Patent Classification using Extreme Multi-label Learning

A Case Study of French Patents

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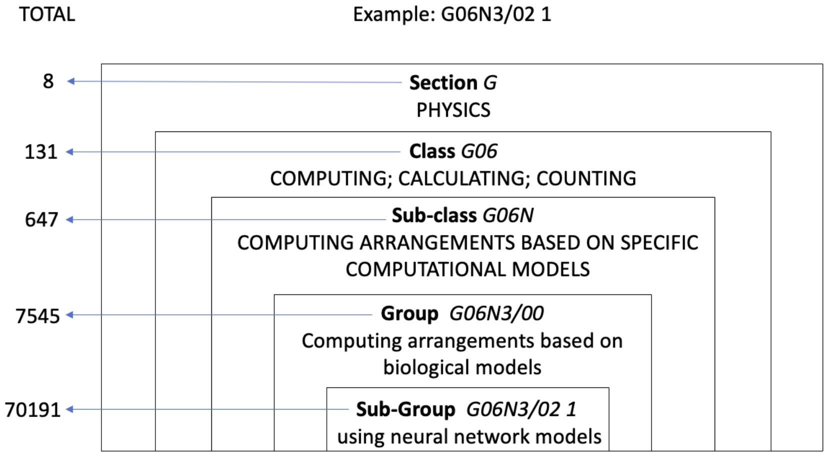
Introduction

- Task: **IPC** classification of **French Patent** documents



Introduction

- Task: **IPC** classification of **French Patent** documents
- Problems:
  1. not enough data in French (EPO, WIPO Delta dataset)
  2. limited to subclass level (with less than 700 labels)

Solutions

We present a French Patents corpus, named INPI-296k

- extracted from the INPI(French Intellectual property Office) internal database
- contains all parts of patent texts (title, abstract, claims, description) published from 2002 to 2021
- with IPC labels at all levels from sections to subgroups

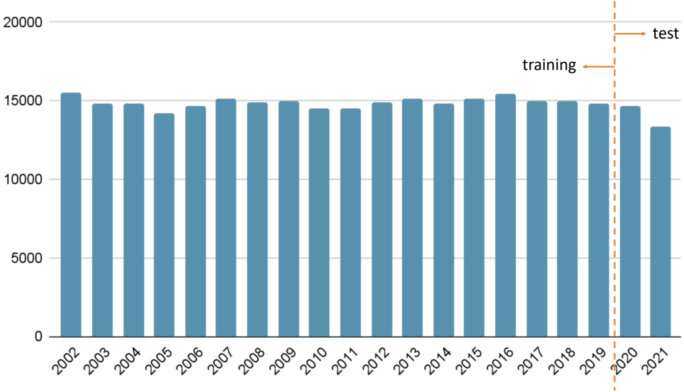
section	title	abstract	description	claims
# items	296 270	295 421	296 216	291 539
# tokens (average)	11	111	4202	725

Table: Description of our French corpus INPI-296k

Solutions

Dataset	N	L_4	$\bar{L}_4$	$\hat{L}_4$	L_6	$\bar{L}_6$	$\hat{L}_6$	L_8	$\bar{L}_8$	$\hat{L}_8$
Train	268254	638	1.73	420.46	6788	2.21	39.52	48932	2.73	5.48
Test	28017	583	1.77	48.06	4351	2.20	6.44	19593	2.64	1.43

Table: Basic Statistics of INPI-296k dataset



- N: number of patents
- L: number of labels
- $\bar{L}$: average number of IPC labels of a document
- $\hat{L}$: average number of documents per label
- The subscripts of 4,6,8 represent respectively IPC's subclass, group, and subgroup levels (4, 6, and 8 correspond to the number of characters used to encode the class)

Solutions

$\hookrightarrow$ to implement eXtreme Multi-label Learning (XML) methods to handle large numbers of classes (at the subclass and group level in our experiments)

Definition

The XML addresses the problem of learning a classifier which can automatically tag a data sample with the most relevant subset of labels from a large label set.

Examples

1) Wikipedia article page categories
2) Amazon product recommendation system

Properties

large number of labels (> 1000) + "long-tailed" label distribution

Experiments and Results

↪ Datasets

- INPI-296k
  subclass, group
- USPTO-2M [Li et al., 2018]
  subclass

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↪ Baselines

- Logistic Regression
- FastText [Mokolov et al., 2016]
- Bert [Devlin et al., 2018]
- Bert for Patents
  [Srebrovic and Yonamine, 2020]

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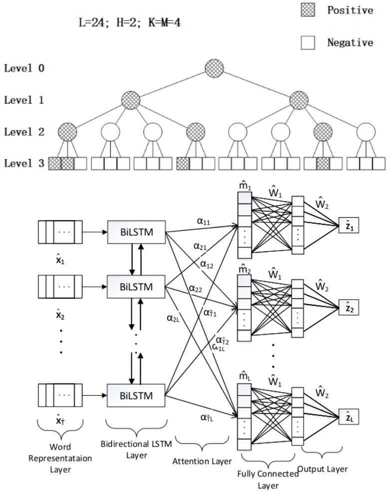
↪ Selected XML models

- XML-CNN [Liu et al., 2017]
- Parabel [Prabhu et al., 2018]
- AttentionXML [You et al., 2019]
- LightXML [Jiang et al., 2021]

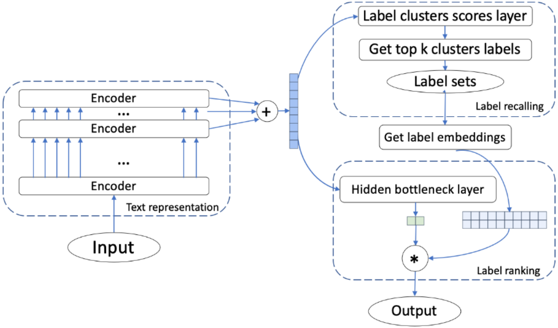
Experiments and Results

- AttentionXML [You et al., 2019]



Experiments and Results

- AttentionXML [You et al., 2019]
- LightXML [Jiang et al., 2021]



Experiments and Results

$\hookrightarrow$ Evaluation: *Precision@k* ($k = 1, 3, 5$)

For a predicted score vector $\hat{y} \in \mathbb{R}^L$ and ground truth label vector $y \in \{0,1\}^L$

$$Precision@k := \frac{1}{k} \sum_{l \in rank_k(\hat{y})} y_l$$

Experiments and Results

↪ Main results

Model	P@1	P@3	P@5
Logistic Regression	74.63	41.66	28.82
FastText	73.89	40.55	28.02
bert-large	83.77	46.27	31.37
Bert for Patents	84.31	46.73	31.73
XML-CNN	57.00	31.22	22.08
Parabel	74.43	41.49	28.50
AttentionXML	82.49	45.15	30.82
LightXML	**84.43**	**46.81**	**31.91**

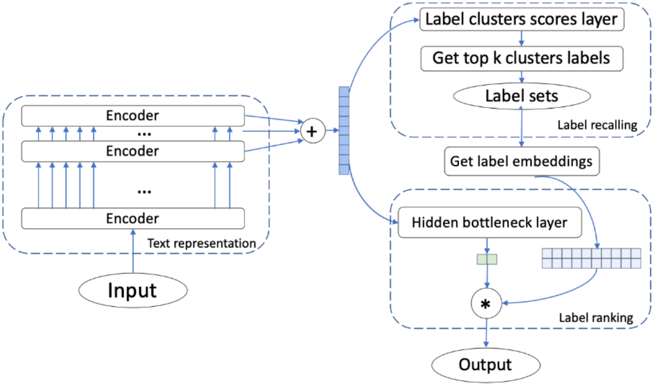
Table: Overall Performance (%) on IPC subclass on USPTO-2M (title + abstract)

Model	subclass			group		
	P@1	P@3	P@5	P@1	P@3	P@5
Logistic Regression	65.87	37.63	26.02	49.12	30.32	22.06
FastText	53.76	30.64	21.31	36.21	22.32	16.35
XML-CNN	43.43	25.50	18.23	17.74	10.20	6.96
Parabel	65.13	36.87	25.32	48.93	30.61	22.28
AttentionXML	72.54	40.68	27.63	54.83	33.78	24.49
LightXML	**76.45**	**42.82**	**29.05**	**60.60**	**36.95**	**26.65**

Table: Overall Performance (%) on IPC subclass and group on INPI-296k (title + abstract)

Experiments and Results

1. LightXML ourperforms all the other models
   - powerful text representation from transformer encoder
   - dynamic negative sampling
   - ensemble learning



Experiments and Results

1. LightXML ourperforms all the other models
2. best combinations of input = title + description

Model	IPC level	P@1	P@3	P@5
AttentionXML	subclass	76.60 (+4.06)	42.45 (+1.77)	28.71 (+1.08)
AttentionXML	group	59.27 (+4.44)	36.23 (+2.45)	26.03 (+1.54)
LightXML	subclass	76.72 (+0.27)	43.01 (+0.19)	29.17 (+0.12)
LightXML	group	62.33 (+1.73)	38.11 (+1.16)	27.48 (+0.83)

Table: Certain model performances (%) on IPC subclass and group on INPI-296k (**title + description**) (The numbers in parentheses indicate the boost relative to the model trained on (title+abstract)).

Experiments and Results

1. LightXML ourperforms all the other models
2. best combinations of input = title + description
3. error analysis
   - weaker models perform worse in learning to classify those "long-tailed" labels
   - tendency to mistake "long-tailed" labels for those more frequent labels

Conclusions

1. proposed a French Patent corpus INPI-296k
2. XML methods can be applied for IPC classification in deeper levels
3. Patents with "low resource" patent language can also achieve good results in patent classification
4. github: https://github.com/ZoeYou/Patent-Classification-2022

Onging and Future Works

1. Limitations on the length of the input text: extracting key sentences and passages as model input
2. "long-tailed" labels: using label descriptions and correlation between labels as input information
3. Evolution of the annual label distribution: adjustment of the training data order during training

Thank you for your attention!

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