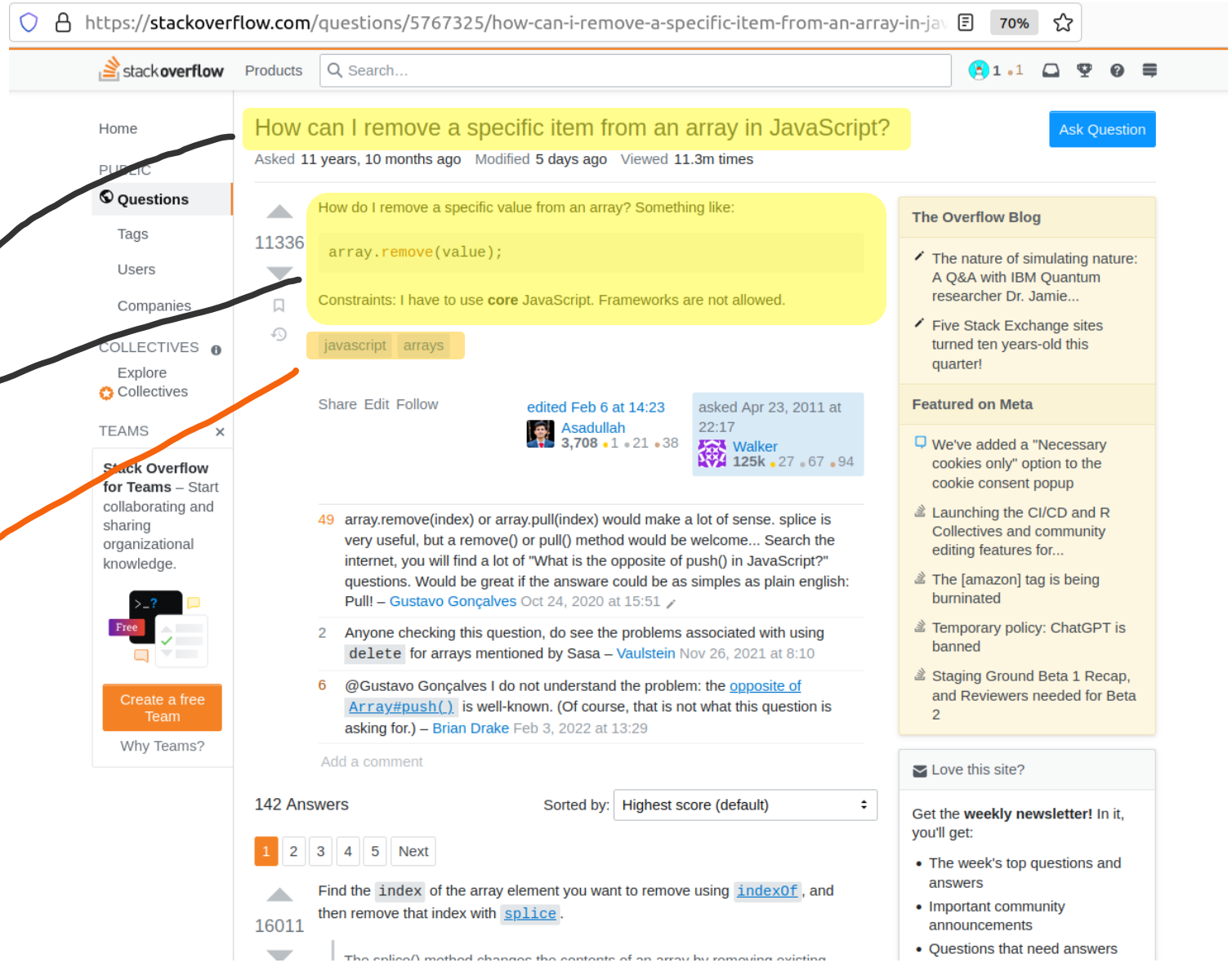
stackoverflow

titre

corps

étiquettes

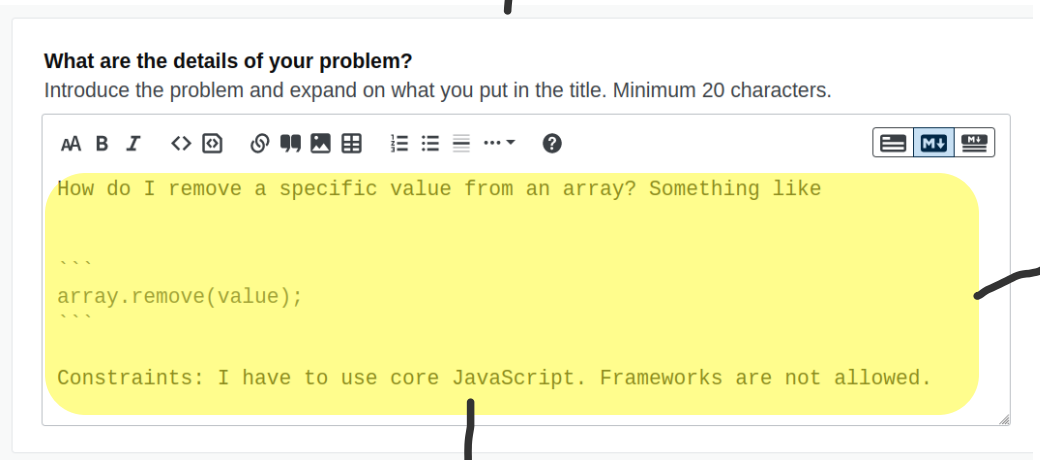
(tags)



Mission

Notre mission:

Input



Texte : question sur programmation (en anglais)

Algorithme de ML

Output

Liste de tags

javascript

arrays

* Avec API

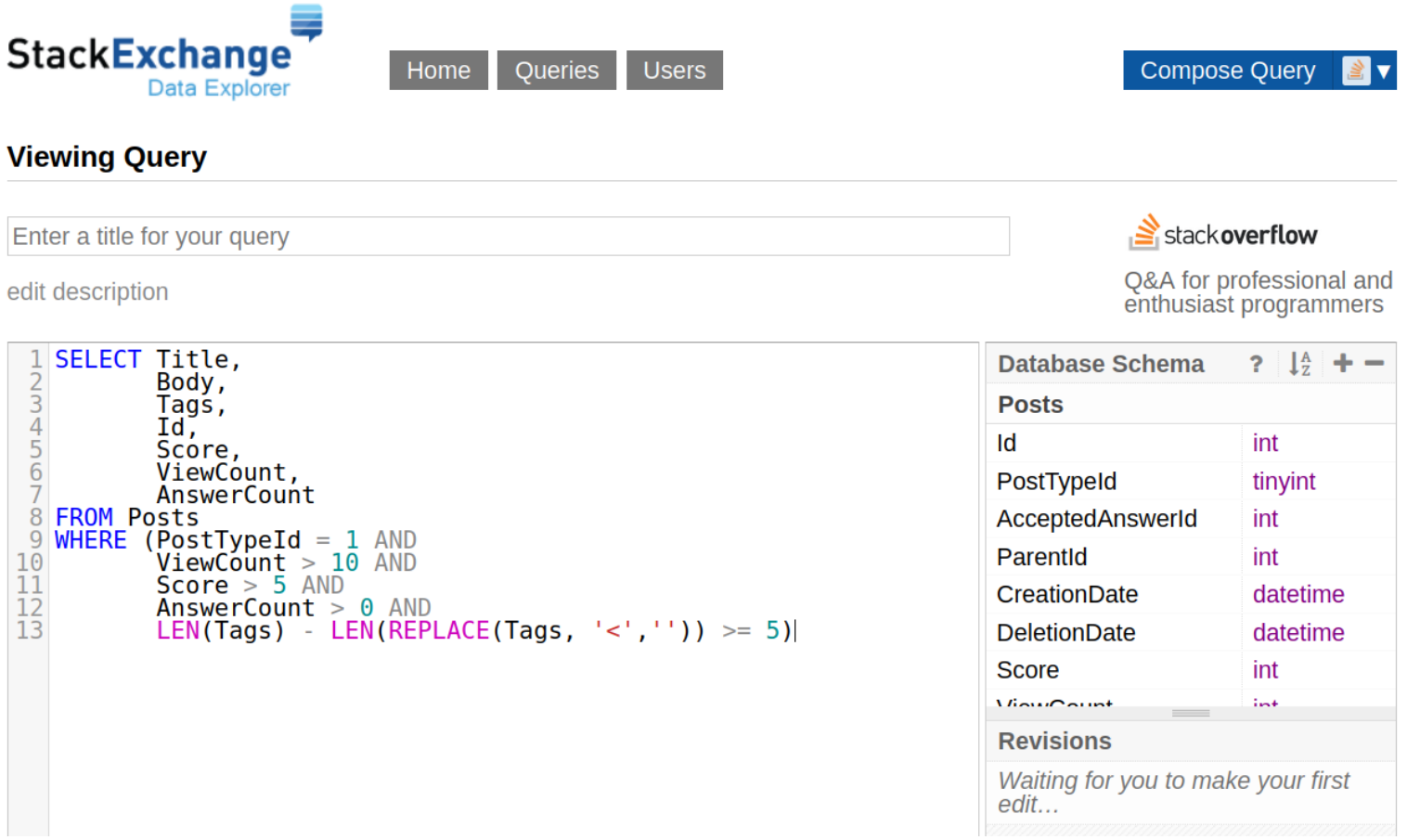
* système gestion version

2

Pre-processing

Pre-processing

Obtention des données avec StackExchange Data Explorer



Pre-processing

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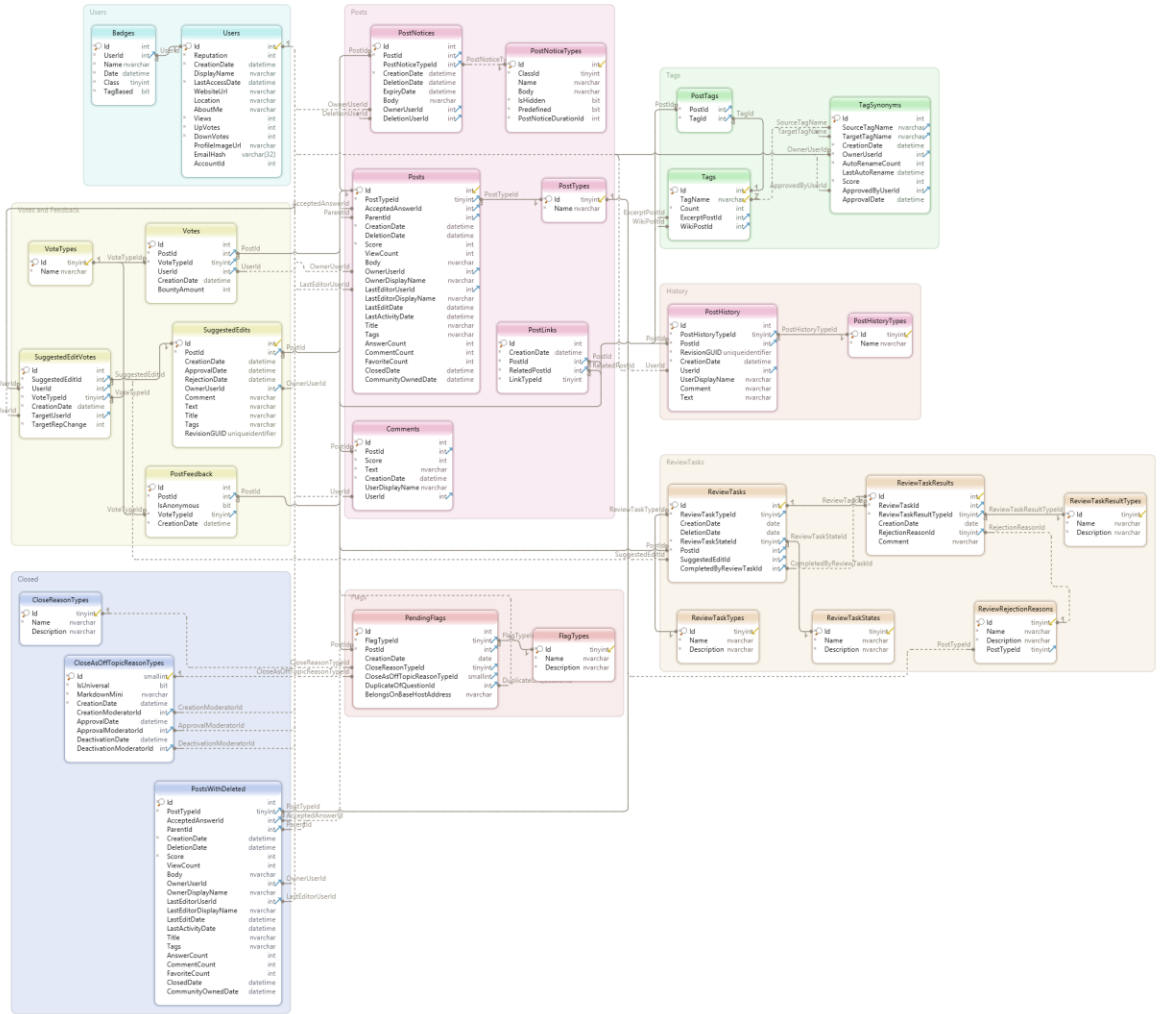

Pre-processing

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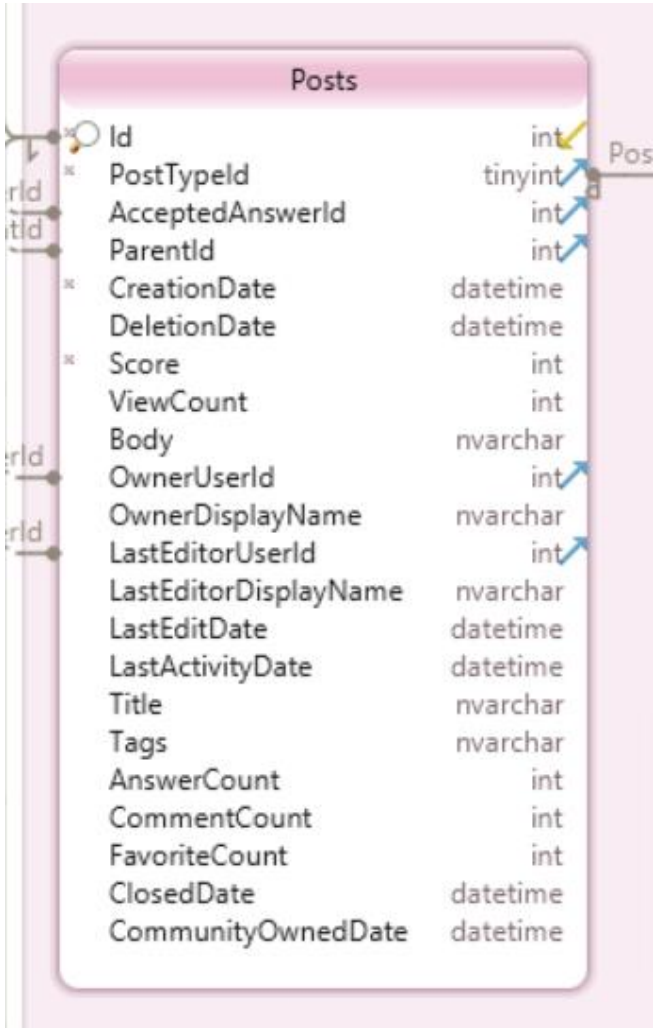

Pre-processing

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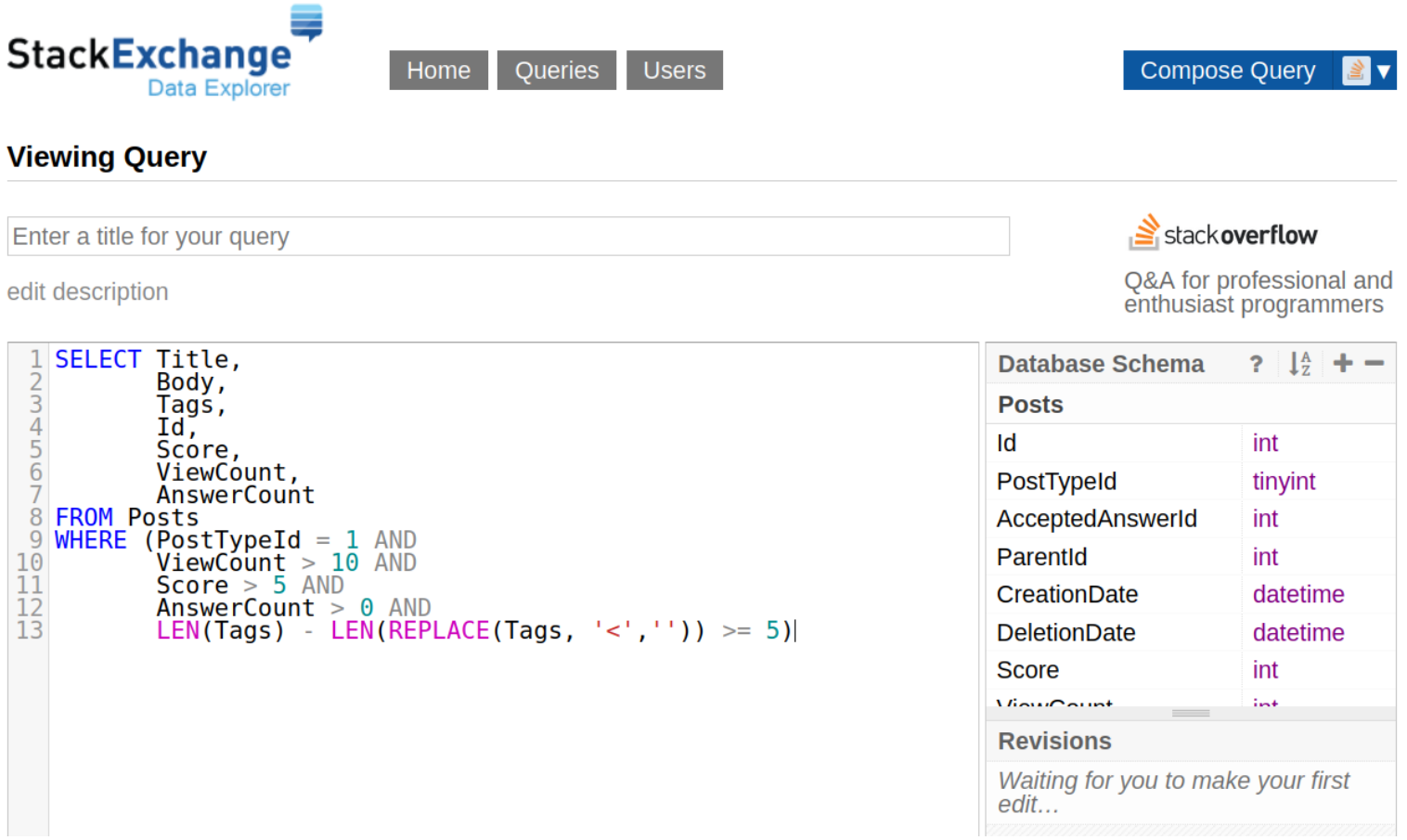
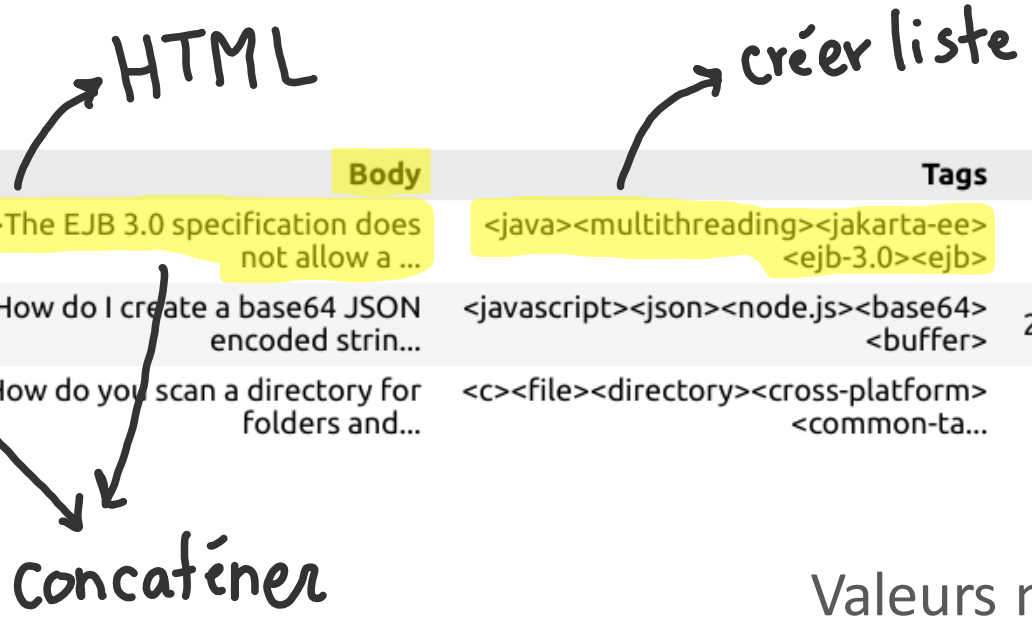


Pre-processing

Aperçu des données



	Title	Body	Tags	Id	Score	ViewCount	AnswerCount
0	Multithreading in a stateless session bean?	<p>The EJB 3.0 specification does not allow a ...	<java><multithreading><jakarta-ee><ejb-3.0><ejb>	3816286	9	13503	4
1	base64 JSON encoded strings in nodejs	<p>How do I create a base64 JSON encoded strin...	<javascript><json><node.js><base64><buffer>	22515180	14	23710	3
2	How do you get a directory listing in C?	<p>How do you scan a directory for folders and...	<c><file><directory><cross-platform><common-ta...	12489	69	142856	9

Taille

Nombre de lignes	50 000
Nombre de colonnes	7

Valeurs manquantes et dtypes

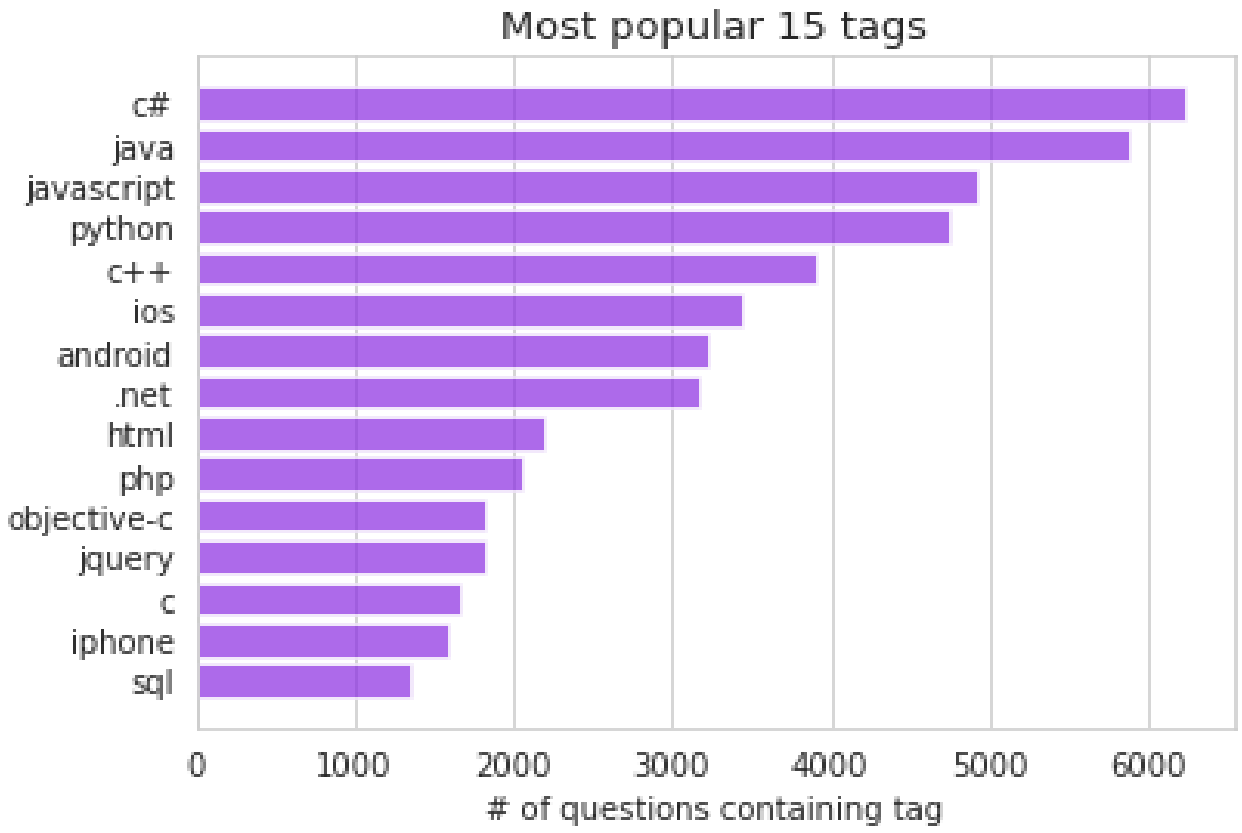
```
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Title        50000 non-null  object
 1   Body         50000 non-null  object
 2   Tags         50000 non-null  object
 3   Id           50000 non-null  int64
 4   Score        50000 non-null  int64
 5   ViewCount    50000 non-null  int64
 6   AnswerCount  50000 non-null  int64
```

Pre-processing

Filtrer ensemble de tags: + garder docs. contenant au moins 1 de ces tags

The total # of popular tags is 38
(appearing in more than 700 questions)

Tag	# of quest
c#	6226.0
java	5880.0
javascript	4920.0
python	4747.0
c++	3904.0
ios	3449.0
android	3223.0
.net	3164.0
html	2197.0
php	2050.0
objective-c	1816.0
jquery	1810.0
c	1655.0
iphone	1592.0
sql	1349.0
asp.net	1339.0
css	1331.0
linux	1286.0
node.js	1253.0
performance	1076.0



Pre-processing

Création de target avec ces 38 tags:

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----------------------------------
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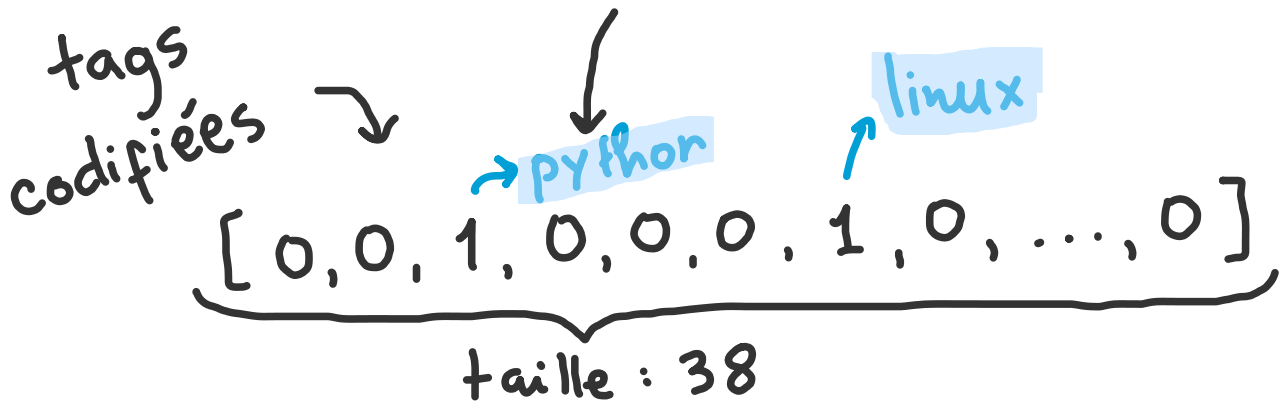
      java       5880.0
javascript       4920.0
    python       4747.0
       c++       3904.0
       ios       3449.0
   android       3223.0
      .net       3164.0
      html       2197.0
       php       2050.0
objective-c      1816.0
    jquery       1810.0
         c       1655.0
    iphone       1592.0
       sql       1349.0
   asp.net       1339.0
       css       1331.0
     linux       1286.0
   node.js       1253.0
performance      1076.0
```

Creating target

```
1 mlb = MultiLabelBinarizer(classes=popular_tags)
2 mlb.fit([popular_tags])
```

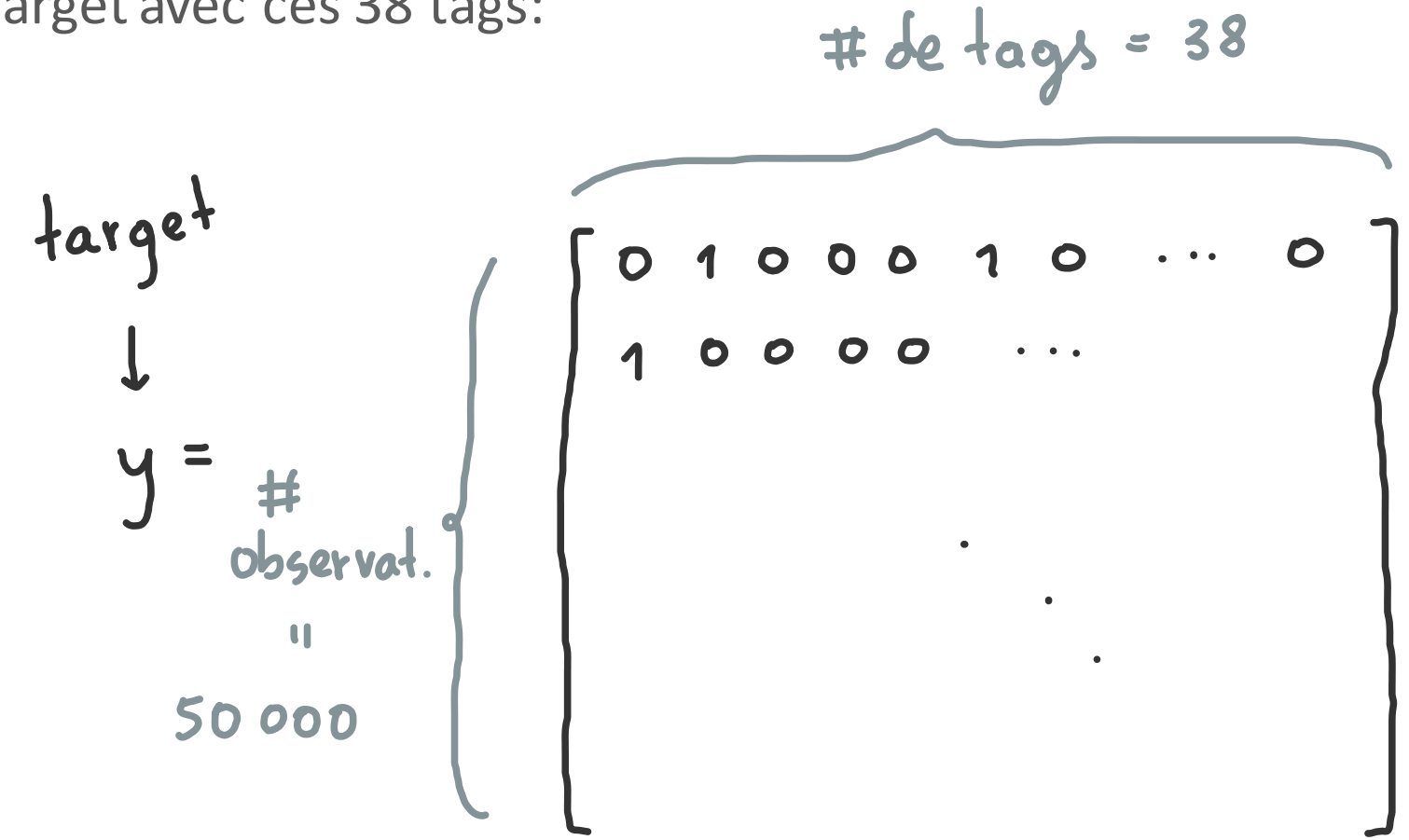
MultiLabelBinarizer

```
MultiLabelBinarizer(classes=['c#', 'java', 'javascript', 'python', 'c++', 'ios',
                             'android', '.net', 'html', 'php', 'objective-c',
                             'jquery', 'c', 'iphone', 'sql', 'asp.net', 'css',
                             'linux', 'node.js', 'performance', 'spring',
                             'windows', 'swift', 'xcode', 'ruby-on-rails',
                             'mysql', 'json', 'sql-server', 'multithreading',
                             'asp.net-mvc', ...])
```



Pre-processing

Création de target avec ces 38 tags:



Pre-processing

Création de fonction de nettoyage/tokenisation de texte

```python
def clean(text,tokenize=False,strict=False, **kwargs):
    """
    Returns a dictionnary with keys 'text' or 'tokens', where
    'tokens' corresponds tothe list of lemmatized tokens from
    the string text. Ommiting stopwords and punctuation, and the text is
    the joint text.

    Parameters:
        - text: str
        - tokenize: bool
            If True returns list of tokens, if False returns string.
        - strict: bool
            If true only keeps nouns
    """


    # Removing <code>some code</code>
    clean_txt = remove_code(text)

    # Removing HTML tags
    soup = BeautifulSoup(clean_txt, features='html.parser')
    clean_txt = soup.get_text()

    # Removing new line character: \n
    clean_txt = clean_txt.replace('\n', ' ')

    # Removing unicode characters
    clean_txt = clean_txt.encode("ascii", "ignore").decode()

    # Removing digits
    clean_txt = ''.join(char for char in clean_txt if not char.isdigit())

```

Pre-processing

Création de fonction de nettoyage/tokenisation de texte

```
32
33      # Replacing 'c ++' and 'c #' for 'c++' and 'c#' and others
34      clean_txt = clean_txt.replace('c ++', 'c++')
35      clean_txt = clean_txt.replace('c #', 'c#')
36      clean_txt = clean_txt.replace('C ++', 'c++')
37      clean_txt = clean_txt.replace('C #', 'c#')
38      clean_txt = clean_txt.replace('C#', 'c#')
39      clean_txt = clean_txt.replace('C ++', 'c++')
40
41      # Adding special case rule
42      special_case = [{ORTH: "c#"}]
43      nlp.tokenizer.add_special_case("c#", special_case)
44      special_case = [{ORTH: ".net"}]
45      nlp.tokenizer.add_special_case(".net", special_case)
46      special_case = [{ORTH: "objective-c"}]
47      nlp.tokenizer.add_special_case("objective-c", special_case)
48      special_case = [{ORTH: "asp.net"}]
49      nlp.tokenizer.add_special_case("asp.net", special_case)
50      special_case = [{ORTH: "node.js"}]
51      nlp.tokenizer.add_special_case("node.js", special_case)
52      special_case = [{ORTH: "ruby-on-rails"}]
53      nlp.tokenizer.add_special_case("ruby-on-rails", special_case)
54      special_case = [{ORTH: "sql-server"}]
55      nlp.tokenizer.add_special_case("sql-server", special_case)
56      special_case = [{ORTH: "unit-testing"}]
57      nlp.tokenizer.add_special_case("unit-testing", special_case)
```

3 Attention aux caractères propres aux noms des langages

C + + → C++

Pre-processing

Création de fonction de nettoyage/tokenisation de texte

```
    # Tokenize with spacy
    doc = nlp(clean_txt)

    # Tokenize properties
    if strict == True:
        tokens = [token.lemma_.lower() for token in doc
                  if token.pos_ in ['NOUN', 'PROPN', 'VERB'] and
                      (not (token.is_stop or
                            token.is_punct or
                            token.is_space
                            )
                       )
                  ]
    else:
        tokens = [token.lemma_.lower() for token in doc
                  if not (token.is_stop or
                          token.is_punct or
                          token.is_space
                          )
                  ]

    clean_txt = ' '.join(tokens)

    # Ask if return text or tokens
    if tokenize == True:
        result = tokens
    else:
        result = clean_txt

    # Option for list of entities in output
    if 'ent' in kwargs:
        result = {'output':result, 'ents': doc.ents}

    return result
```

4 Tokenisation avec spaCy

5 Filtrer : noms
noms propres
verbes

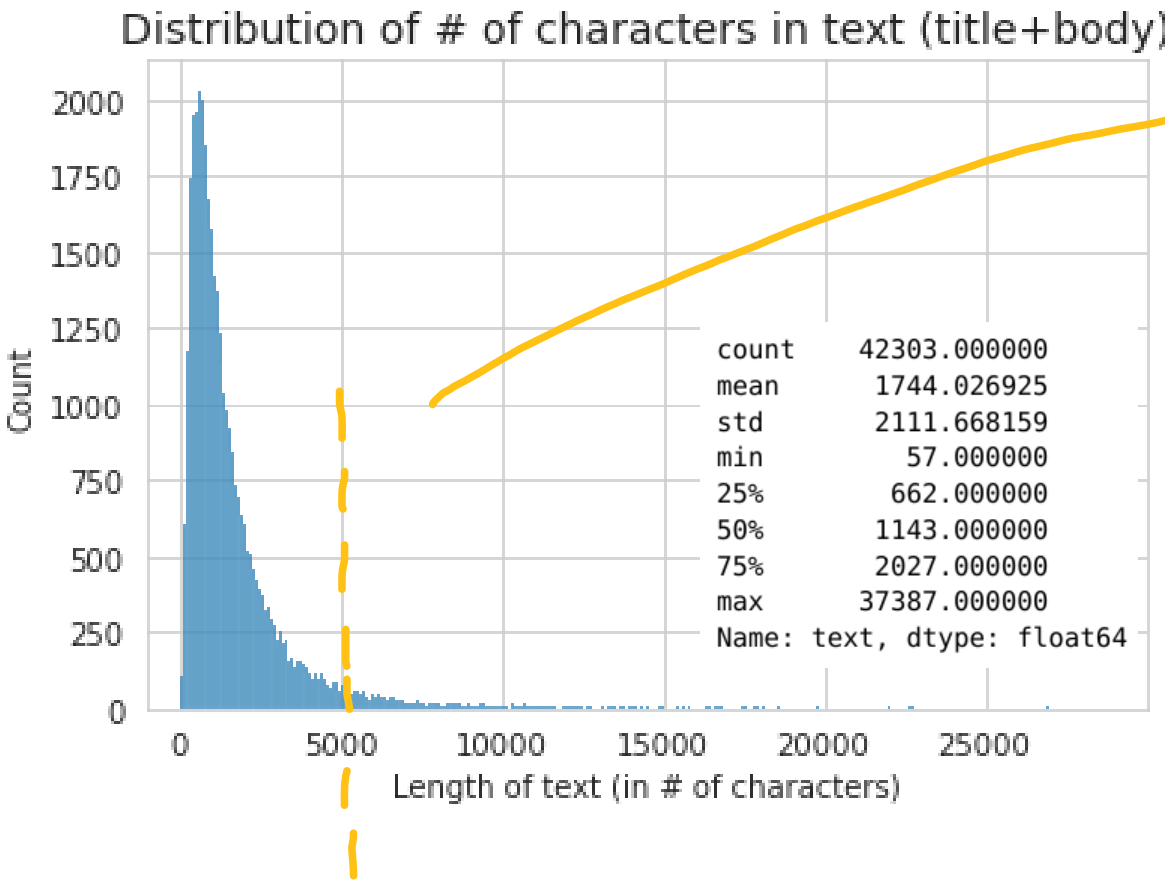
6 Résultat → texte ou tokens

Pre-processing

Voir example dans notebook

Pre-processing

Derniers détails préparation texte



1. Concaténer
2. filtrer (≤ 5000 car.)

```
Shape of dataset before filter: (42303, 45)
Shape of dataset after filter: (40166, 45)
Number of deleted rows: 2137
```

3. Appliquer ma fonction nettoyage

```
Total time to process text: 1233.7 seconds. (= 20.56 minutes)
```

↓

EXPORTER DONNÉES !

3

Modélisation + choix de modèle

Modélisation

Notre problème :

texte

(raw HTML)

associer

/prédire

étiquettes : tags

C# python linux

sql pandas

↓

plusieurs sont possibles

pour 1 seul input

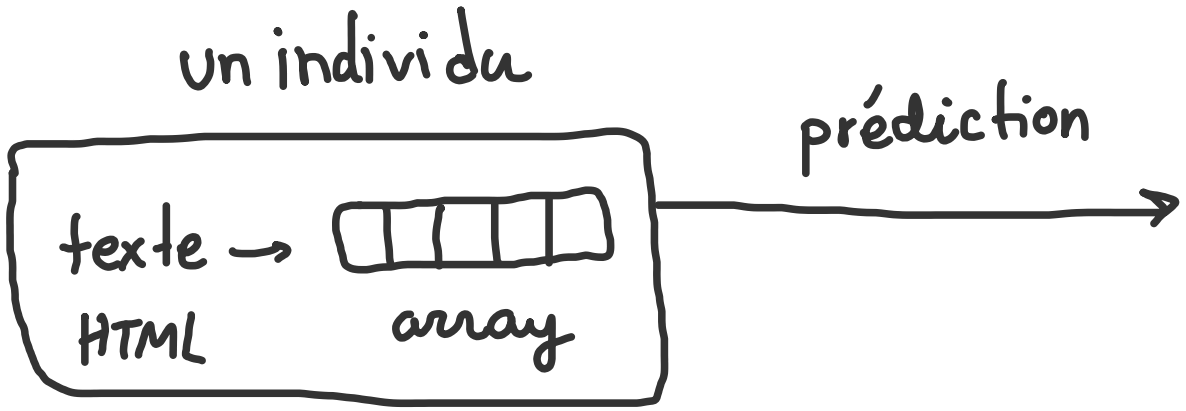
CLASSIFICATION

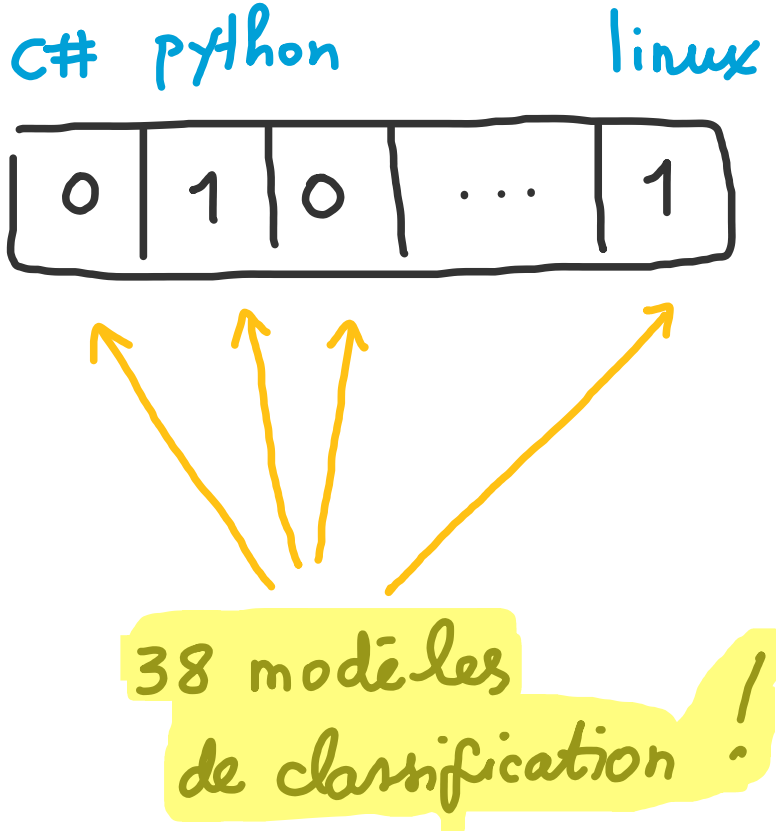
MULTILABEL

⇐

Modélisation

Notre stratégie : scikit learn OneVsRestClassifier

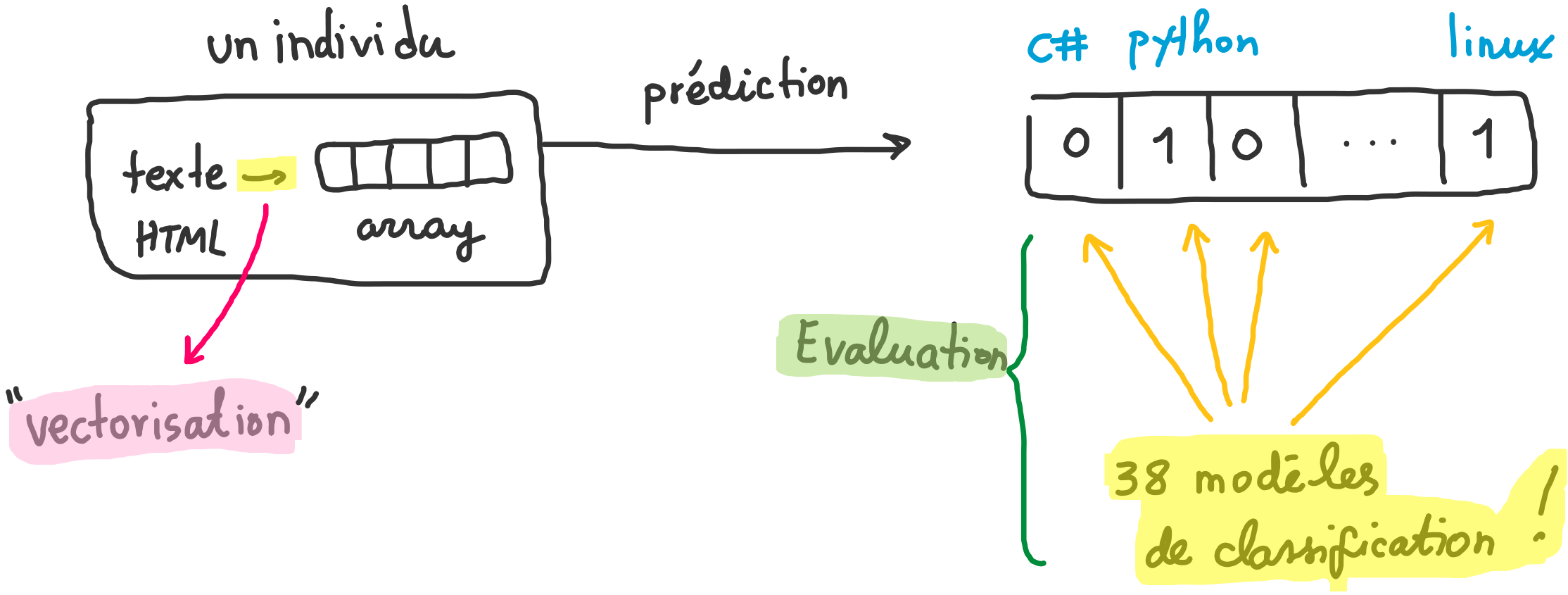




CLASSIFICATION MULTILABEL

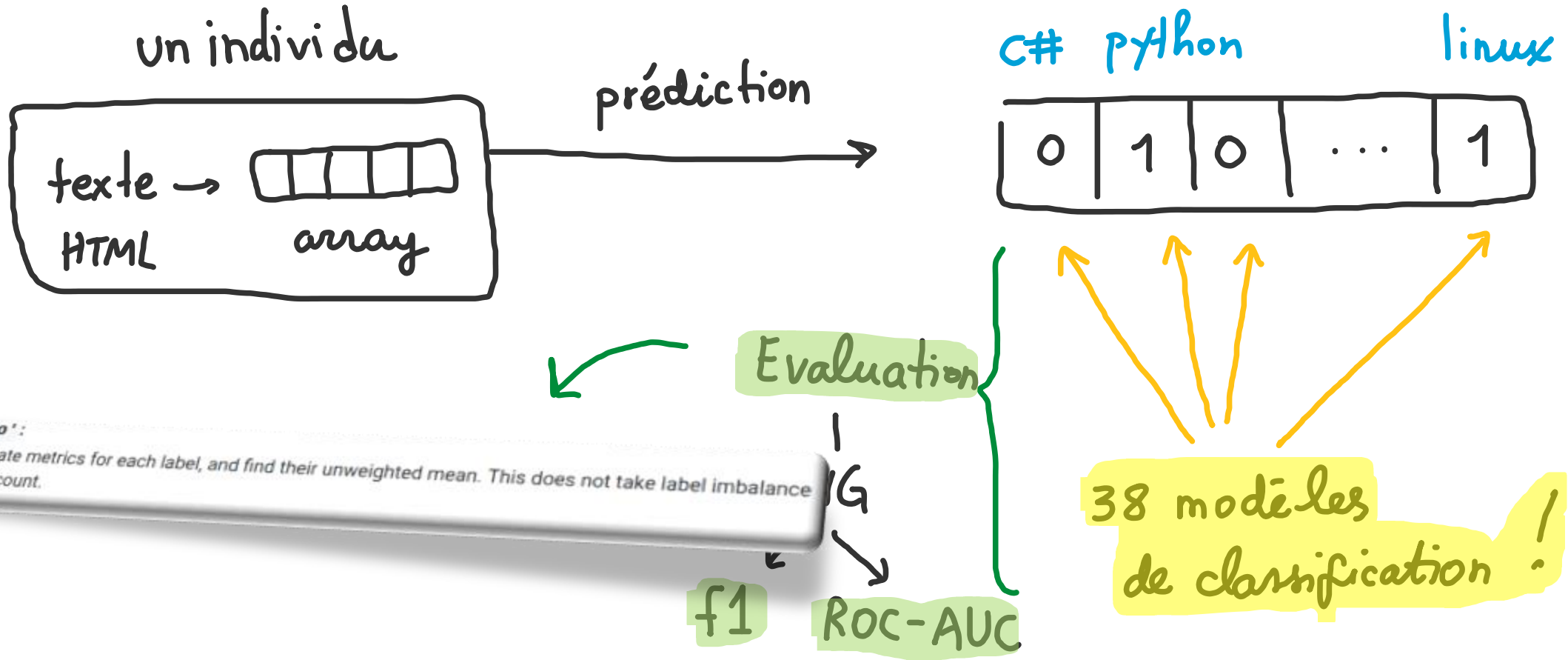
Modélisation

Notre stratégie : scikit learn OneVsRestClassifier

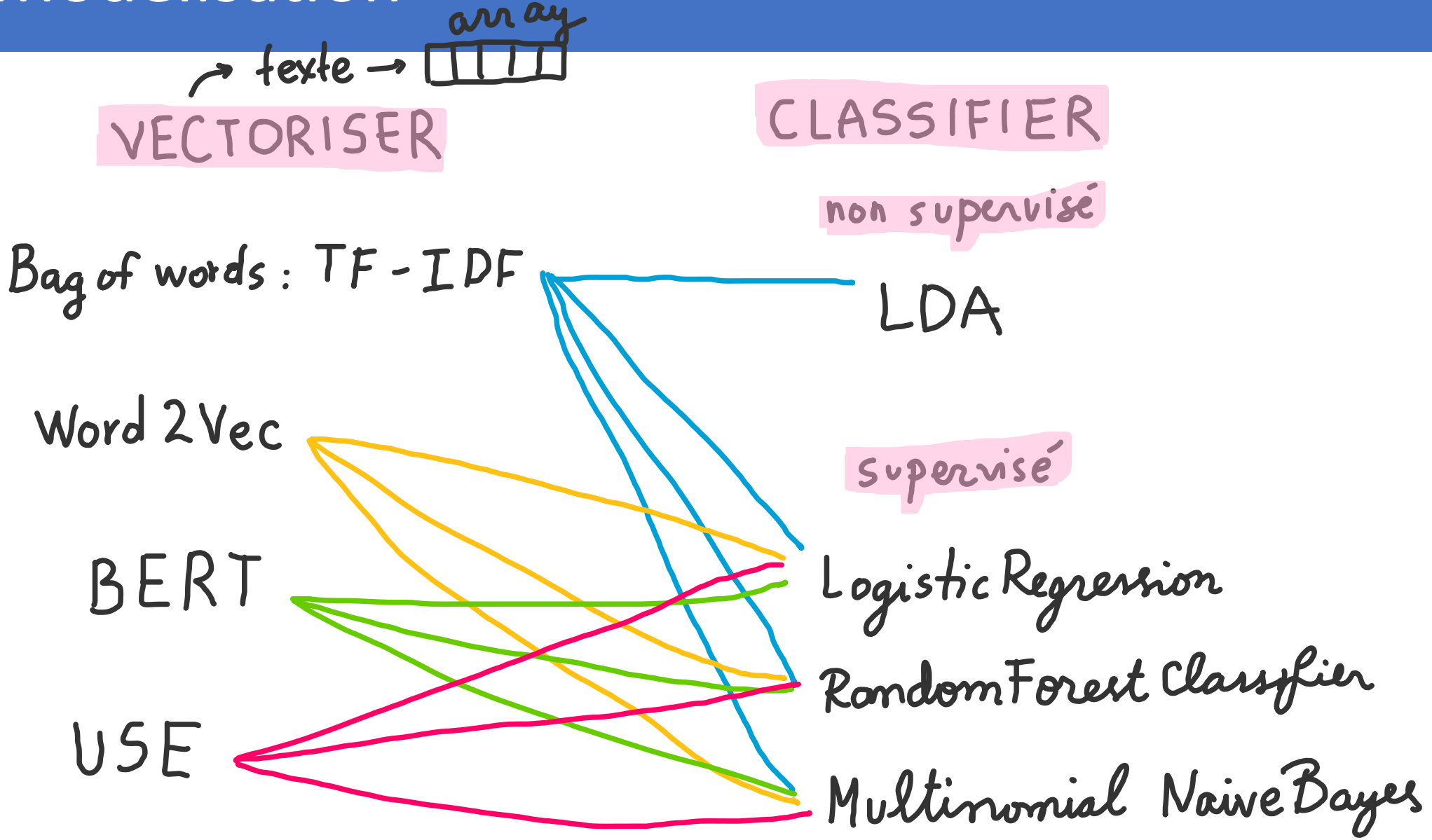


Modélisation

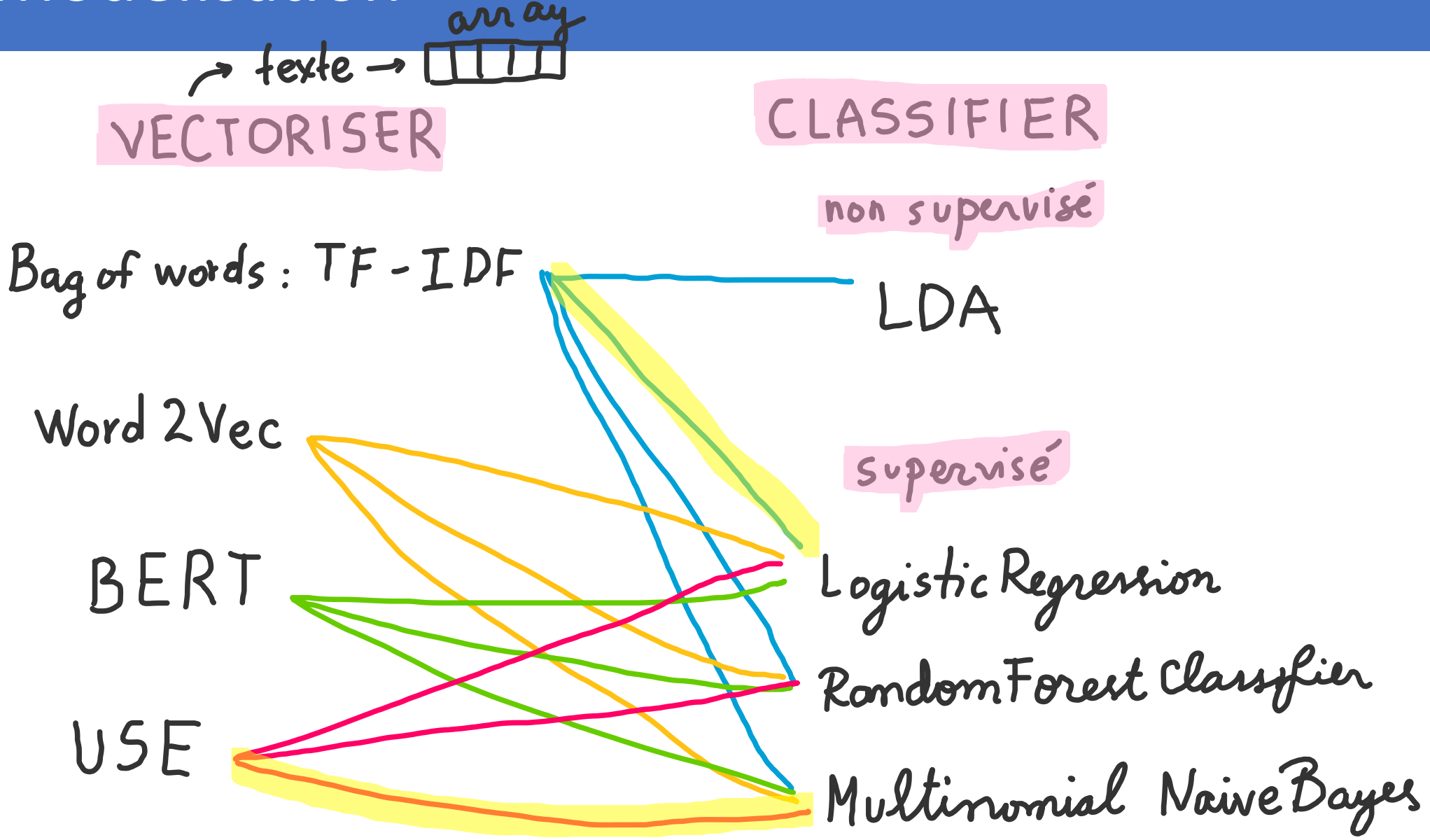
Notre stratégie : scikit learn OneVsRestClassifier



Modélisation



Modélisation



Modélisation (supervisée)

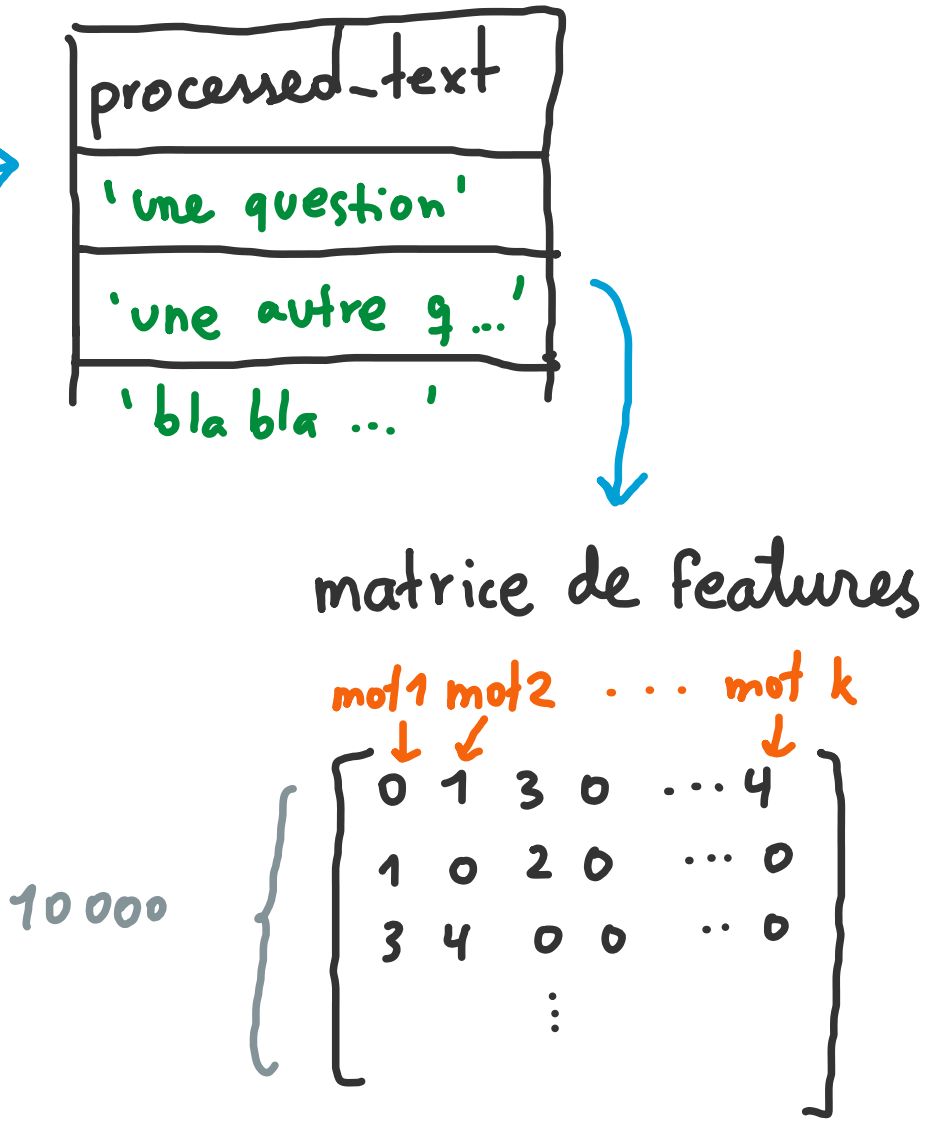
Bag of words: TF-IDF

```python
# Instantiate the vectorizer
tfidf = TfidfVectorizer(max_df=0.75,
                        min_df=0.0015
                        )

# Vectorize the processed text
X = tfidf.fit_transform(df.processed_text)

# Defining target vector
columns_tags = ['tag_'+tag for tag in tag_list]
y = df[columns_tags]

# Splitting into train and test set
X_train, X_test, y_train, y_test = train_test_split(
    X,y, test_size=0.33, random_state=5
)
```



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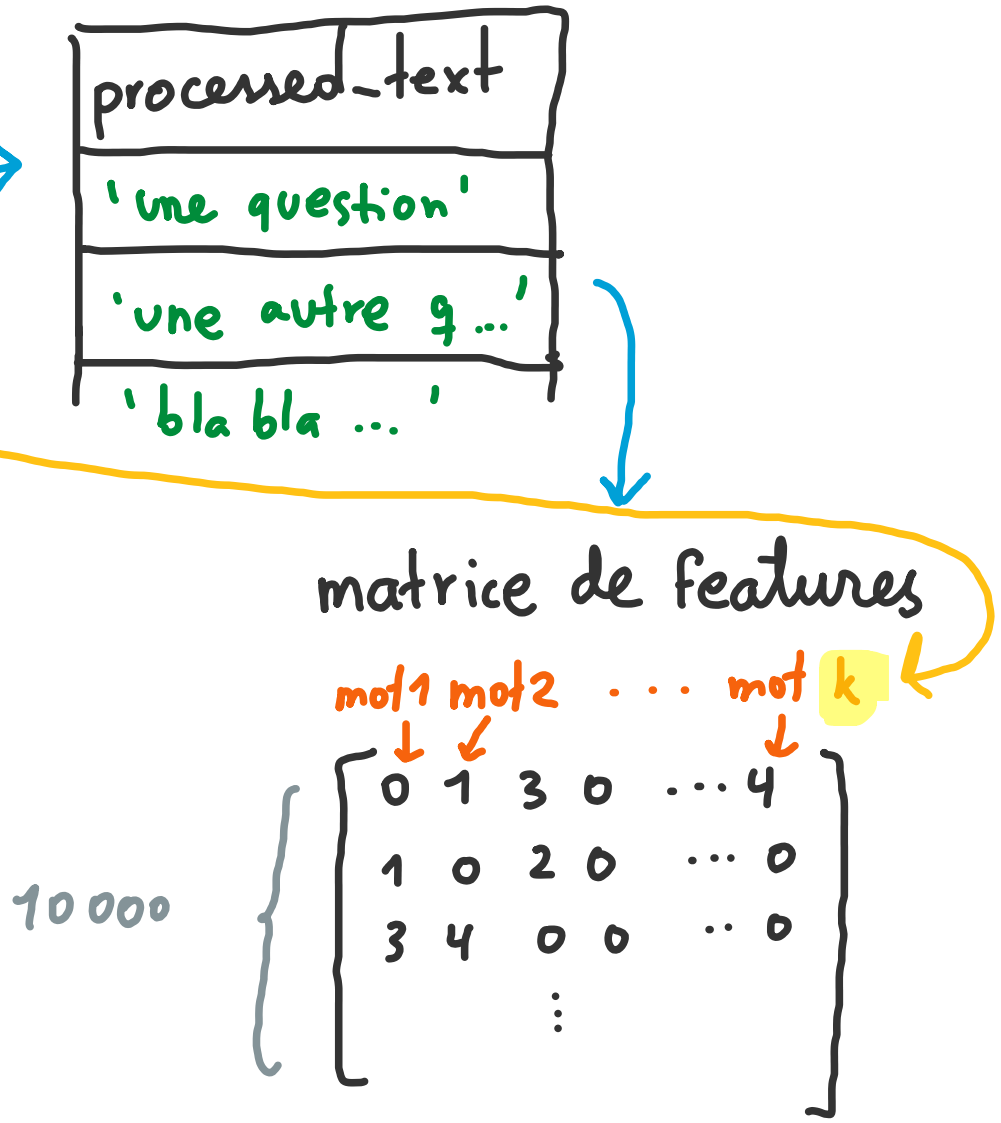

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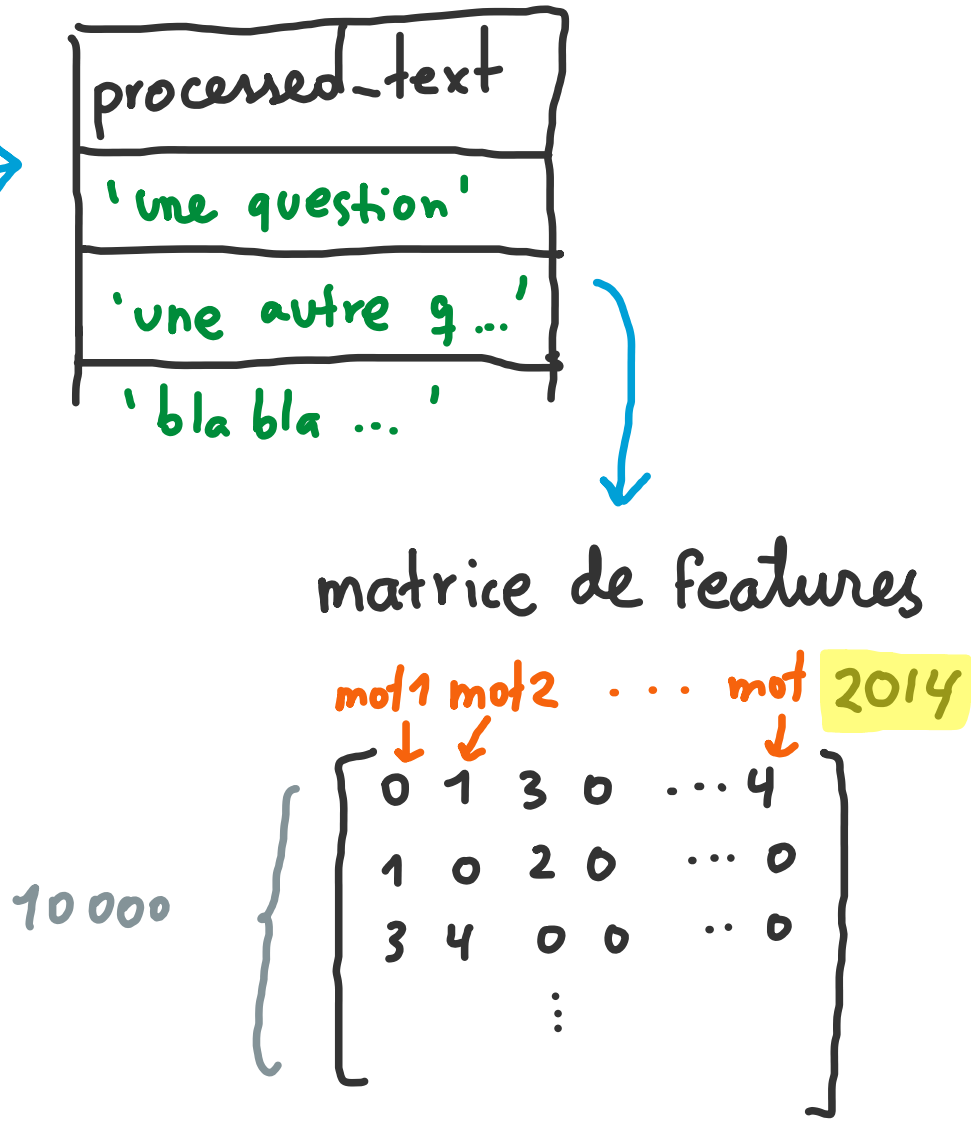

Modélisation (supervisée)

Bag of words: TF-IDF → term frequency

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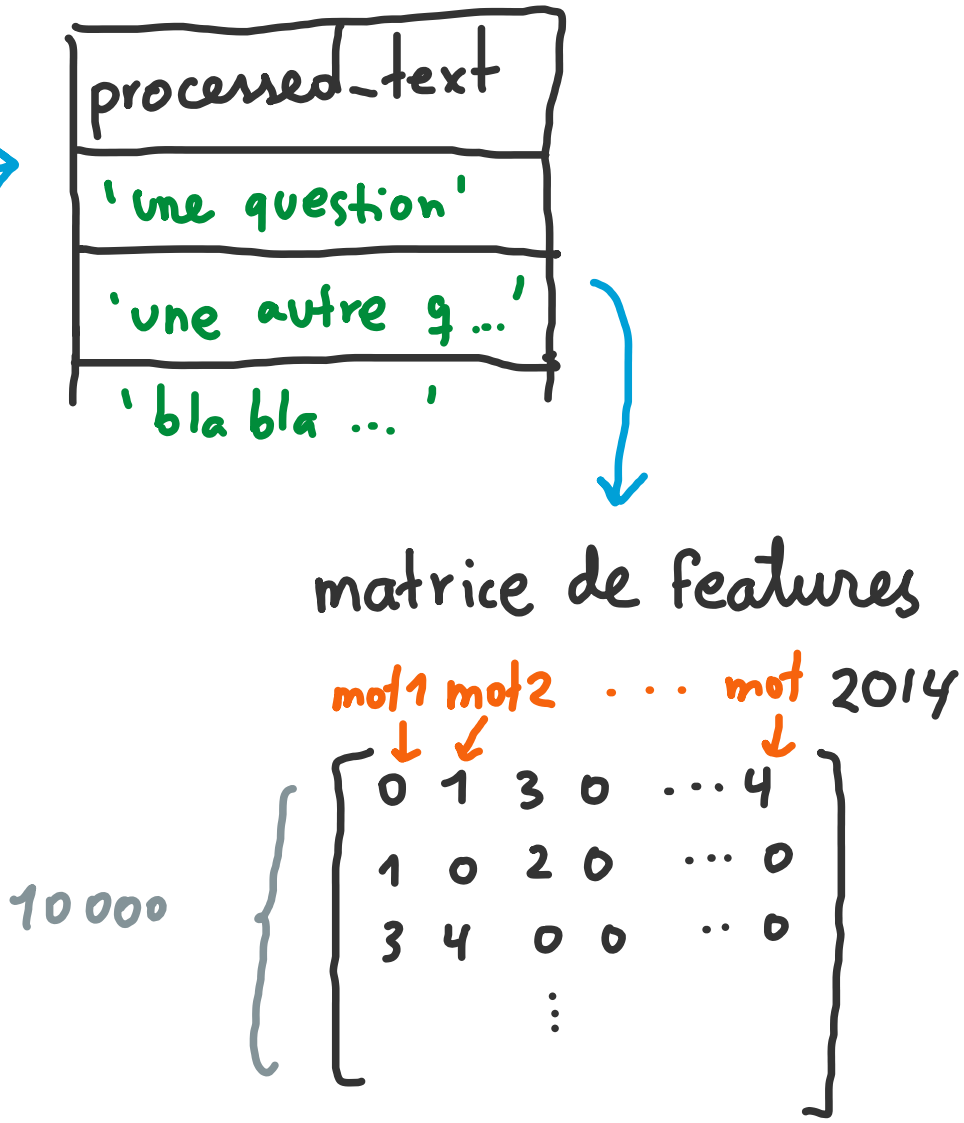

Modélisation (supervisée)

Bag of words: TF-IDF → term frequency

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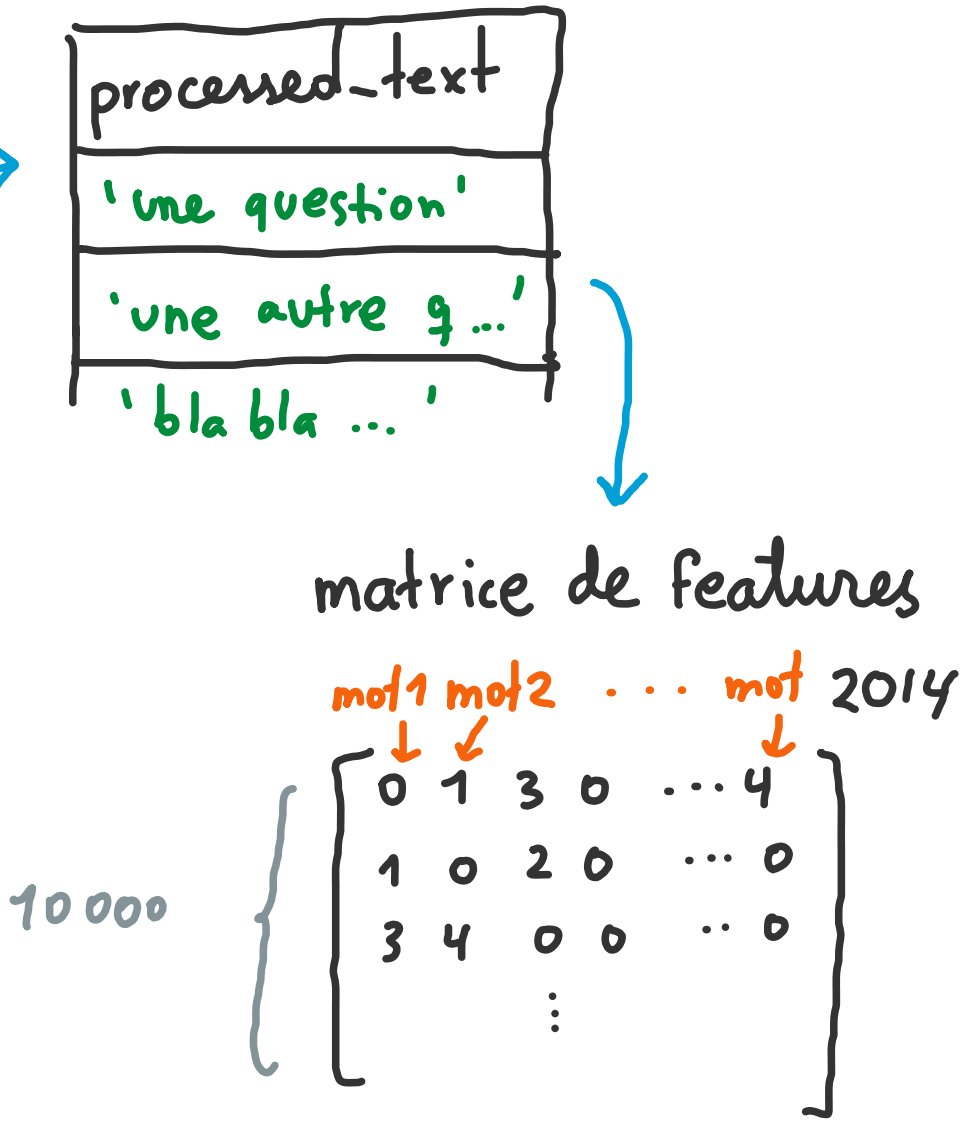

Modélisation (supervisée)

Bag of words: TF-IDF → term frequency X Inverse doc. frequency

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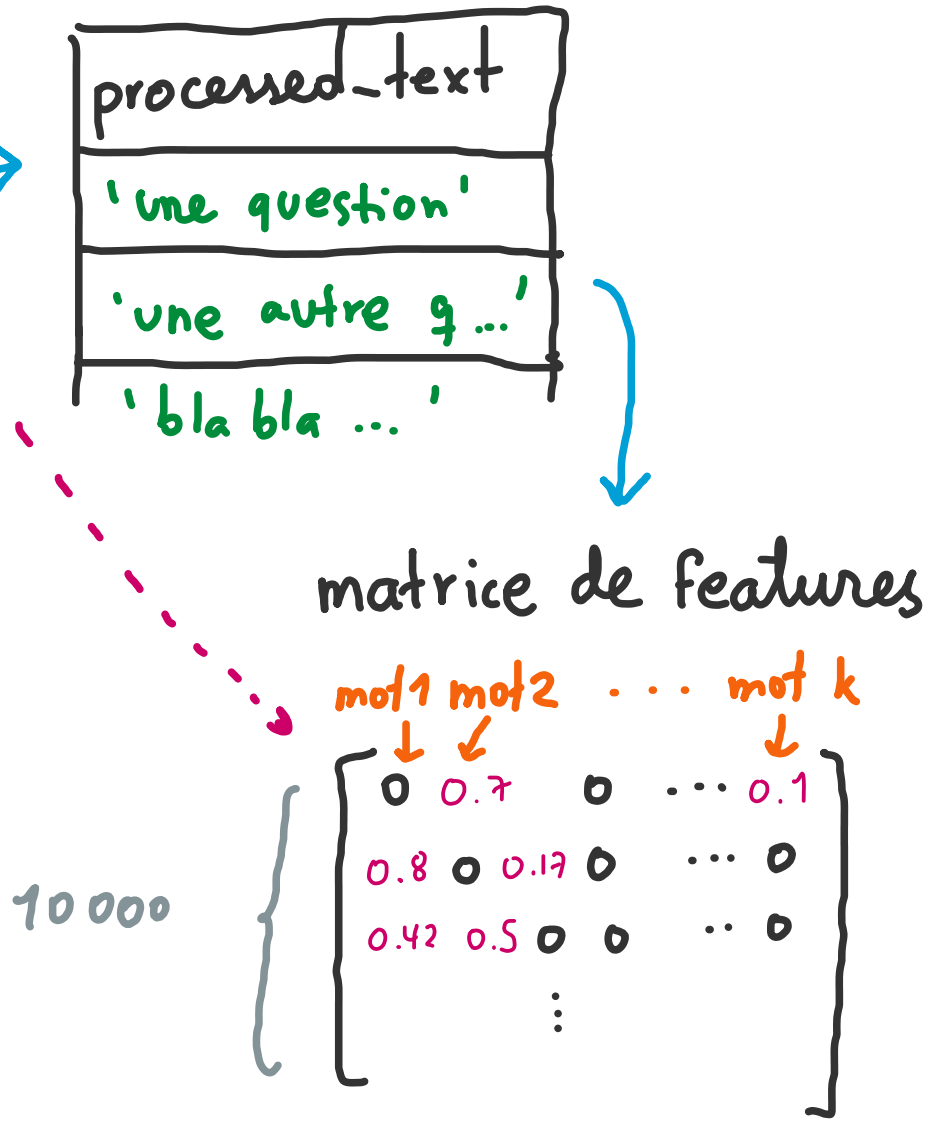


Modélisation (supervisée)

Bag of words: TF-IDF + **LogisticRegression**

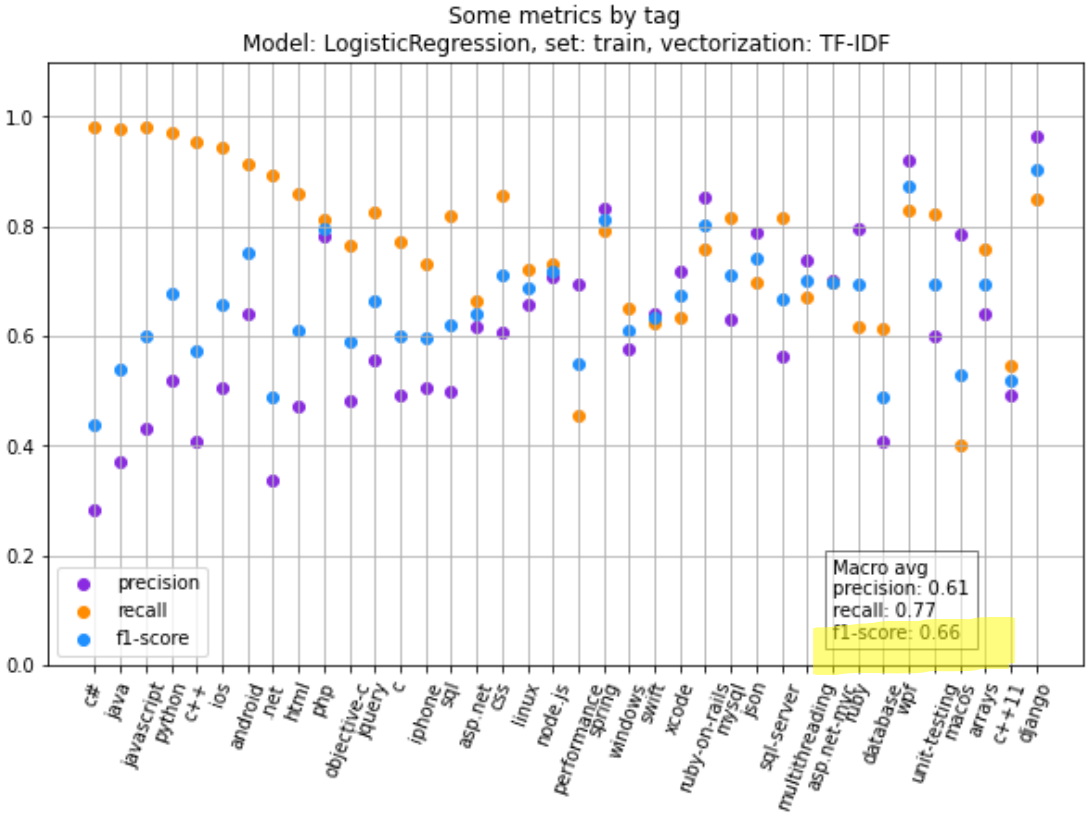
```python
# Hyperparameters for logistic regression
parameters = {
    'estimator__penalty' : ['l1', 'l2'],
    'estimator__tol' : [1e-6, 1e-5, 1e-4, 1e-3],
    'estimator__C' : [0.01,0.05 ,0.1, 0.5, 0.7, 1],
    'estimator__fit_intercept' : [True, False],
    'estimator__solver' : ['liblinear','sag', 'saga']
}

# Instantiating OneVsRest Classifier
cl = OneVsRestClassifier(LogisticRegression())

# Random search for best hyperparameters
random_search = RandomizedSearchCV(
    estimator = cl,
    param_distributions= parameters,
    n_iter=40,
    scoring='roc_auc_ovr',
    random_state=5,
    n_jobs=-1
)

# Perform random search
random_search.fit(X_train, y_train)

# Instantiating BEST OneVsRest Classifier
cl = random_search.best_estimator_

# Fitting classifier
start = time.time()
cl.fit(X_train,y_train)
finish = time.time()
fittime = finish - start
print(f'fit time: {fittime} secs.')

```

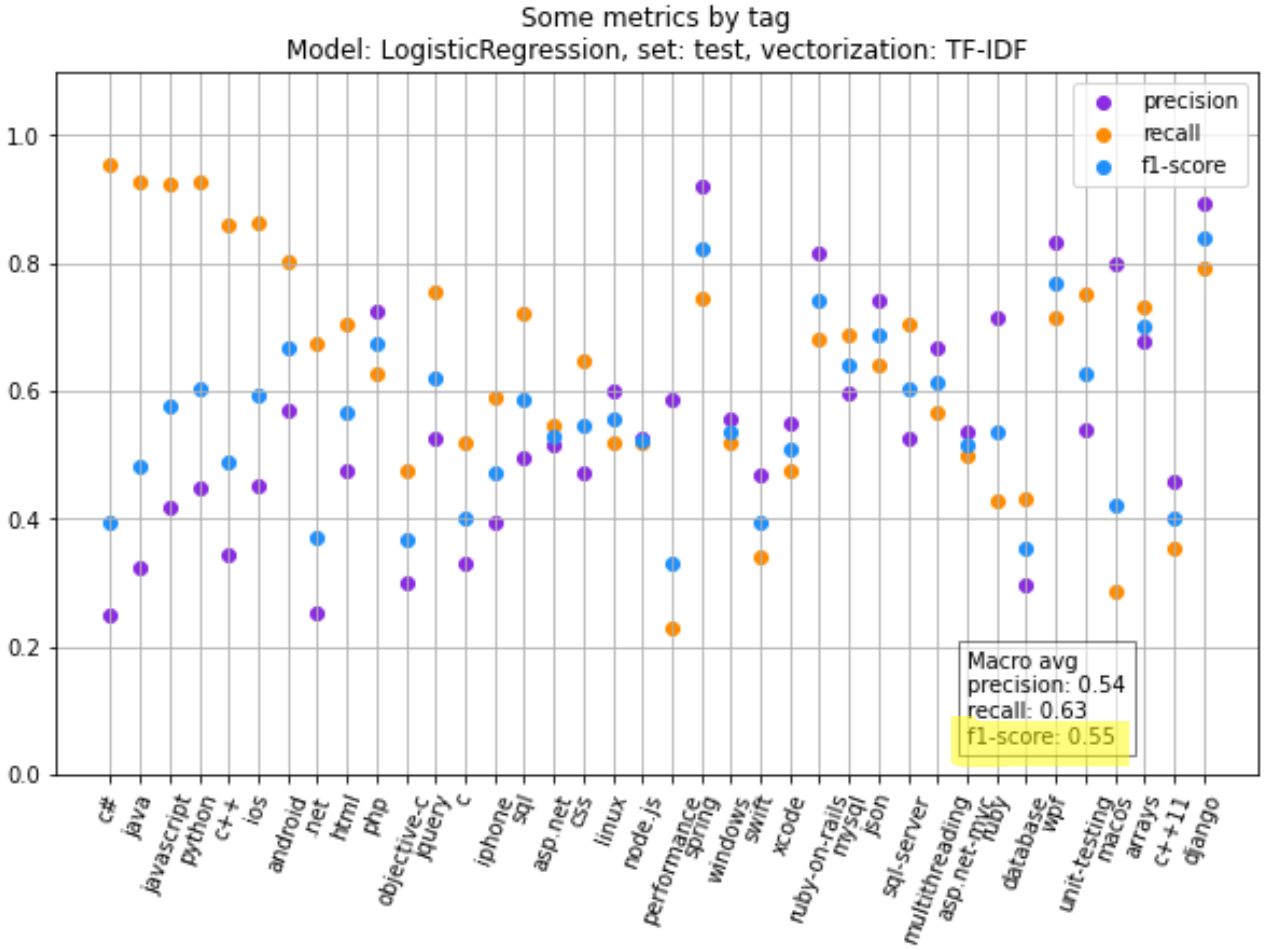
validation croisée avec Randomized Search

évaluation du temps aussi

Modélisation (supervisée)

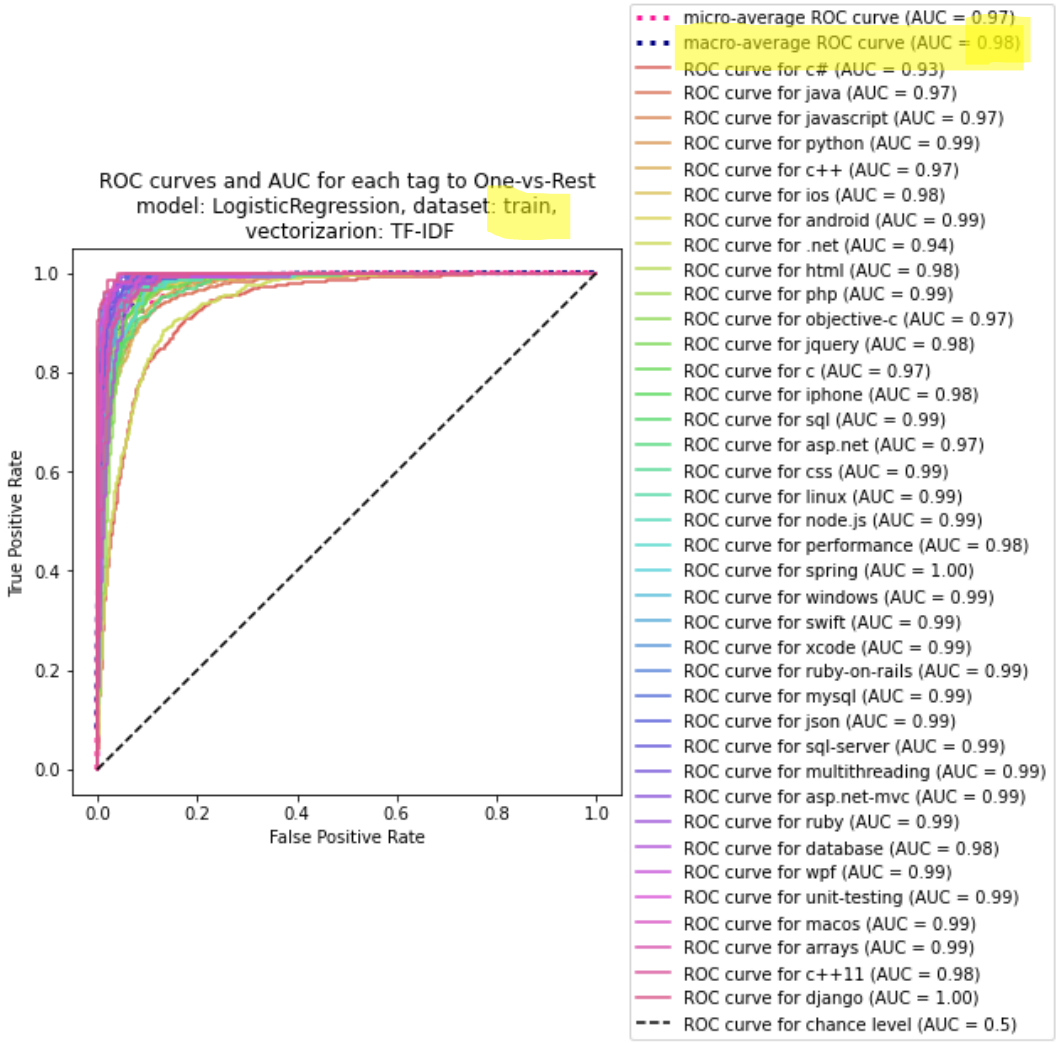
Bag of words: TF-IDF + LogisticRegression **--> Évaluation**





Modélisation (supervisée)

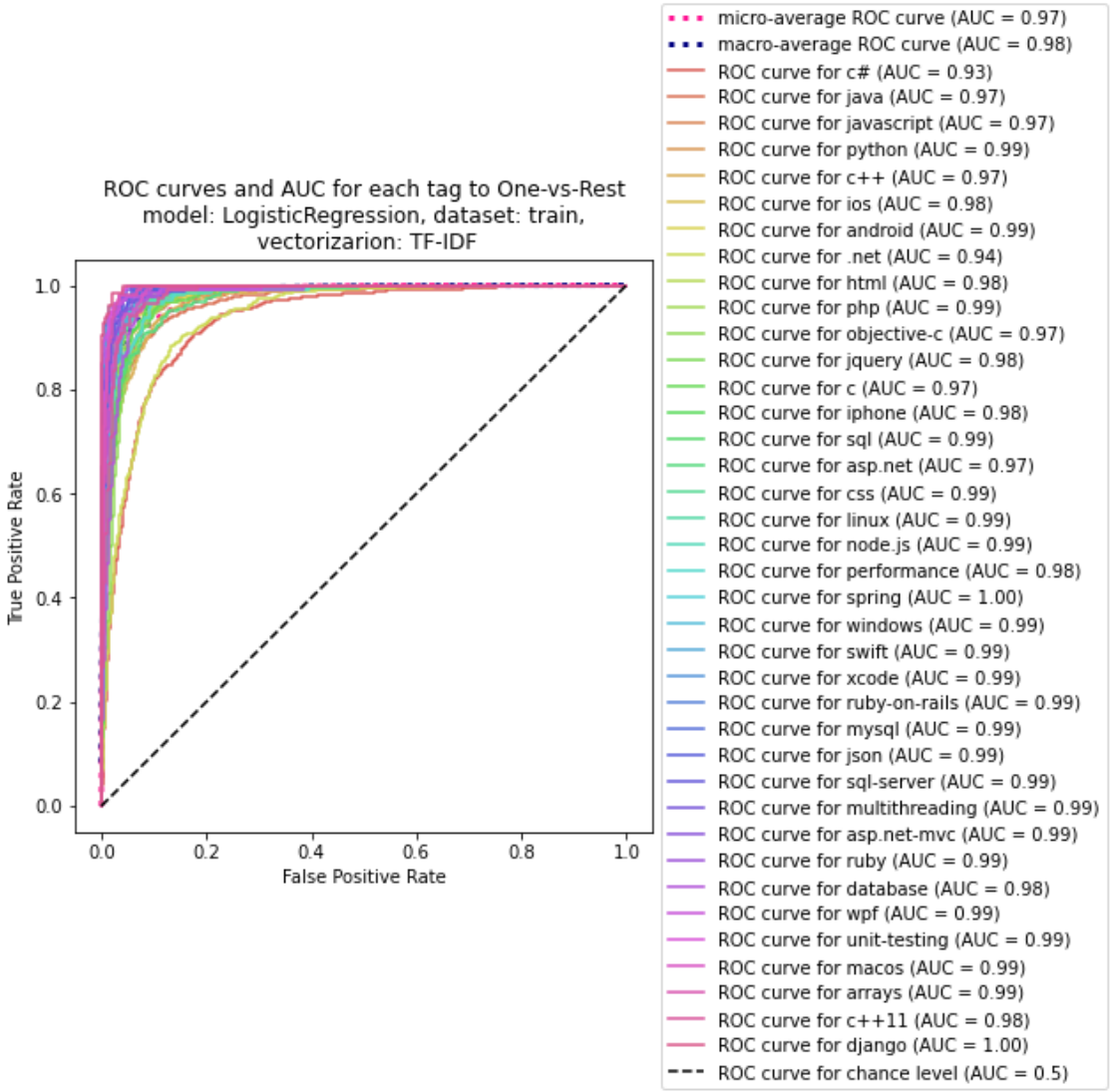
Bag of words: TF-IDF + LogisticRegression **--> Évaluation**

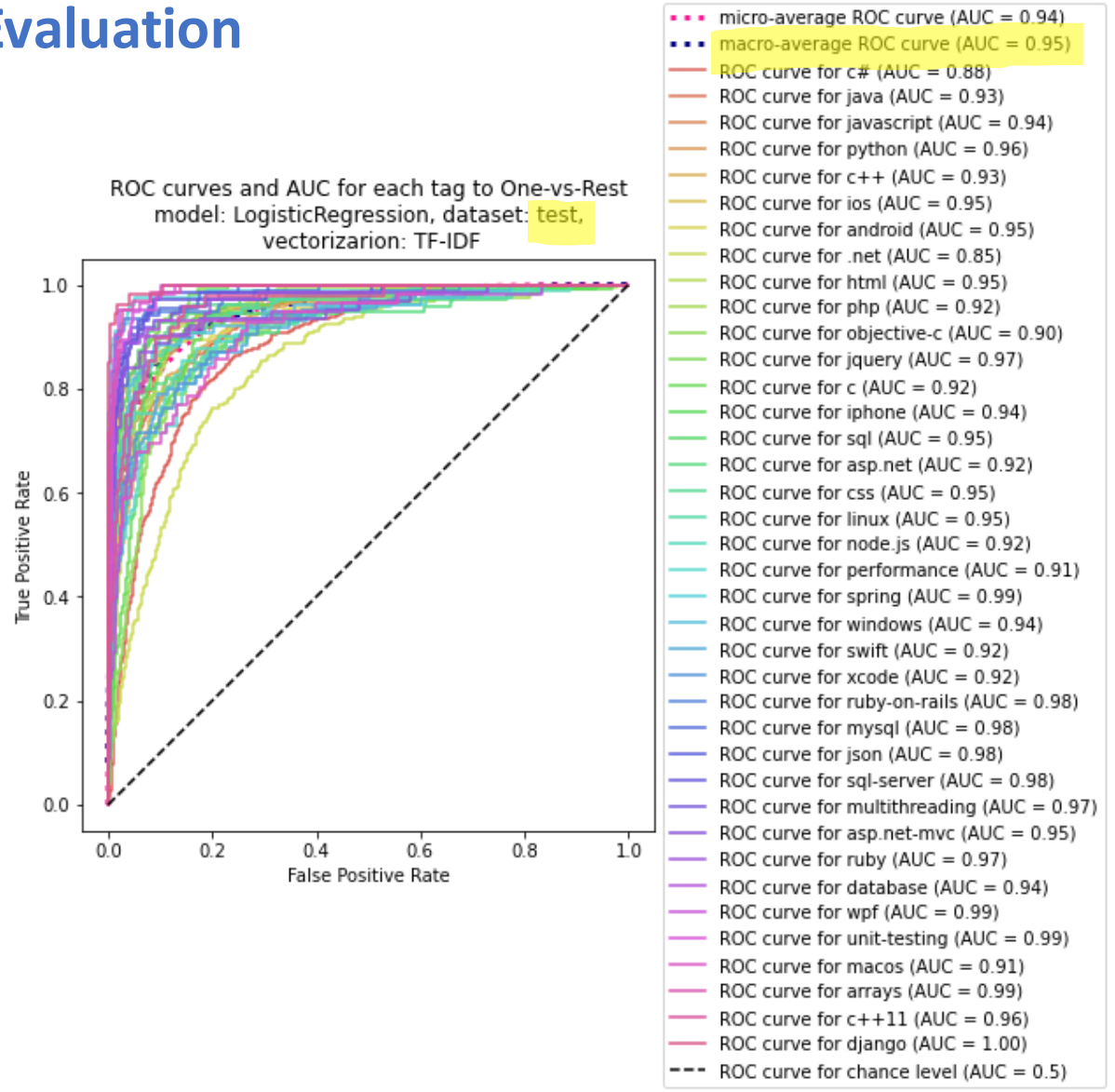


ROC pour chacun des classifieurs

Modélisation (supervisée) 3

Bag of words: TF-IDF + LogisticRegression --> Évaluation





Modélisation (supervisée)

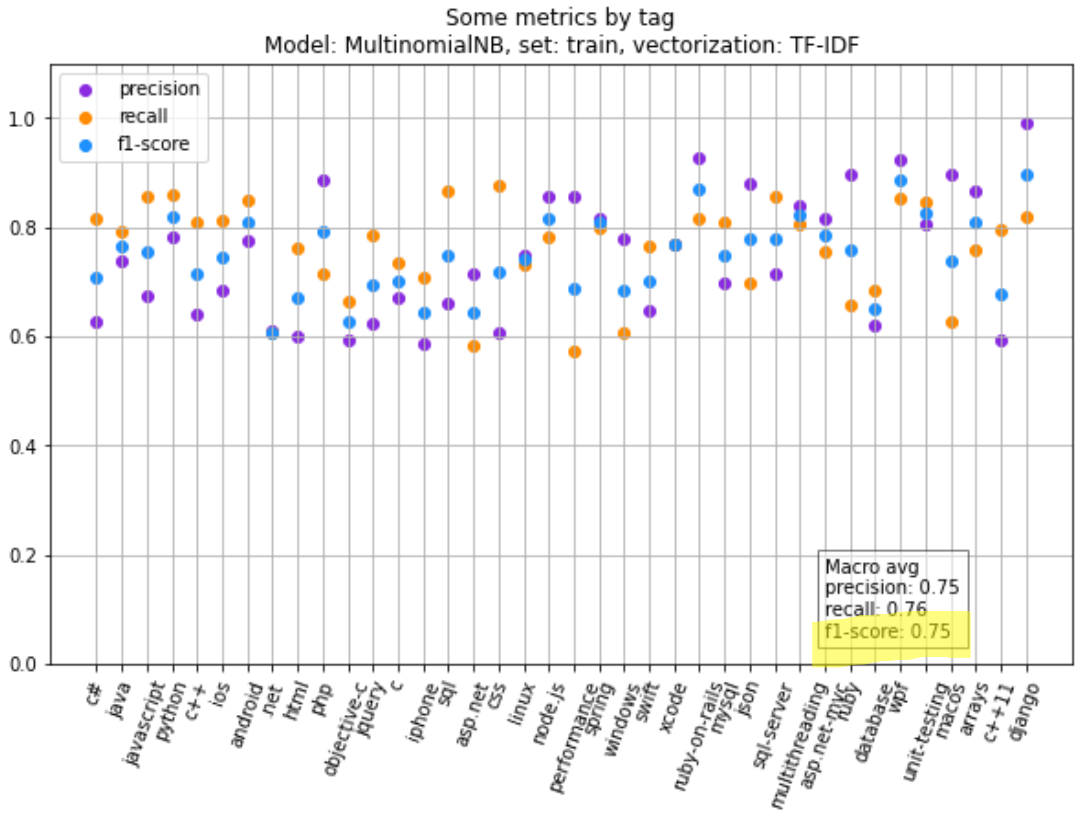
Bag of words: TF-IDF + **Naïve-Bayes classifier**

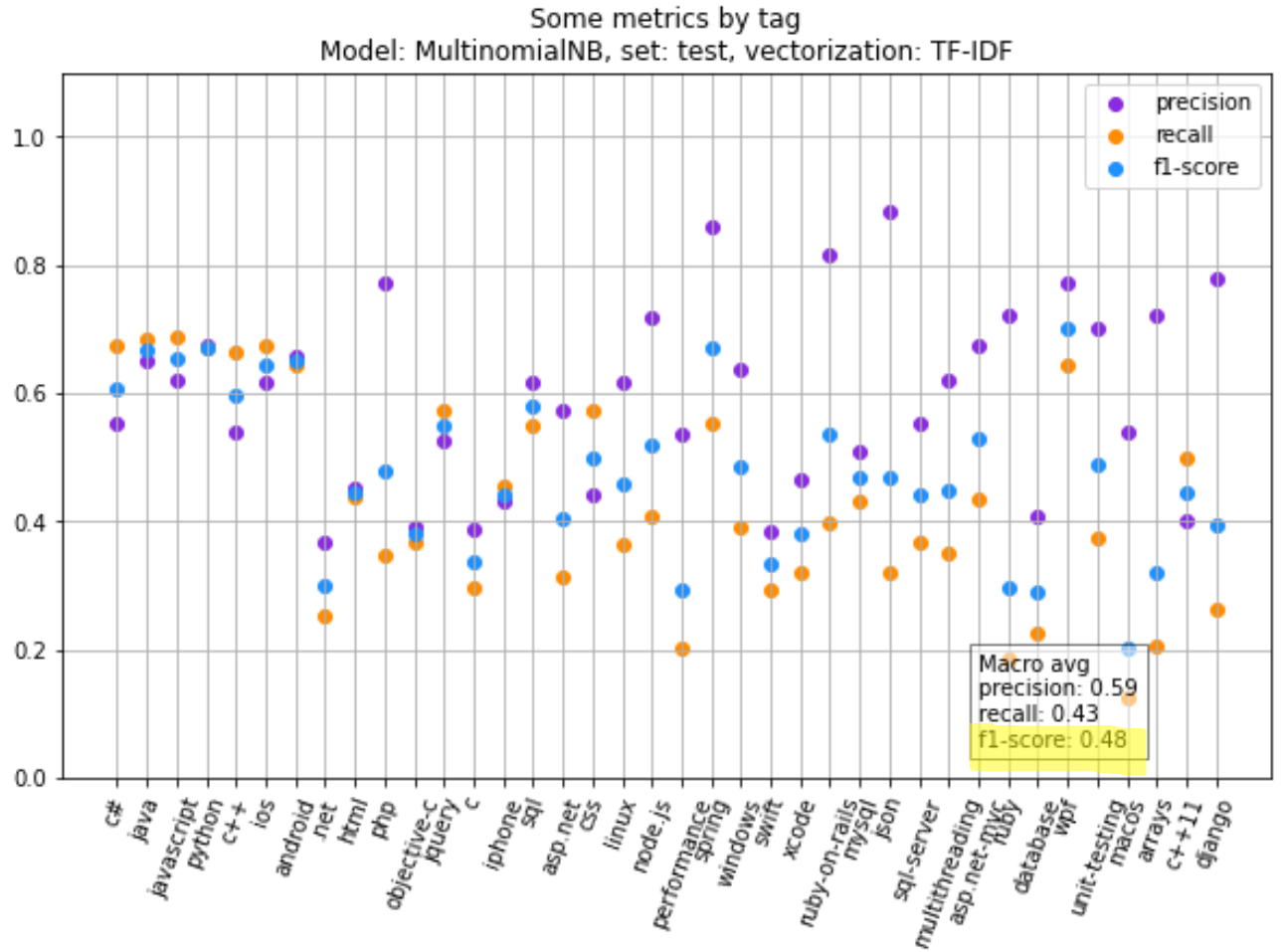
```python
parameters = {
    'estimator__alpha' : [0.05, 0.2, 0.5, 1],
    'estimator__fit_prior' : [True, False]
}

# Instantiating OneVsRest Classifier
cl = OneVsRestClassifier(MultinomialNB())

# Grid search for best hyperparameters
grid_search = GridSearchCV(
    estimator = cl,
    param_grid= parameters,
    scoring='roc_auc_ovr',
    verbose=2,
    n_jobs=-1
)
```

Validation croisée pour trouver hyperparamètres adaptés

Modélisation (supervisée)

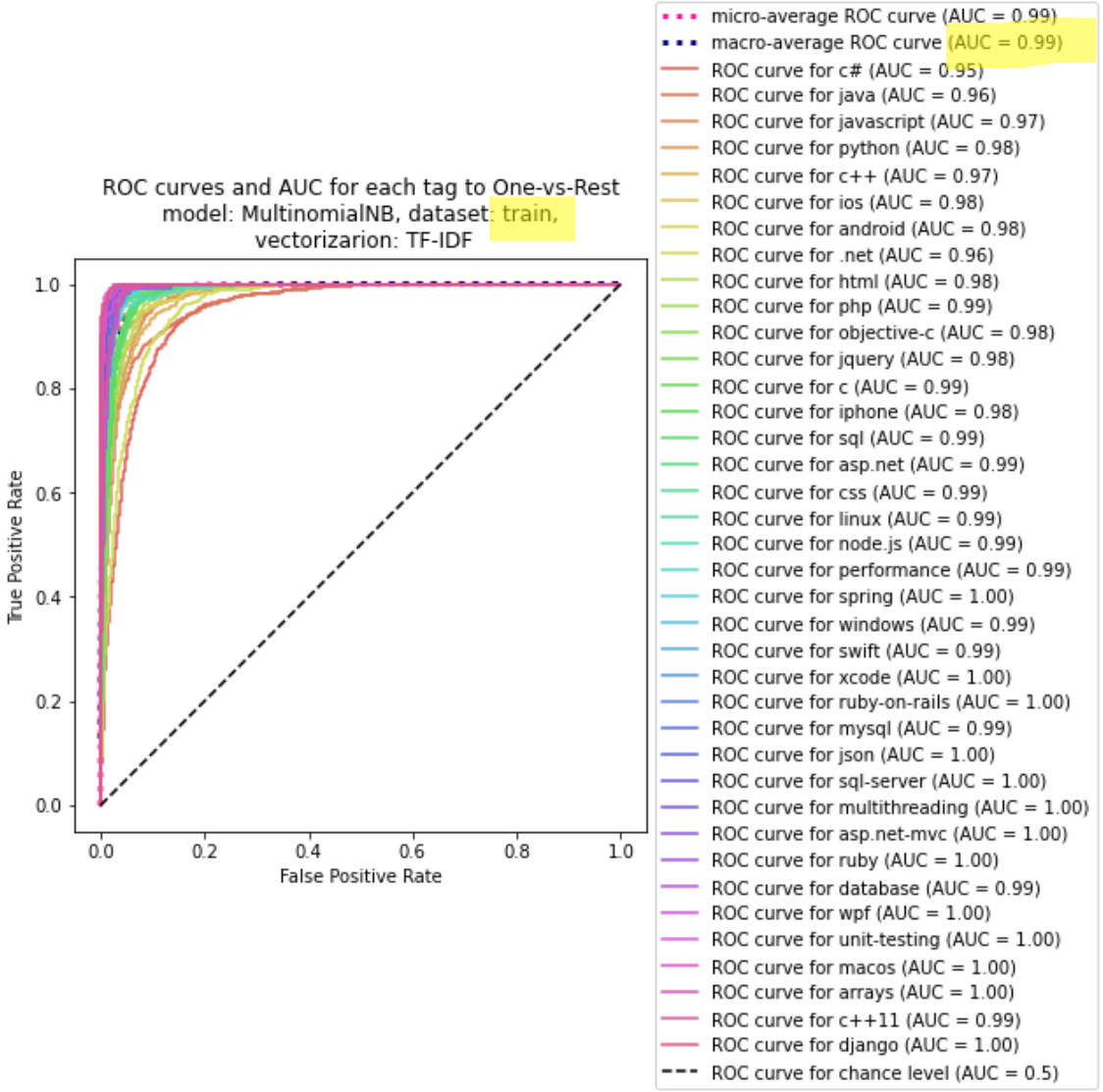
Bag of words: TF-IDF + **Naïve-Bayes classifier --> Évaluation**

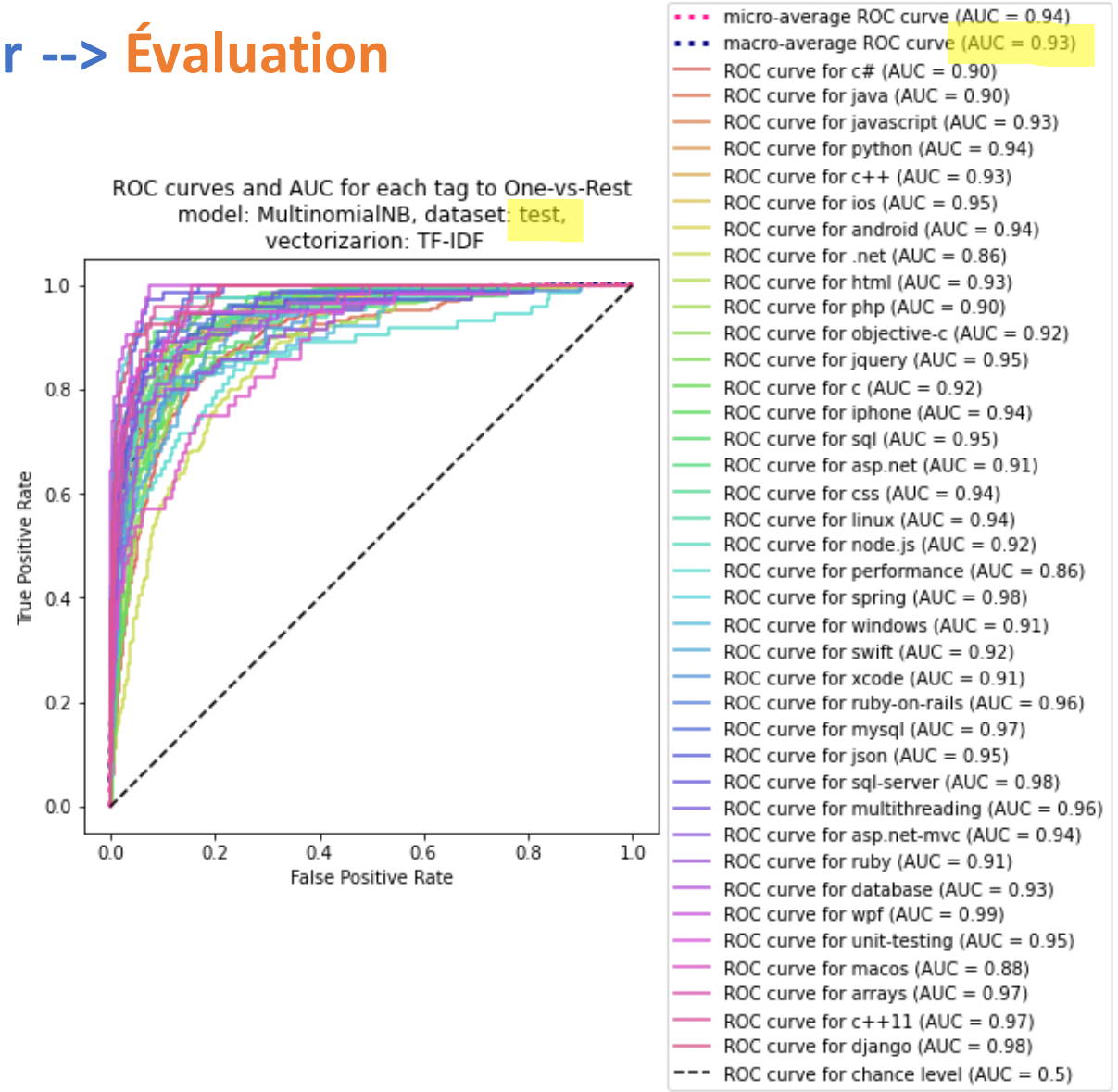




Modélisation (supervisée)

Bag of words: TF-IDF + **Naïve-Bayes classifier** --> **Évaluation**





Modélisation (supervisée)

Bag of words: TF-IDF + **RandomForestClassifier**

```
# Hyperparameter tuning for RandomForest

# parameters = {
#     'estimator__n_estimators' : [50, 100, 150, 200, 250],
#     'estimator__max_depth' : [int(x) for x in np.linspace(10, 110, num = 11)],
#     'estimator__min_samples_split' : [2,5,10],
#     'estimator__min_samples_leaf' : [1,2,4],
#     'estimator__bootstrap' : [True, False],
#     'estimator__max_features' : ['sqrt', 'log2', None]
# }

# # Instantiating OneVsRest Classifier
# cl = OneVsRestClassifier(RandomForestClassifier())

# # Random search for best hyperparameters
# random_search = RandomizedSearchCV(
#     estimator = cl,
#     param_distributions= parameters,
#     n_iter=30,
#     scoring='roc_auc_ovr',
#     verbose=2,
#     random_state=5,
#     n_jobs=-1
# )
```

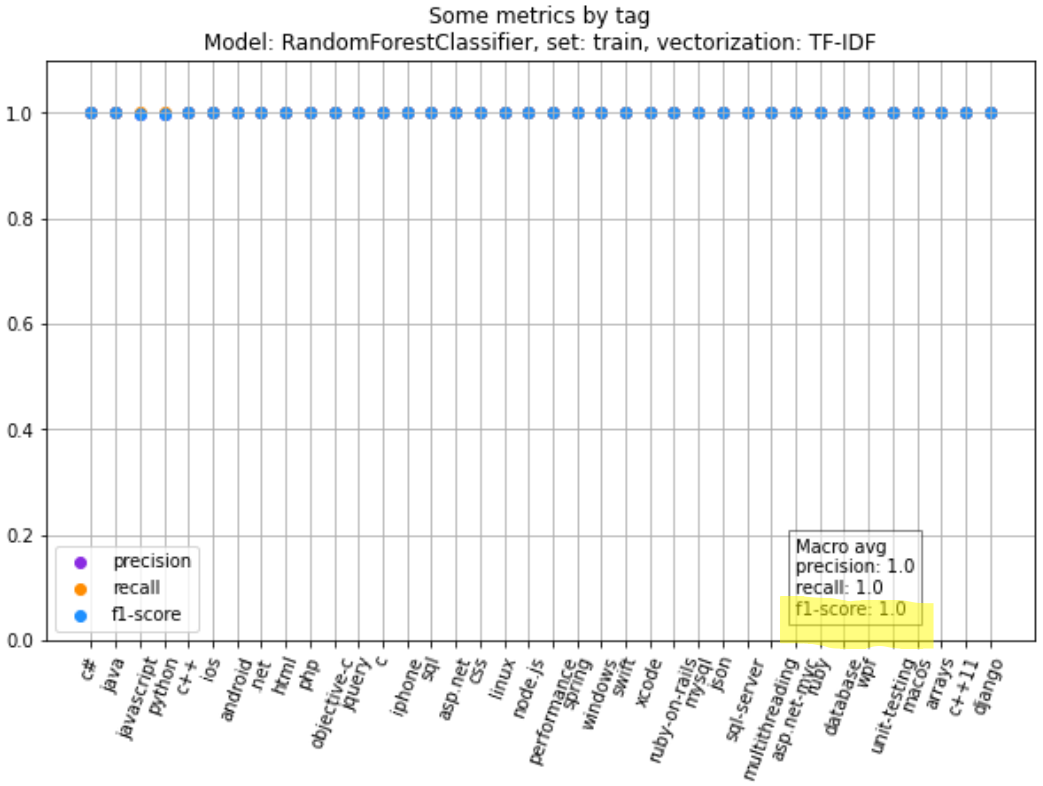
100
None
2
2
True
sqrt

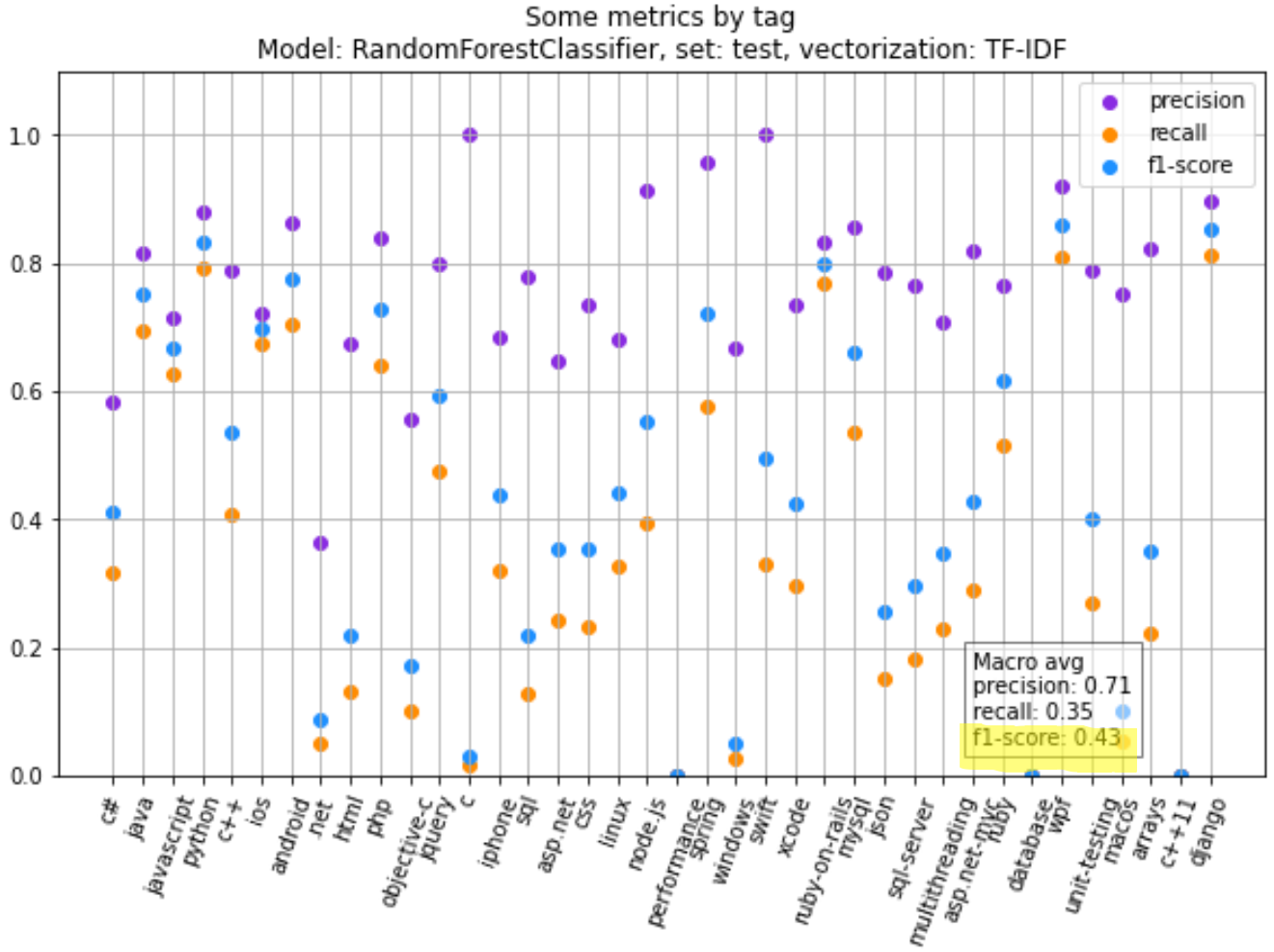
Nous ressources de calcul **n'ont pas permis** de faire une validation croisée pour RandomForest.

Solution: entraînement (très long) avec paramètres par défaut.

Modélisation (supervisée) 3

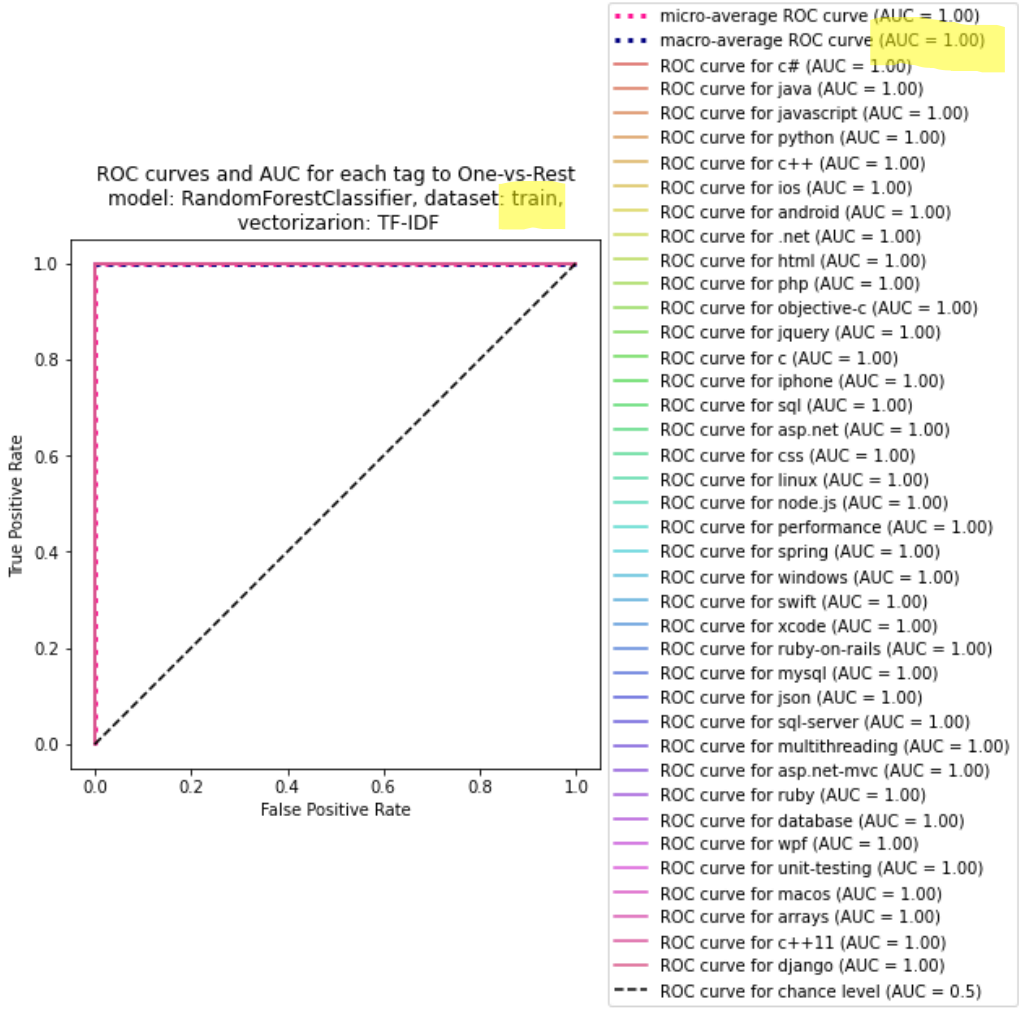
Bag of words: TF-IDF + **RandomForestClassifier --> Évaluation**

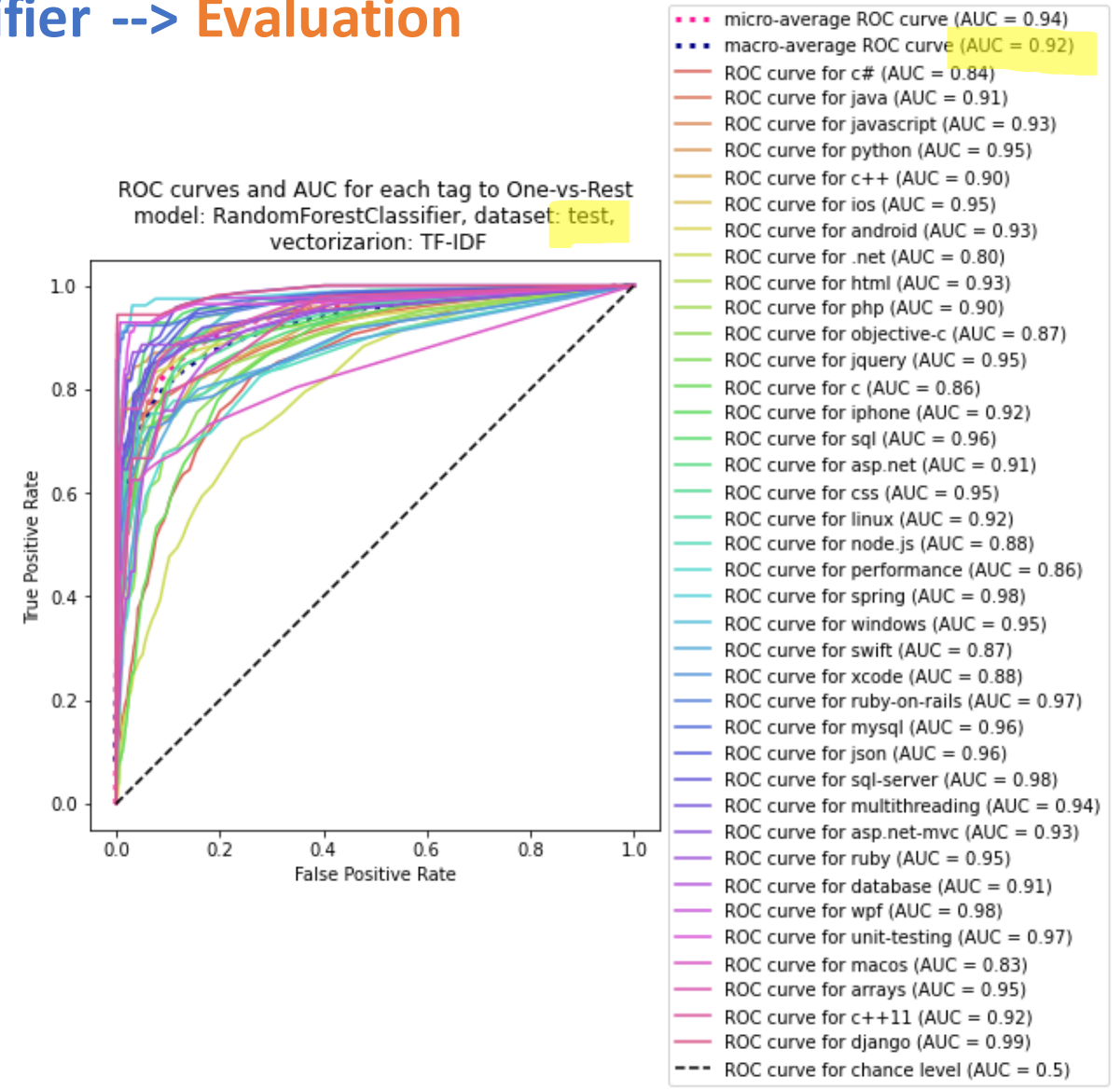




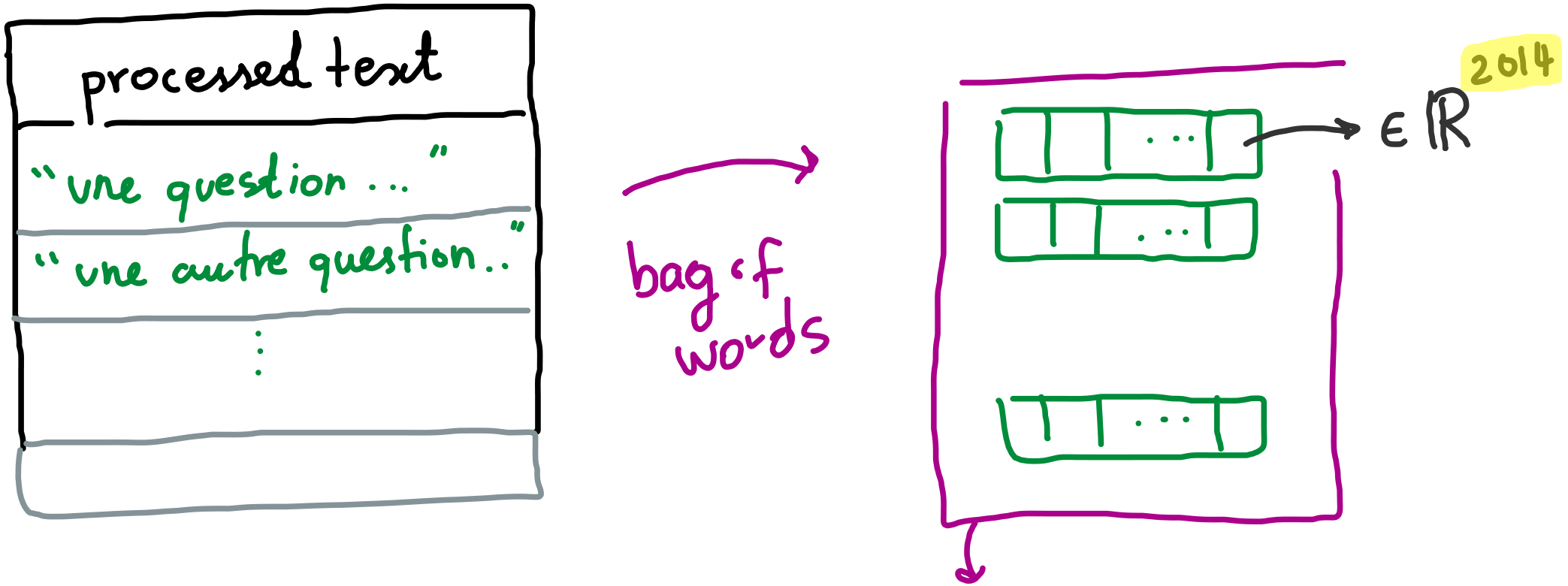
Modélisation (supervisée)

Bag of words: TF-IDF + **RandomForestClassifier** --> **Évaluation**

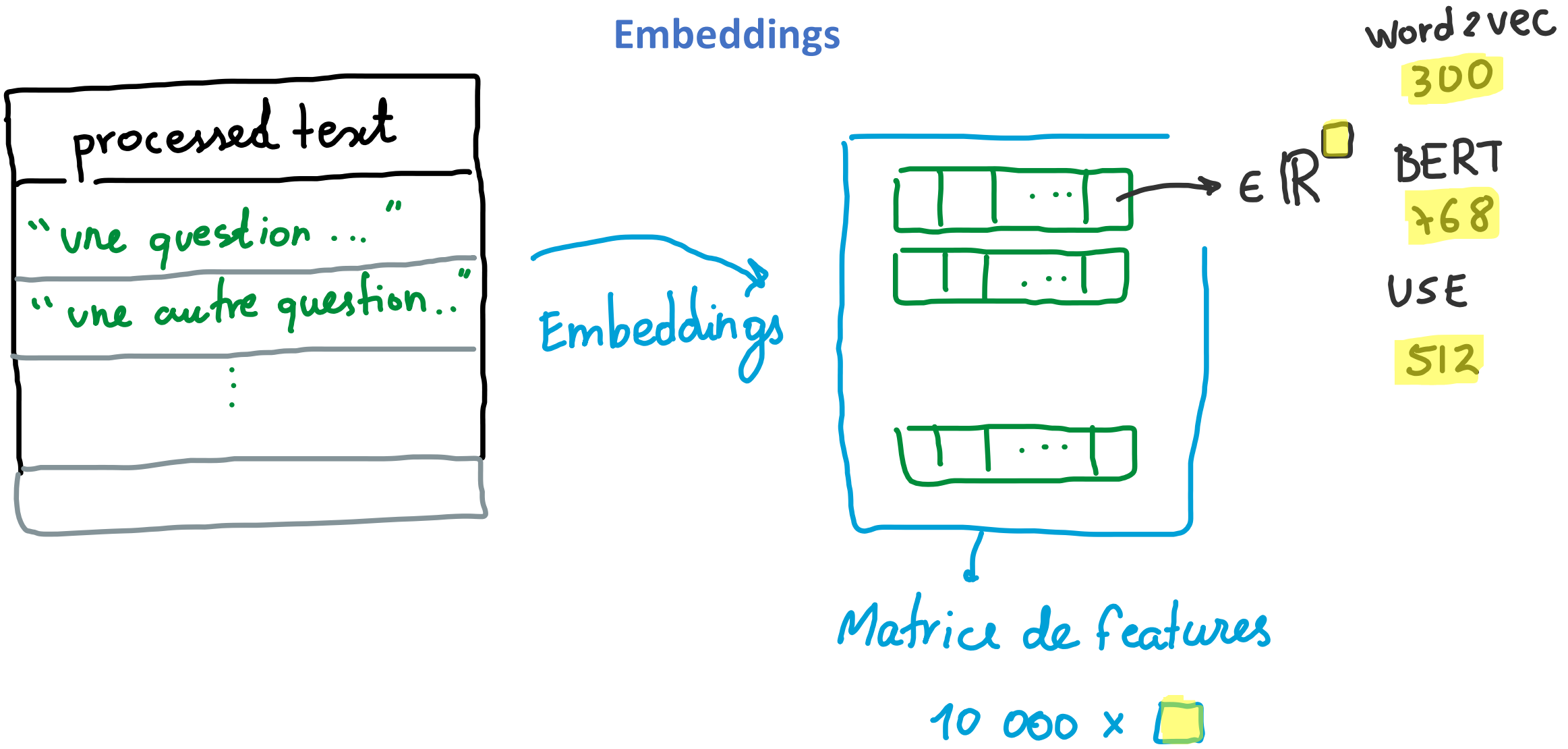




Modélisation (supervisée)



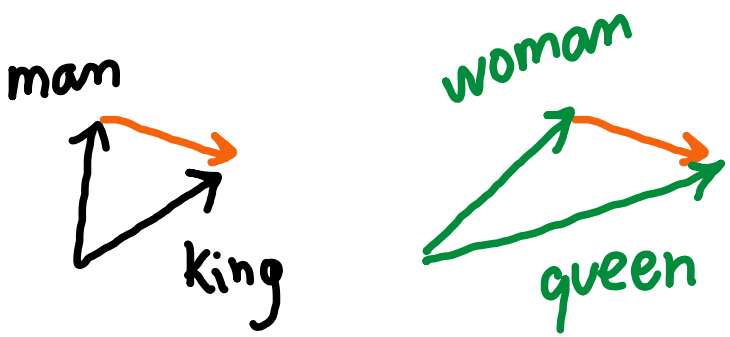
Modélisation (supervisée)



Modélisation (supervisée)

Embeddings

Word2Vec



- basée : réseaux de neurones
- CBOW, skipgram

BERT

Bidirectional **E**ncoder **R**epresentations from **T**ransformers

basée : Transformers

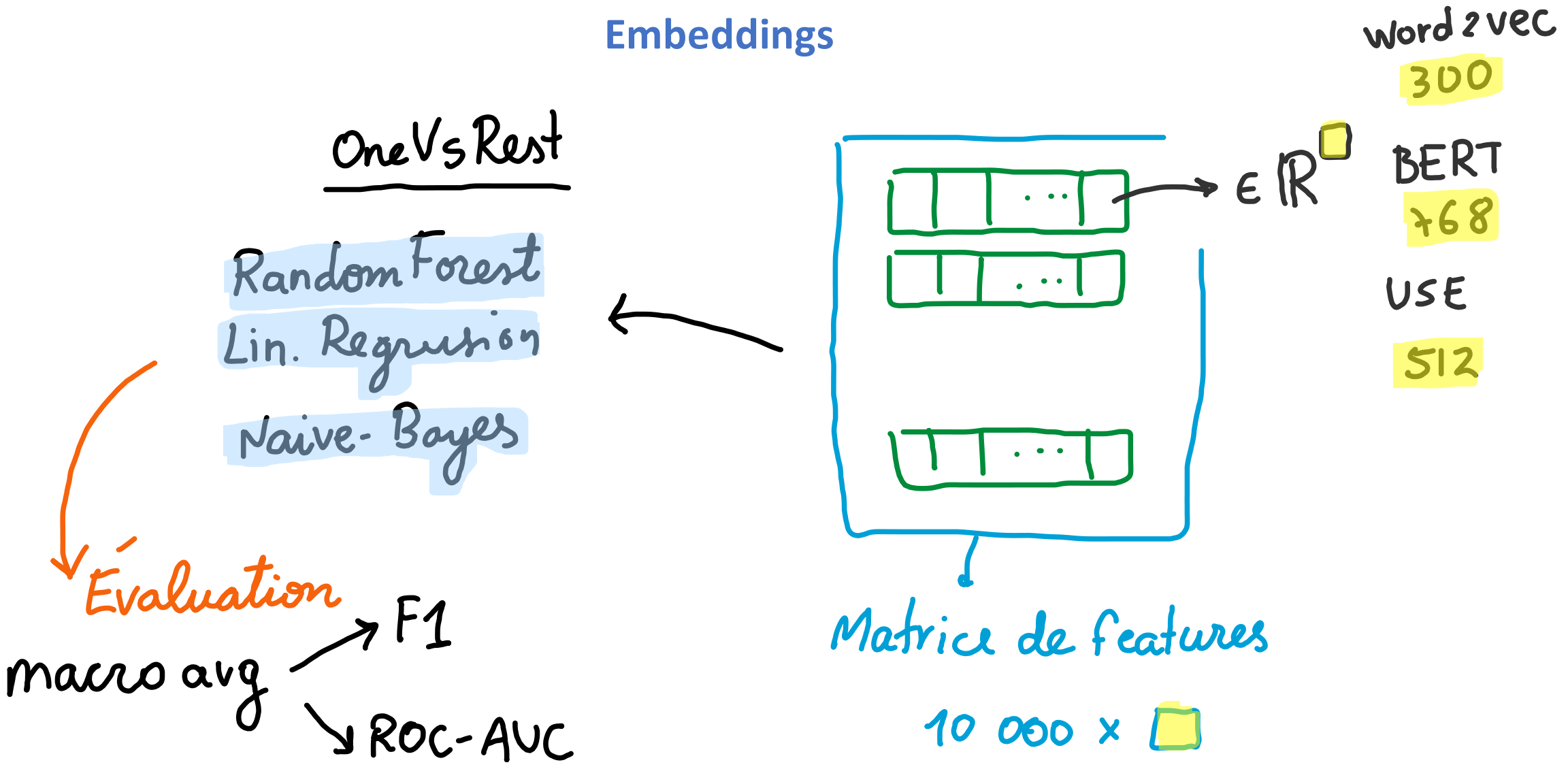
- pré-entrainement en masquant des mots

USE

Universal **S**entence **E**ncoder

phrase entière → embedding

Modélisation (supervisée)



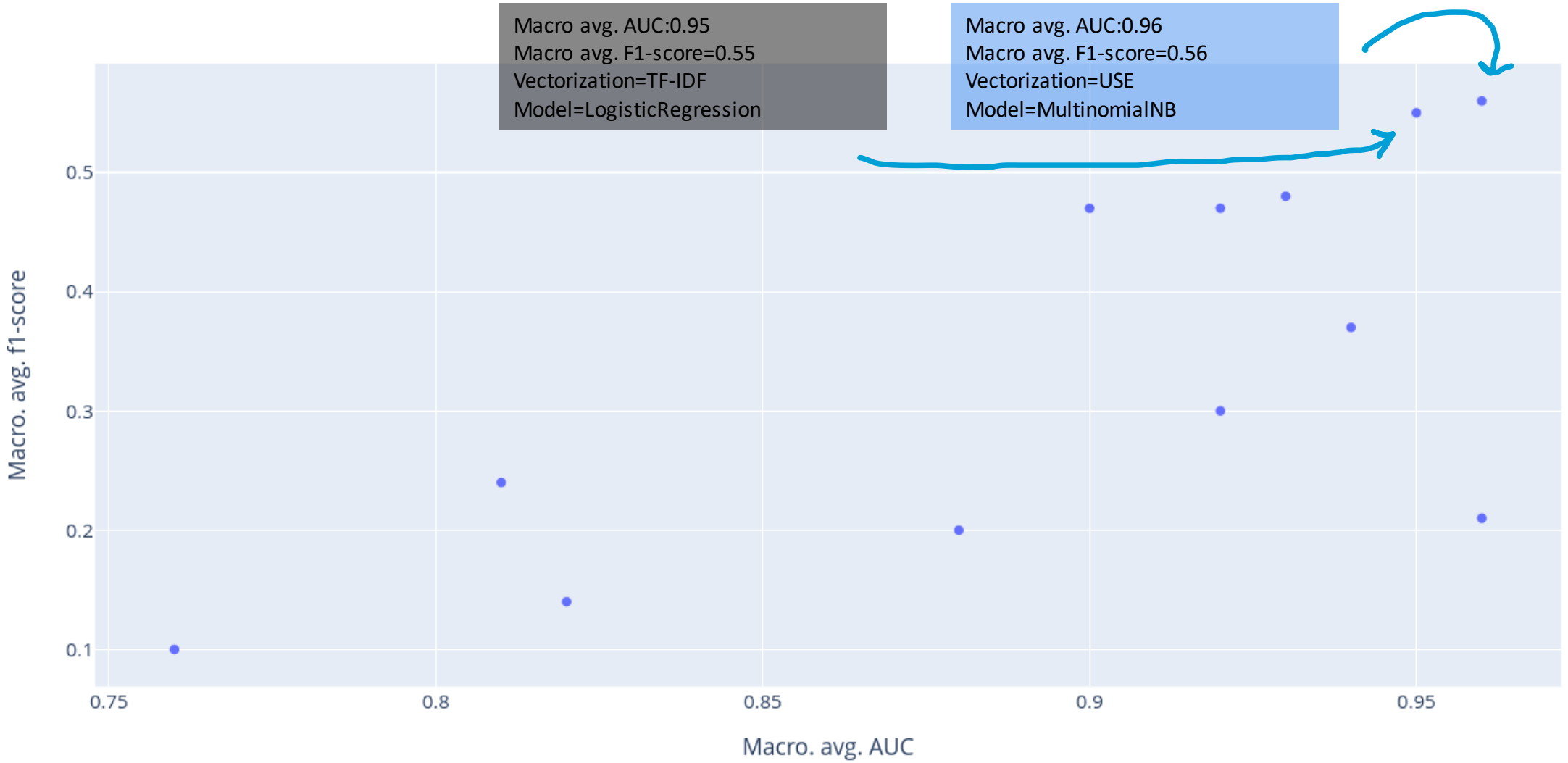
Modélisation (supervisée)

Comparaison performances tous les modèles supervisés

	Vectorization	Model	Macro. avg. f1-score	Macro. avg. AUC	Fit time
0	TF-IDF	LogisticRegression	0.55	0.95	3.87
1	TF-IDF	MultinomialNB	0.48	0.93	3.87
2	TF-IDF	RandomForestCl	0.43	0.92	86.42
3	Word2Vec	LogisticRegression	0.47	0.92	25.08
4	Word2Vec	RandomForest	0.15	0.82	401.76
5	Word2Vec	MultinomialNB	0.20	0.88	401.76
6	BERT	LogisticRegression	0.47	0.90	259.71
7	BERT	RandomForest	0.10	0.76	984.06
8	BERT	MultinomialNB	0.24	0.81	1.91
9	USE	LogisticRegression	0.21	0.96	19.21
10	USE	RandomForest	0.37	0.94	443.52
11	USE	MultinomialNB	0.56	0.96	0.62

Modélisation (supervisée)

Comparaison performances tous les modèles supervisés



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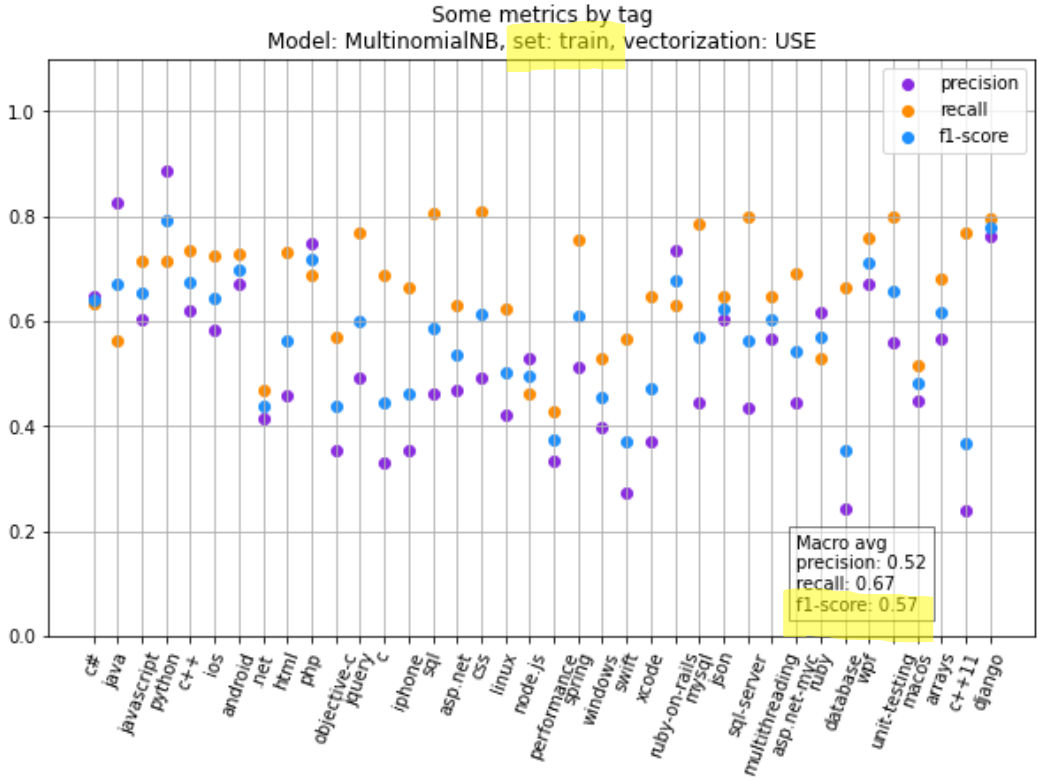
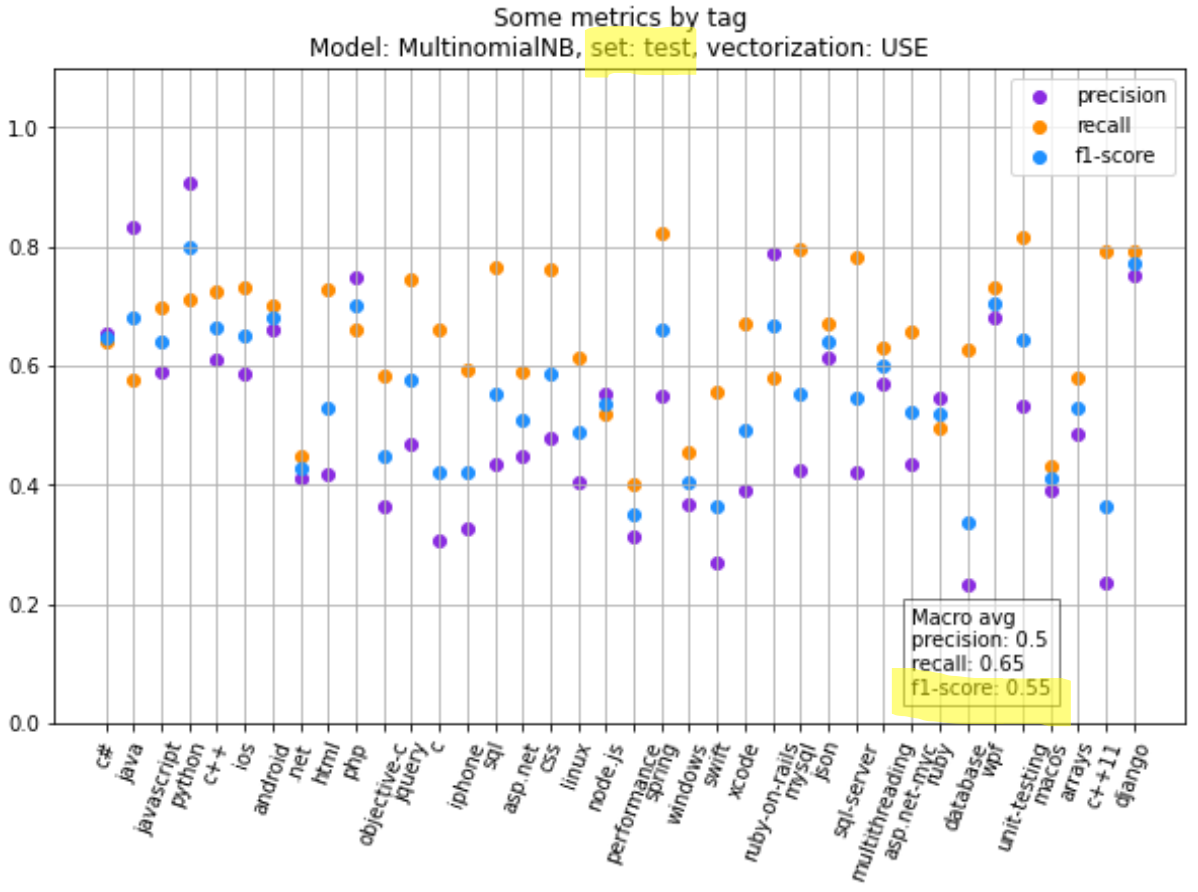
Modélisation (supervisée)

Entraînement OneVsRest(Naïve Bayes Multinomial) avec toutes les données

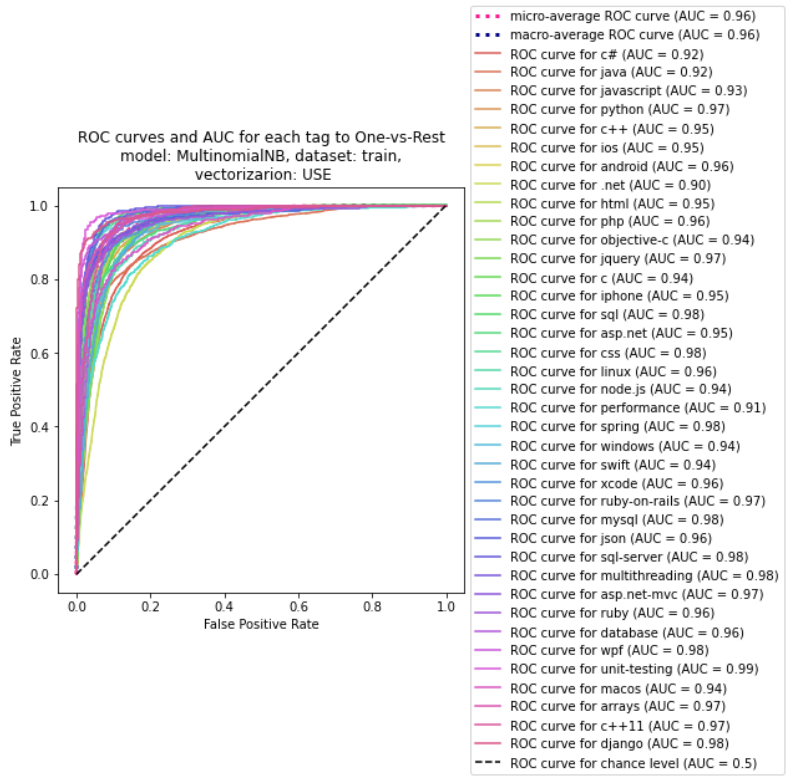


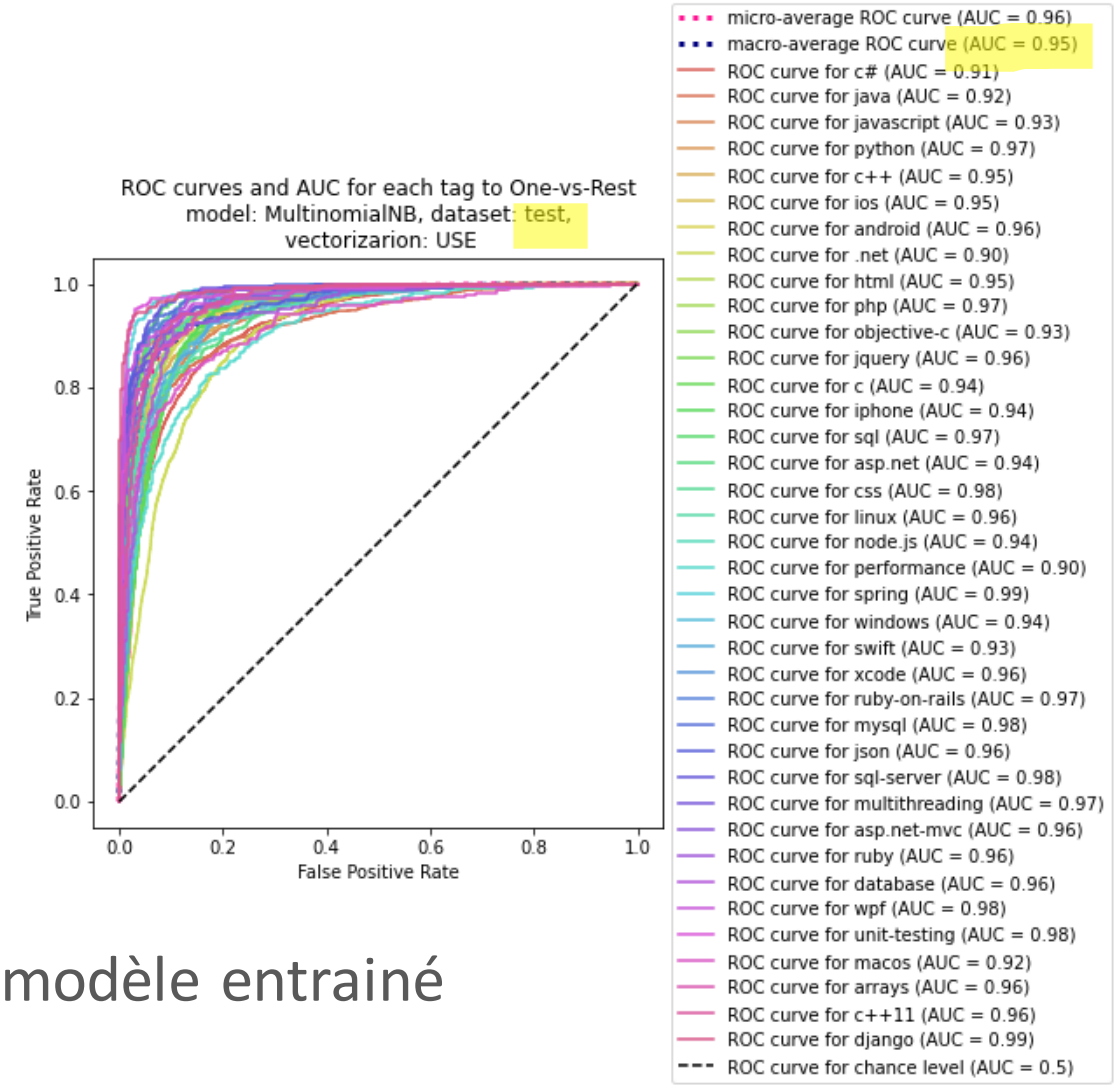


Exporter modèle entrainé

Modélisation (supervisée)

Entraînement OneVsRest(Naïve Bayes Multinomial) avec toutes les données

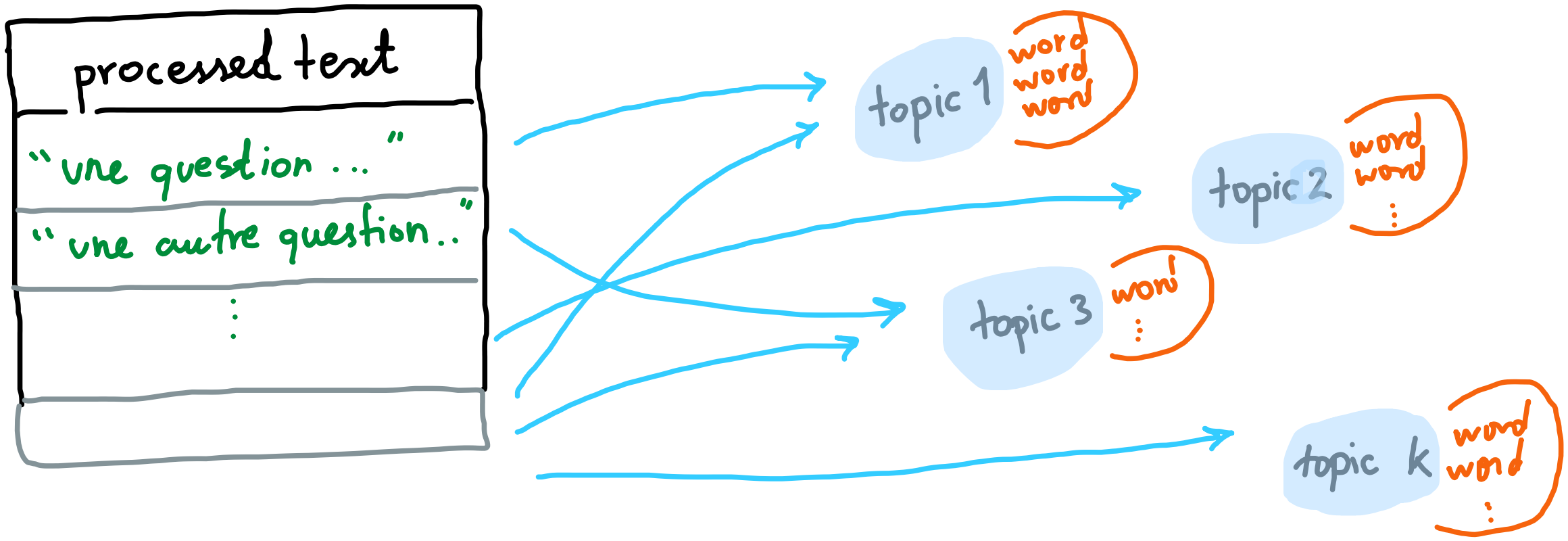




Exporter modèle entrainé

Modélisation (**non**-supervisée)

LDA : Latent Dirichlet Allocation



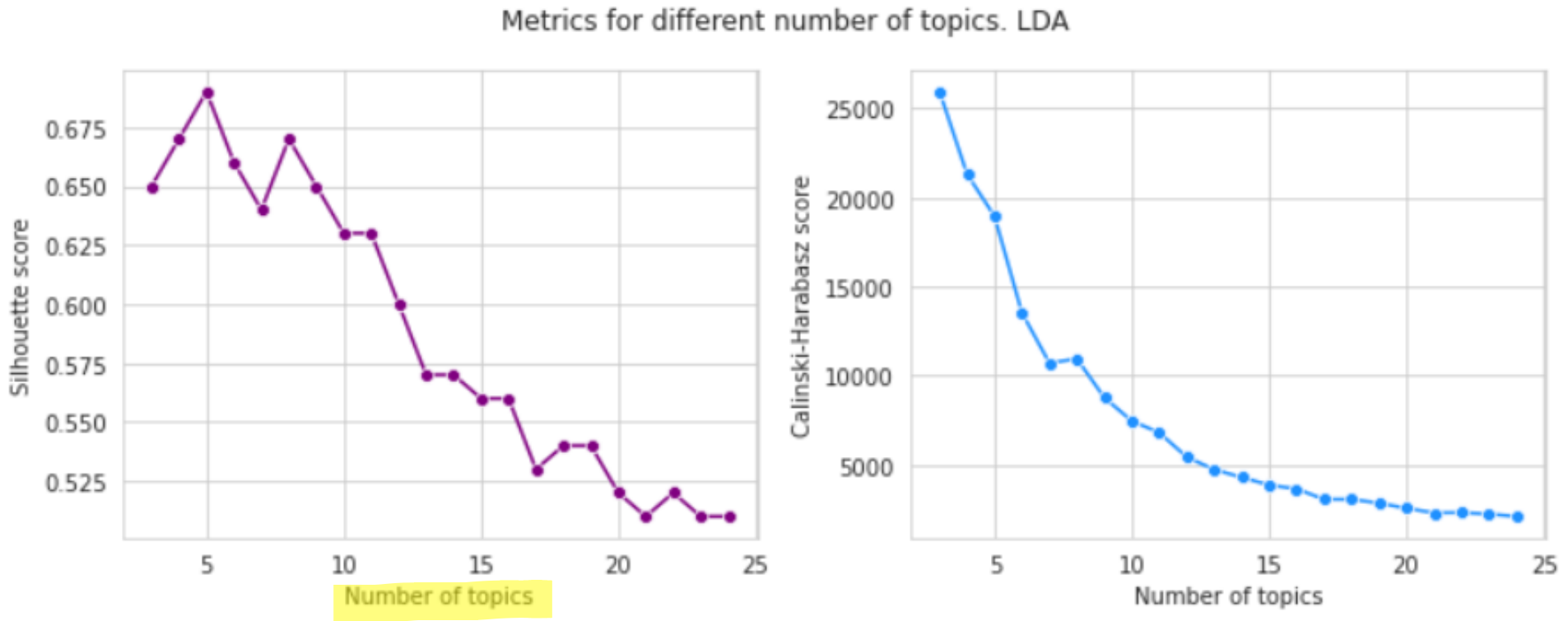
Modélisation (**non**-supervisée)

LDA : Latent Dirichlet Allocation

Modélisation (**non**-supervisée)

LDA : Latent Dirichlet Allocation. --> **Pas très adapté à notre but !**

Mes approches :

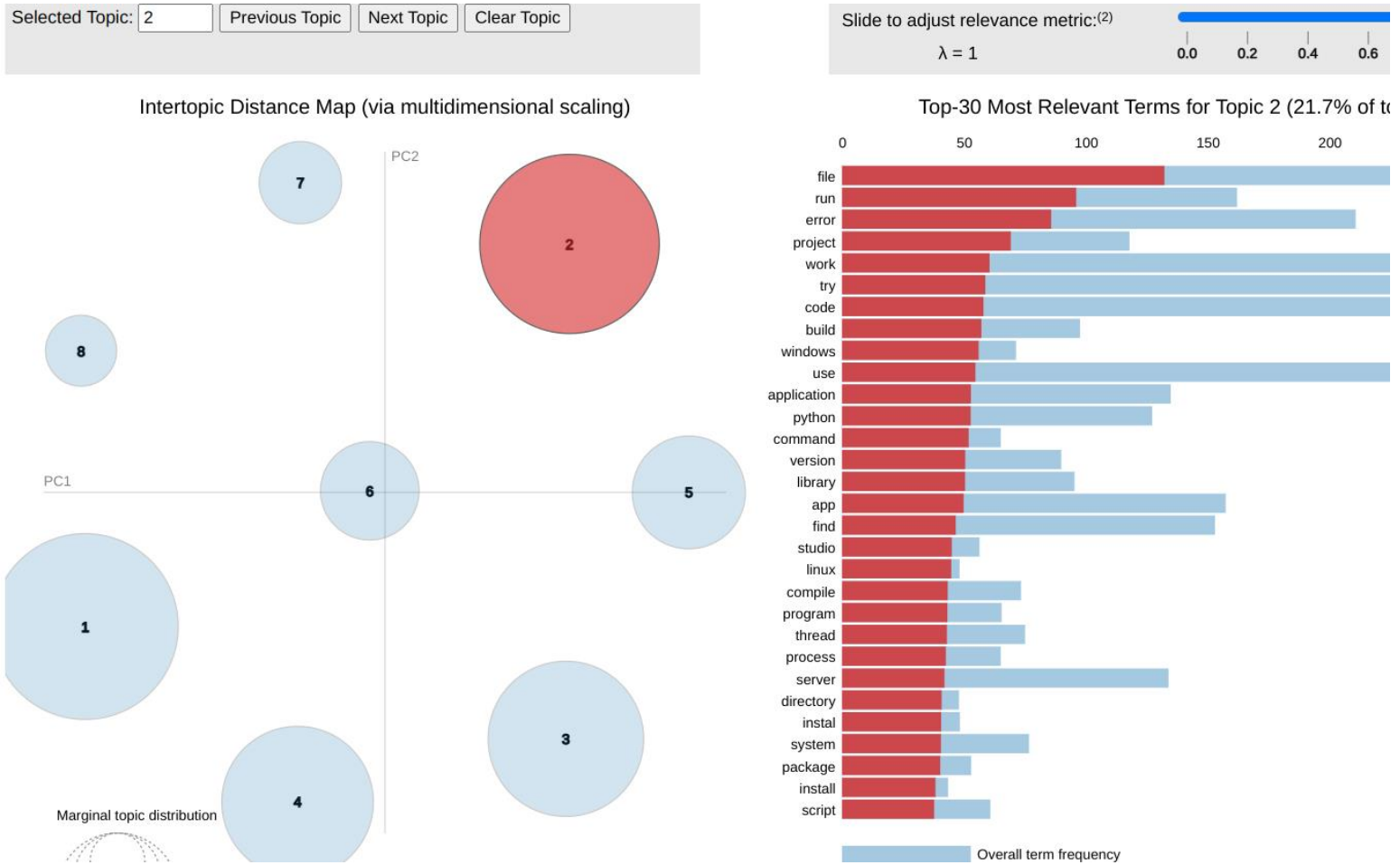


hyperparamètre

Modélisation (**non**-supervisée)

LDA : Latent Dirichlet Allocation. --> **Pas très adapté à notre but !**

Mes approches :



Distribution de mots par sujet

↓

idée

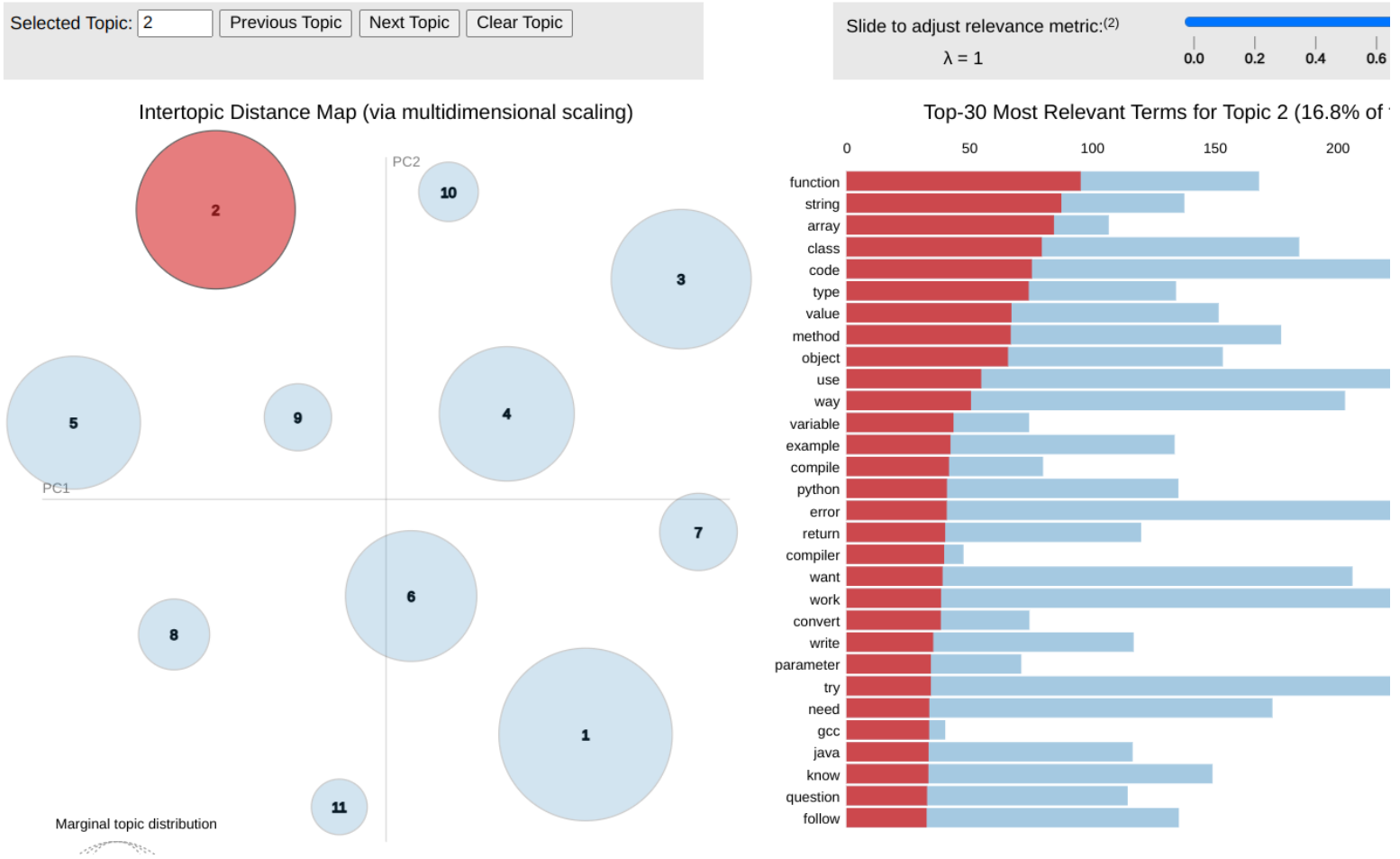
↓

intersection avec mes tags

Modélisation (**non**-supervisée)

LDA : Latent Dirichlet Allocation. --> **Pas très adapté à notre but !**

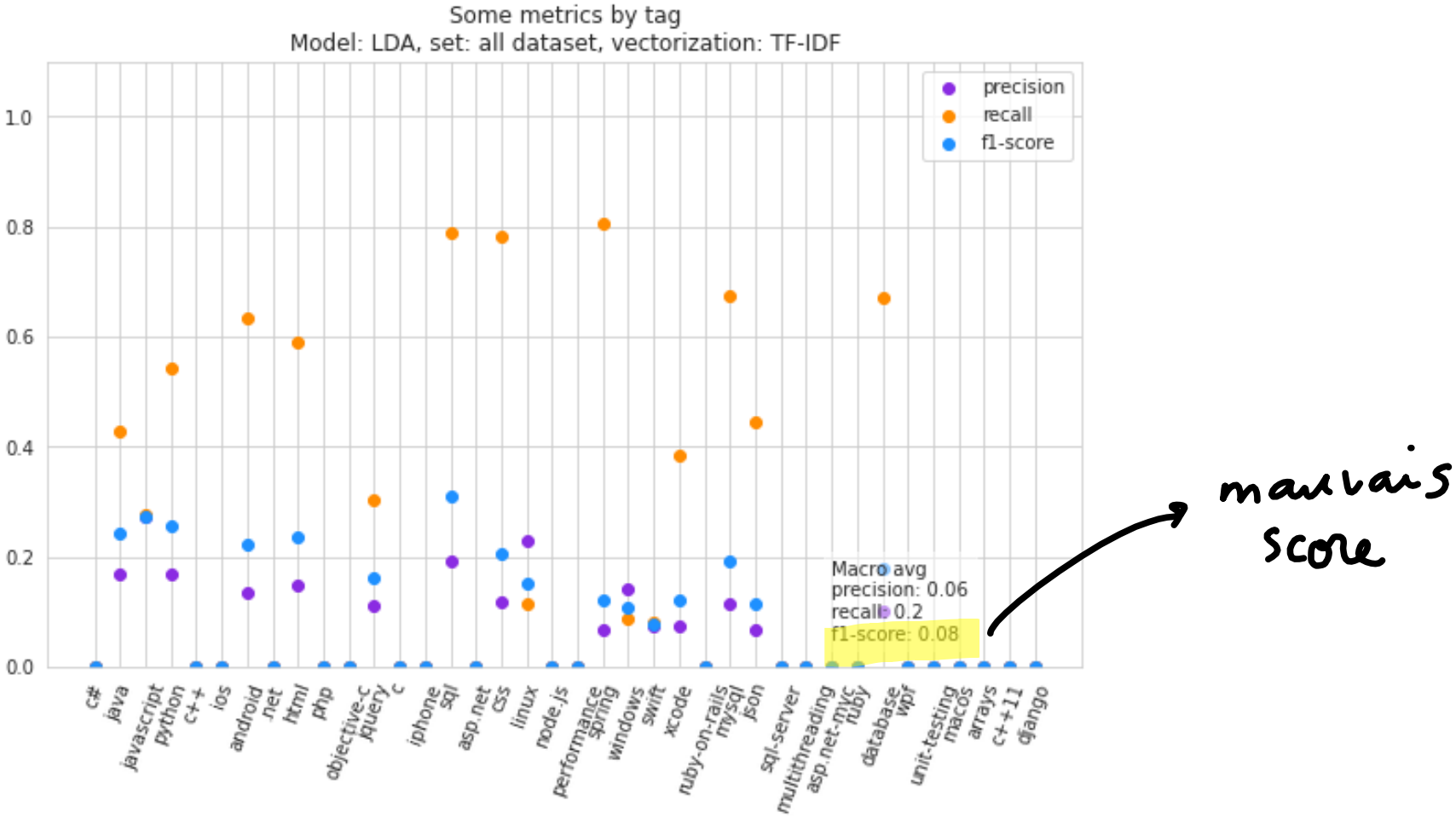
Mes approches :



Modélisation (**non**-supervisée) 3

LDA : Latent Dirichlet Allocation. --> **Pas très adapté à notre but !**

Mes approches :



4

API

API

Avec gradio

```python
def tag_suggestion(raw_text):
    """
    Returns a list of tags suggested for the question raw_text.
    """
    # Clean text first
    clean_text = clean(raw_text)
    document = [clean_text]

    # Find an embedding of the text with USE
    X = embed(document)

    # Predict a tag set with our classification model
    pred = my_pred(X)

    return binary_to_tag_list(pred)


# API ##

demo = gr.Interface(fn=tag_suggestion,
                    inputs="text",
                    outputs=["text"],
                    examples=examples)


if __name__ == "__main__":
    demo.launch()
```

1 Nettoyer texte avec notre fonction

↓ embed avec USE

2

↓ prediction OneVsRest Naive Bayes

3

↓ traduction

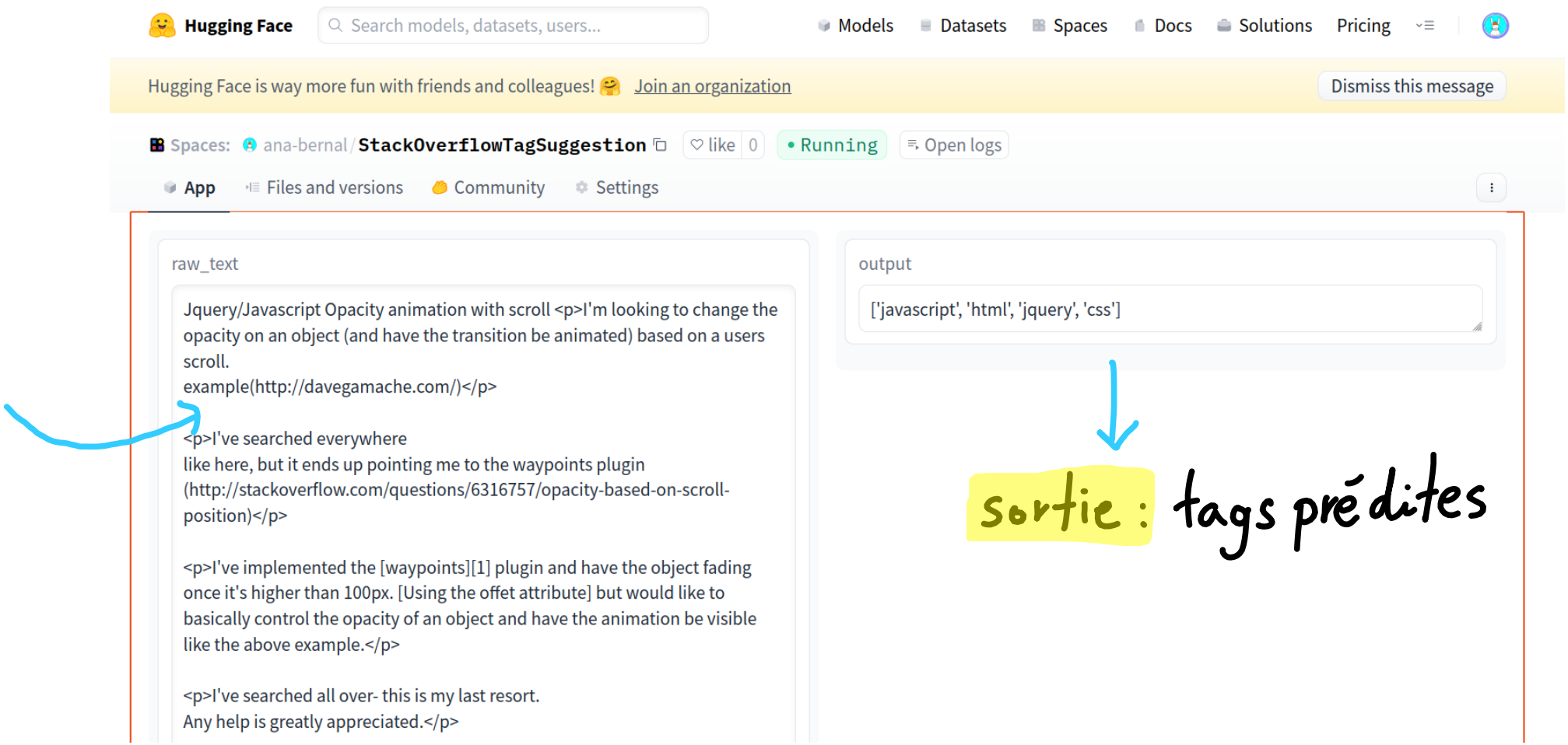
4

javascript php

API

Hébergé sur spaces de Hugging Face

aller à l'API



5

Conclusions

Conclusions

Suggestions des tags + Projet OC

- Fonctionnement **satisfaisant** avec le meilleur modèle.
- Beaucoup de **nouveaux apprentissages**: NLP, version control, API avec Gradio et HuggingFace.
- Traitement de texte : cas **complexe** pour un premier approche à NLP --> du code dans le texte, HTML, etc.

Pour aller + loin

- Inclure plus de tags: il faut plus de ressources de calcul. (nous: 40 sur 18 000)
- Inclure plus de questions (nous: 50 000 sur ∞)
- Améliorer visualisation API, rajouter des options.
- Prédictions avec des réseaux de neurones.
- Analyse exploratoire + profond.