CodeForces problems classification

By Ahmed Bouali

ENV SETUP

```
!unzip code_classification_dataset.zip
!pip install pytorch-lightning
```

```
  inflating: code_classification_dataset/sample_2335.json
  inflating: code_classification_dataset/sample_2339.json
  inflating: code_classification_dataset/sample_2344.json
  inflating: code_classification_dataset/sample_2349.json
  inflating: code_classification_dataset/sample_2352.json
  inflating: code_classification_dataset/sample_2361.json
  inflating: code_classification_dataset/sample_2364.json
  inflating: code_classification_dataset/sample_2376.json
  inflating: code_classification_dataset/sample_2377.json
  inflating: code_classification_dataset/sample_2378.json
  inflating: code_classification_dataset/sample_2382.json
  inflating: code_classification_dataset/sample_2383.json
  inflating: code_classification_dataset/sample_2384.json
  inflating: code_classification_dataset/sample_2387.json
  inflating: code_classification_dataset/sample_2391.json
  inflating: code_classification_dataset/sample_2392.json
  inflating: code_classification_dataset/sample_2398.json
  inflating: code_classification_dataset/sample_2414.json
  inflating: code_classification_dataset/sample_2415.json
  inflating: code_classification_dataset/sample_2416.json
  inflating: code_classification_dataset/sample_2426.json
  inflating: code_classification_dataset/sample_2430.json
  inflating: code_classification_dataset/sample_2435.json
  inflating: code_classification_dataset/sample_2438.json
  inflating: code_classification_dataset/sample_2440.json
  inflating: code_classification_dataset/sample_2447.json
  inflating: code_classification_dataset/sample_2449.json
  inflating: code_classification_dataset/sample_2456.json
  inflating: code_classification_dataset/sample_2457.json
  inflating: code_classification_dataset/sample_2465.json
  inflating: code_classification_dataset/sample_2485.json
  inflating: code_classification_dataset/sample_2486.json
  inflating: code_classification_dataset/sample_2488.json
  inflating: code_classification_dataset/sample_2499.json
  inflating: code_classification_dataset/sample_2506.json
  inflating: code_classification_dataset/sample_2510.json
  inflating: code_classification_dataset/sample_2520.json
  inflating: code_classification_dataset/sample_2522.json
  inflating: code_classification_dataset/sample_2524.json
  inflating: code_classification_dataset/sample_2529.json
  inflating: code_classification_dataset/sample_2531.json
  inflating: code_classification_dataset/sample_2538.json
  inflating: code_classification_dataset/sample_2540.json
  inflating: code_classification_dataset/sample_2557.json
  inflating: code_classification_dataset/sample_2565.json
  inflating: code_classification_dataset/sample_2571.json
  inflating: code_classification_dataset/sample_2572.json
  inflating: code_classification_dataset/sample_2573.json
  inflating: code_classification_dataset/sample_2585.json
  inflating: code_classification_dataset/sample_2592.json
  inflating: code_classification_dataset/sample_2596.json
  inflating: code_classification_dataset/sample_2601.json
  inflating: code_classification_dataset/sample_2603.json
  inflating: code_classification_dataset/sample_2607.json
  inflating: code_classification_dataset/sample_2608.json
  inflating: code_classification_dataset/sample_2617.json
  inflating: code_classification_dataset/sample_2622.json
  inflating: code_classification_dataset/sample_2645.json
```

```
import json
import sys
import os

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import pytorch_lightning as pl
import torch


from time import sleep
from collections import Counter
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score, classification_report
from sklearn.preprocessing import MultiLabelBinarizer

from openai import AzureOpenAI

from torch import cuda, nn
from torch.utils.data import Dataset, DataLoader


from transformers import Trainer, TrainingArguments
from transformers import BertTokenizerFast, AutoTokenizer
from transformers import BertConfig, BertModel, get_linear_schedule_with_warmup

from torchmetrics.classification import MulticlassF1Score
```

```
os.environ["AZURE_OPENAI_API_KEY"] = "AZOAI KEY"
os.environ["AZURE_OPENAI_ENDPOINT"] = "AZOAI EP"

os.environ["OPENAI_API_TYPE"] = "azure"
os.environ["OPENAI_API_VERSION"] = "VERSION"

os.environ["TOKENIZERS_PARALLELISM"] = "false"
device = 'cuda' if cuda.is_available() else 'cpu'
print(device)
```

```
cpu
```

```
os.environ["AZURE_OPENAI_API_KEY"] = "YOUR AZOAI KEY"
os.environ["AZURE_OPENAI_ENDPOINT"] = "YOUR AZOIA ENDPOINT"

os.environ["OPENAI_API_TYPE"] = "azure"
os.environ["OPENAI_API_VERSION"] = "VERSION"

os.environ["TOKENIZERS_PARALLELISM"] = "false"
device = 'cuda' if cuda.is_available() else 'cpu'
print(device)
```

```
cpu
```

DATA EXPLORING

```
directory_path = '/content/code_classification_dataset/'
all_files = os.listdir(directory_path)
json_files = [f for f in all_files if f.endswith('.json')]
```

```
all_data = []
for file_name in json_files:
  file_path = os.path.join(directory_path, file_name)
  with open(file_path, 'r') as f:
    data = json.load(f)
    all_data.append(data)
```

```
#Lets see what a codeforces problem data sample looks like
all_data[1]
```


```
{'prob_desc_time_limit': '2 seconds',
 'prob_desc_sample_outputs': '["4427477", "4478"]',
 'src_uid': '8ce1ba0a98031c1bc28f53c11905391c',
 'prob_desc_notes': 'NoteIn the first sample the number changes in the following sequence: 
4727447\u2009→\u20094427447\u2009→\u20094427477\u2009→\u20094427447\u2009→\u20094427477.In the second sample: 
4478\u2009→\u20094778\u2009→\u20094478.',
 'prob_desc_description': "Petya loves lucky numbers. Everybody knows that lucky numbers are positive integers whose decimal 
representation contains only the lucky digits 4 and 7. For example, numbers 47, 744, 4 are lucky and 5, 17, 467 are not.Petya 
has a number consisting of n digits without leading zeroes. He represented it as an array of digits without leading zeroes. 
Let's call it d. The numeration starts with 1, starting from the most significant digit. Petya wants to perform the following 
operation k times: find the minimum x (1\u2009≤\u2009x\u2009&lt;\u2009n) such that dx\u2009=\u20094 and 
dx\u2009+\u20091\u2009=\u20097, if x is odd, then to assign dx\u2009=\u2009dx\u2009+\u20091\u2009=\u20094, otherwise to assign 
dx\u2009=\u2009dx\u2009+\u20091\u2009=\u20097. Note that if no x was found, then the operation counts as completed and the 
array doesn't change at all.You are given the initial number as an array of digits and the number k. Help Petya find the result 
of completing k operations.",
 'prob_desc_output_spec': 'In the single line print the result without spaces — the number after the k operations are 
fulfilled.',
 'prob_desc_input_spec': 'The first line contains two integers n and k 
(1\u2009≤\u2009n\u2009≤\u2009105,\u20090\u2009≤\u2009k\u2009≤\u2009109) — the number of digits in the number and the number of 
completed operations. The second line contains n digits without spaces representing the array of digits d, starting with d1. It 
is guaranteed that the first digit of the number does not equal zero.',
 'prob_desc_output_to': 'standard output',
 'prob_desc_input_from': 'standard input',
```

```
 'lang': 'Python 3',
 'lang_cluster': 'Python',
 'difficulty': 1500,
 'file_name': 'train_021.jsonl',
 'code_uid': 'f1e020a8afc8535f9b870a7df58949d8',
 'prob_desc_memory_limit': '256 megabytes',
 'prob_desc_sample_inputs': '["7 4\\n4727447", "4 2\\n4478"]',
 'exec_outcome': 'PASSED',
 'source_code': "# 447 or 477 start with odd\n\n\nn, k = map(int, input().split())\ns = input()\ns = list(s)\n\nfor i in range(n - 1):\n    if not k:\n        break\n    if s[i] != '4':\n        continue\n    tt = ''.join(s[i:i + 3])\n    if tt in ('447', '477') and i % 2 == 0:\n        if k % 2 == 1 and tt == '447':\n            s[i + 1] = '7'\n        if k % 2 == 1 and tt == '477':\n            s[i + 1] = '4'\n        break\n    if s[i] == '4' and s[i + 1] == '7':\n        if i % 2 == 0:\n            s[i + 1] = '4'\n        else:\n            s[i] = '7'\n        k -= 1\n\nprint(''.join(s))\n",
 'prob_desc_created_at': '1319727600',
 'tags': ['strings'],
 'hidden_unit_tests': ''}
```

```
df_combined = pd.DataFrame(all_data)
display(df_combined.head())
```

	prob_desc_time_limit	prob_desc_sample_outputs	src_uid	prob_desc_notes	prob_desc_description	prol
0	2 seconds	["36", "1728"]	9a5bd9f937da55c3d26d5ecde6e50280	NoteIn the first sample n = 2·3 = 6. The divis...	Ayrat has number n, represented as it's prime ...	P
1	2 seconds	["4427477", "4478"]	8ce1ba0a98031c1bc28f53c11905391c	NoteIn the first sample the number changes in ...	Petya loves lucky numbers. Everybody knows tha...	In t
2	2 seconds	["1\n0\n9\n7\n6"]	867b01e7141ef077964a8a0d4c6b762b	NoteIn the first test case, we can perform one...	You are given a square grid with $$$n$$$ rows ...	For
3	1 second	["0", "1", "2"]	a32db37cb2ebe8945a4c2f32fa2d7fc8	None	Polycarp loves geometric progressions — he col...	se
4	1 second	["2 5", "1 8", "6 9"]	1d4aaf15e5c6fcde50515880aae74720	None	In this problem we consider a special type of ...	sho

5 rows × 21 columns

```
df_combined.shape
```

```
(4982, 21)
```

```
df_combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4982 entries, 0 to 4981
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   prob_desc_time_limit      4982 non-null   object
 1   prob_desc_sample_outputs  4982 non-null   object
 2   src_uid                   4982 non-null   object
 3   prob_desc_notes           3632 non-null   object
 4   prob_desc_description     4982 non-null   object
 5   prob_desc_output_spec     4897 non-null   object
 6   prob_desc_input_spec      4949 non-null   object
 7   prob_desc_output_to       4981 non-null   object
 8   prob_desc_input_from      4981 non-null   object
 9   lang                      4982 non-null   object
 10  lang_cluster              4982 non-null   object
 11  difficulty                4943 non-null   float64
 12  file_name                 4982 non-null   object
 13  code_uid                  4982 non-null   object
 14  prob_desc_memory_limit    4982 non-null   object
 15  prob_desc_sample_inputs   4982 non-null   object
 16  exec_outcome              4982 non-null   object
 17  source_code               4982 non-null   object
 18  prob_desc_created_at      4982 non-null   object
 19  tags                      4982 non-null   object
 20  hidden_unit_tests         4982 non-null   object
dtypes: float64(1), object(20)
memory usage: 817.5+ KB
```

```
dup_value_counts = df_combined.drop(columns=['tags']).apply(lambda s: s.value_counts().gt(1).sum())
dup_value_counts.sort_values(ascending=True)
```

	0
src_uid	0
prob_desc_description	0
code_uid	0
source_code	0
exec_outcome	1
hidden_unit_tests	1
lang_cluster	1
prob_desc_output_to	3
prob_desc_input_from	3
lang	5
prob_desc_memory_limit	9
prob_desc_time_limit	18
prob_desc_input_spec	21
difficulty	29
prob_desc_notes	35
prob_desc_output_spec	61
prob_desc_sample_inputs	66
file_name	111
prob_desc_sample_outputs	277
prob_desc_created_at	1109

dtype: int64

```
df_combined.isna().sum()
```

	0
prob_desc_time_limit	0
prob_desc_sample_outputs	0
src_uid	0
prob_desc_notes	1350
prob_desc_description	0
prob_desc_output_spec	85
prob_desc_input_spec	33
prob_desc_output_to	1
prob_desc_input_from	1
lang	0
lang_cluster	0
difficulty	39
file_name	0
code_uid	0
prob_desc_memory_limit	0
prob_desc_sample_inputs	0
exec_outcome	0
source_code	0
prob_desc_created_at	0
tags	0
hidden_unit_tests	0

dtype: int64

Most importantly we don't have duplications in **src_uid** and **prob_desc_description** so we can assume that the problems are unique

```
df_combined.difficulty.describe()
```

	difficulty
count	4943.000000
mean	1668.336031
std	568.273766
min	-1.000000
25%	1200.000000
50%	1700.000000
75%	2100.000000
max	3500.000000

dtype: float64

```
#lets take a look into the DESC columns to see which ones we will keep
display(df_combined[['prob_desc_notes','prob_desc_description','prob_desc_output_spec','prob_desc_input_spec']].iloc[1].to_dict
```


```
{'prob_desc_notes': 'NoteIn the first sample the number changes in the following sequence:
4727447\u2009→\u20094427447\u2009→\u20094427477\u2009→\u20094427447\u2009→\u20094427477.In the second sample:
4478\u2009→\u20094778\u2009→\u20094478.',
 'prob_desc_description': "Petya loves lucky numbers. Everybody knows that lucky numbers are positive integers whose decimal
representation contains only the lucky digits 4 and 7. For example, numbers 47, 744, 4 are lucky and 5, 17, 467 are not.Petya
has a number consisting of n digits without leading zeroes. He represented it as an array of digits without leading zeroes.
Let's call it d. The numeration starts with 1, starting from the most significant digit. Petya wants to perform the following
operation k times: find the minimum x (1\u2009≤\u2009x\u2009&lt;\u2009n) such that dx\u2009=\u20094 and
dx\u2009+\u20091\u2009=\u20097, if x is odd, then to assign dx\u2009=\u2009dx\u2009+\u20091\u2009=\u20094, otherwise to assign
dx\u2009=\u2009dx\u2009+\u20091\u2009=\u20097. Note that if no x was found, then the operation counts as completed and the
array doesn't change at all.You are given the initial number as an array of digits and the number k. Help Petya find the result
of completing k operations.",
 'prob_desc_output_spec': 'In the single line print the result without spaces — the number after the k operations are
```


All DESC columns are informative, should be kept (but we need to deal with the empty vals)

```
df_combined[['lang','lang_cluster']].drop_duplicates()
```

	lang	lang_cluster
0	Python 2	Python
1	Python 3	Python
2	PyPy 3-64	Python
4	PyPy 3	Python
18	PyPy 2	Python

All problems are in python, we can drop lang

FEATURE ENGINEERING AND DATASET FILTERING BASED ON GIVEN TAGS

```
data = df_combined.copy()
```

```
#lets keep only relevant cols
data = data[['src_uid','prob_desc_notes','prob_desc_description','prob_desc_output_spec','prob_desc_input_spec','difficulty','s
```

```
data.shape, data.dropna().shape
```

```
((4982, 8), (3527, 8))
```

```
#We concatenate problem features into one big paragraph
data['problem_description'] = data['prob_desc_description'].fillna("") + " " + data['prob_desc_notes'].fillna("")  + " " + data
```

```
data = data[['src_uid','problem_description','difficulty','source_code','tags']]
```

```
# lets drop rows with empty difficulty values (we only lose around 40 exp, less than 1% of the dataset)
data.shape, data.dropna().shape
```

```
((4982, 5), (4943, 5))
```

```
data = data.dropna()
```

```
tags = list(set().union(*data.tags.values.tolist()))
```

```
len(tags)
```

```
37
```

```
#How are tags distributed accross dataset ?
tags_occ = Counter()
for row in data.tags.values.tolist():
  tags_occ.update(row)
```

```
len(tags_occ)
```

```
37
```

```
focus_tags = ['math', 'graphs', 'strings', 'number theory', 'trees', 'geometry', 'games', 'probabilities']
```

```
tags_occ_sorted = sorted(tags_occ.items(), key=lambda x: x[1], reverse=True)
```

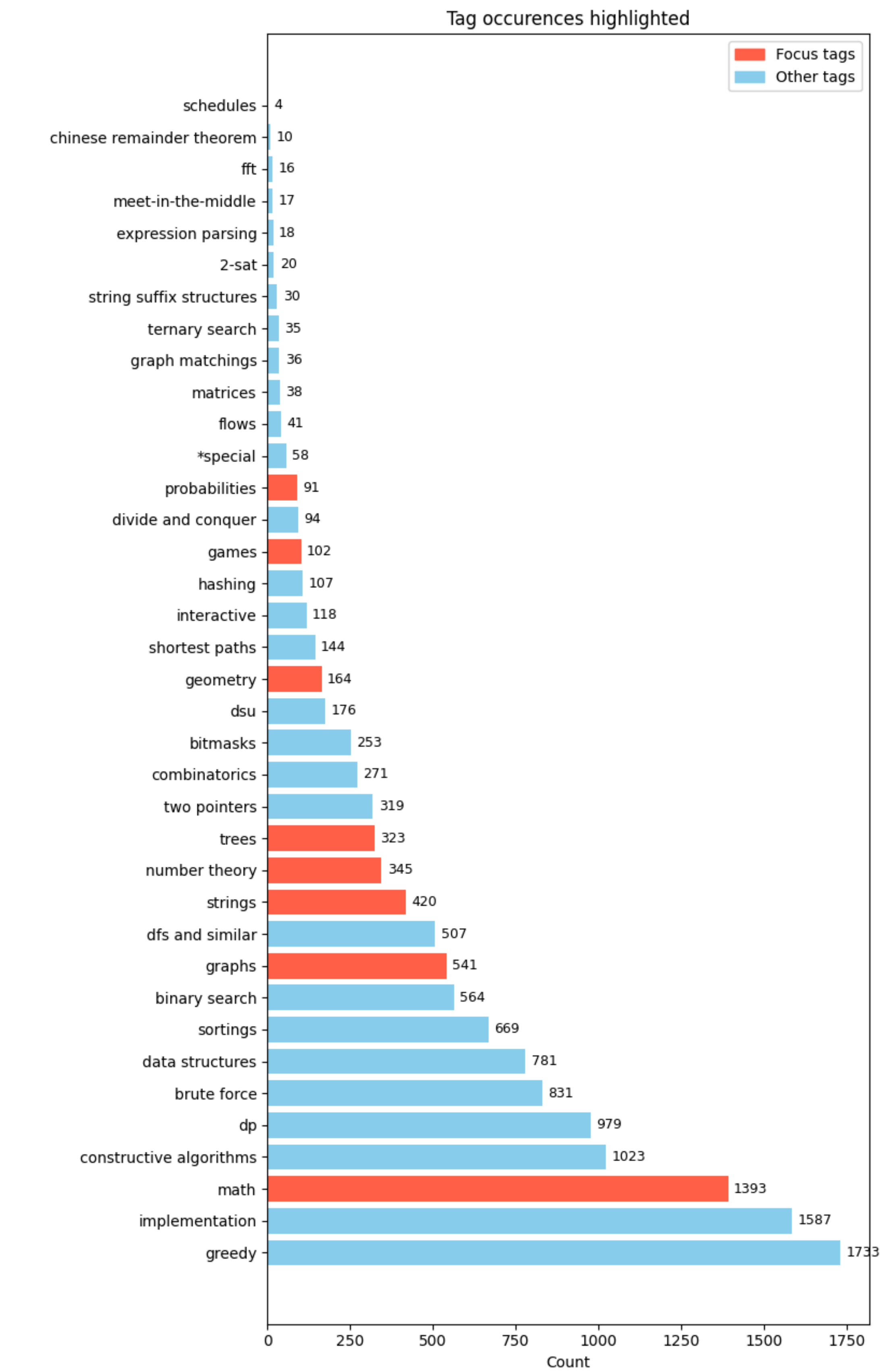
```
focus_color = 'tomato'
other_color = 'skyblue'
tags_sorted = [tag[0] for tag in tags_occ_sorted]
colors = [focus_color if tag in focus_tags else other_color for tag in tags_sorted]
counts = [tags_occ[tag] for tag in tags_sorted]

plt.figure(figsize=(8, max(4, len(tags) * 0.35)))
y = range(len(tags_sorted))
bars = plt.barh(y, counts, color=colors)
plt.yticks(y, tags_sorted)
plt.xlabel('Count')
plt.title('Tag occurences highlighted')


for bar, count in zip(bars, counts):
    width = bar.get_width()
    plt.text(width + max(1, 0.01 * max(counts)),
             bar.get_y() + bar.get_height() / 2,
             str(count),
             va='center', ha='left', fontsize=9)

plt.legend([mpatches.Patch(color=focus_color), mpatches.Patch(color=other_color)],
           ['Focus tags', 'Other tags'])

plt.tight_layout()
plt.show()
```



We can see that the 8 chosen classes are not the top 8 classes in the dataset, There's still a huge disparity between the largest class (math : 1409) and the smallest (probabilities : 92)

But let's ask ourselves this question :
can an example be of class probabilites without being of class maths ?

```
data[data.tags.apply(lambda x: 'probabilities' in x and 'math' not in x)][['problem_description','tags']].head(5)
```

	problem_description	tags
282	The Bad Luck Island is inhabited by three kind...	[dp, probabilities]
530	Dexterina and Womandark have been arch-rivals ...	[games, probabilities, matrices]
831	Masha lives in a country with $$$n$$$ cities n...	[dp, probabilities, graphs, brute force]
854	You are given a string $$$s$$$ consisting of $...	[brute force, dp, greedy, probabilities]
861	One night, having had a hard day at work, Pety...	[probabilities, sortings, binary search, dfs a...

```
data[data.tags.apply(lambda x: 'probabilities' in x and 'math' not in x)][['problem_description','tags']].shape
```

```
(46, 2)
```

```
tags_occ['probabilities']
```

```
91
```

Now we know that we have a multilabel classification problem with distinct labels. An exercice that is labeled as "probabilities" can be labeles also as "math" and can be labeled only as "probabilities". We have also an imbalanced dataset.

Lets filter the dataset based on the 8 tags

```
data.tags = data.tags.apply(lambda x: list(set(x).intersection(set(focus_tags))))
```

```
data.isna().sum()
```

	0
src_uid	0
problem_description	0
difficulty	0
source_code	0
tags	0

dtype: int64

```
#Since tags col is a list col, we will check for empty values seperately
data[data.tags.apply(lambda x: len(x) == 0)]
```

	src_uid	problem_description	difficulty	source_code	tags
2	867b01e7141ef077964a8a0d4c6b762b	You are given a square grid with $$$n$$$ rows ...	1200.0	import sys\n\ninput = lambda: sys.stdin.readli...	[]
3	a32db37cb2ebe8945a4c2f32fa2d7fc8	Polycarp loves geometric progressions — he col...	2200.0	def main():\n n = int(input())\n l = tup...	[]
4	1d4aaf15e5c6fcde50515880aae74720	In this problem we consider a special type of ...	800.0	garbage = int(input())\nz = list(map(int, inpu...	[]
5	91be5db48b44a44adff4c809ffbb8e3e	Caisa is going to have a party and he needs to...	1200.0	n,s=map(int,raw_input().strip().split())\n\nma...	[]
6	bc937cacda9ebff9ec0b7f00f0f97508	Sereja has an n × m rectangular table a, each ...	2200.0	#!/usr/bin/python\n\nimport sys\nfrom math imp...	[]
...	...	...	...	...	...
4970	e745f777e5676c2629f806e09f83a739	Vitaly enrolled in the course Advanced Useless...	2200.0	import os\r\nimport sys\r\nfrom io import Byte...	[]
4971	a04cfd22f90b2b87f7c5b48dfe3de873	Consider a hallway, which can be represented a...	2400.0	import sys\r\ninput = lambda: sys.stdin.readli...	[]

```
data[data.tags.apply(lambda x: any(each!=each for each in x))]
```

src_uid	problem_description	difficulty	source_code	tags

```
data.loc[data.tags.apply(lambda x: len(x) == 0),'tags'] = None
```

```
data = data.dropna()
```

```
data.shape, data.src_uid.nunique()
```

```
((2656, 5), 2656)
```

```
data
```

	src_uid	problem_description	difficulty	source_code	tags
0	9a5bd9f937da55c3d26d5ecde6e50280	Ayrat has number n, represented as it's prime ...	2000.0	from collections import Counter\nfrom operator...	[number theory, math]
1	8ce1ba0a98031c1bc28f53c11905391c	Petya loves lucky numbers. Everybody knows tha...	1500.0	# 447 or 477 start with odd\n\n\nn, k = map(in...	[strings]
7	16d4035b138137bbad247ccd5e560051	One day Polycarp published a funny picture in ...	1200.0	from collections import defaultdict\n\nn=int(i...	[graphs, trees]
8	d3b9ffa76436b957ca959cf9204f9873	You've got another problem dealing with arrays...	1700.0	n, k = map(int, input().split())\na = sorted(m...	[math]
10	6f0d3a7971ffc2571838ecd8bf14238d	You are given a grid with $$$n$$$ rows and $$$...	800.0	test = int(input())\r\nsteps = 0\r\nans = []\r...	[math]
...	...	...	...	...	...
4976	f26a979dc042ec9564cfecce29e5a1cf	Egor is a famous Russian singer, rapper, actor...	2500.0	import sys\ninput = sys.stdin.readline\nfrom c...	[graphs]
4978	816a82bee65cf79ba8e4d61babcd0301	You are given a tuple generator	2900.0	import sys\nimport	[number

Next steps: Generate code with `data` New interactive sheet

Modelling Approaches

```
X_data = data.drop(columns=['tags'])
y_data = data.tags
X_train, X_test, y_train, y_test = train_test_split(X_data, y_data, test_size=0.25, random_state=42)
###  Here what I usually do in in imbalanced classification problems
###  is a "stratified" train_test_split, here we have a MultiClass-Multilabel
###  classification problem, so the stratification proposed by sklearn can't handle the labels
###  What I do in this case is to use 'iterative_train_test_split' from 'skmultilearn',
###  some data transformation should be done first, for now I will not use iterative_train_test_split
###  because for the first modelling approach I'm going to use an LLM with one/few shot learning.
```

```
X_data
```

	src_uid	problem_description	difficulty	source_code
0	9a5bd9f937da55c3d26d5ecde6e50280	Ayrat has number n, represented as it's prime ...	2000.0	from collections import Counter\nfrom operator...
1	8ce1ba0a98031c1bc28f53c11905391c	Petya loves lucky numbers. Everybody knows tha...	1500.0	# 447 or 477 start with odd\n\n\nn, k = map(in...
7	16d4035b138137bbad247ccd5e560051	One day Polycarp published a funny picture in ...	1200.0	from collections import defaultdict\n\nn=int(i...
8	d3b9ffa76436b957ca959cf9204f9873	You've got another problem dealing with arrays...	1700.0	n, k = map(int, input().split())\na = sorted(m...
10	6f0d3a7971ffc2571838ecd8bf14238d	You are given a grid with $$$n$$$ rows and $$$...	800.0	test = int(input())\r\nsteps = 0\r\nans = []\r...
...	...	...	...	...
4976	f26a979dc042ec9564cfecce29e5a1cf	Egor is a famous Russian singer, rapper, actor...	2500.0	import sys\ninput = sys.stdin.readline\nfrom c...
4978	816a82bee65cf79ba8e4d61babcd0301	You are given a tuple generator $$$f^{(k)} = (...	2900.0	import sys\nimport time\nmod=1000000007\ndef s...

Next steps: Generate code with `X_data` New interactive sheet

1st Approach : LLM in one shot.

```
#lets test if our api is functional
client = AzureOpenAI()
```

```
response = client.chat.completions.create(
                model="gpt-4o-mini",
                messages=[
                    {"role": "system", "content": "You are a JSON-only response generator."},
                    {"role": "user", "content": "yoo"}
                ],
                response_format={"type": "json_object"},
            )
print(response.choices[0].message.content)
```

```
{
  "response": "Hello! How can I assist you today?"
}
```

The modelling (or the training) part here, is simply to iterate through prompts until finding the best prompt, for this we will use some examples of the training set, once we have the best prompt we will scale and test it on the test set.

```
## 1st iteration

SYSTEM_PROMPT = """
You are an AI assisstant that labels CODEFORCES.
"""

USER_PROMPT_1 = """
Based on a PROBLEM_DESCRIPTION of a Codeforces exercies and its respective SOURCE_CODE solution,
You will label the problem by suggesting relevant tags.
The suggested tags have to be drawn from this list : ['math', 'graphs', 'strings', 'number theory', 'trees', 'geometry', 'games
Don't create any other tags.

You need to understand the problem, the solution, the meaning of each tag and only output the best tag or tags that match the p
Output a json list of tags separated by commas.

PROBLEM_DESCRIPTION : {problem_description}
SOURCE_CODE : {source_code}

"""

## 2nd iteration

USER_PROMPT_2 = """
Based on a PROBLEM_DESCRIPTION of a Codeforces exercies and its respective SOURCE_CODE solution,
You will label the problem by suggesting relevant tags.
The suggested tags have to be drawn from this list : ['math', 'graphs', 'strings', 'number theory', 'trees', 'geometry', 'games
No other tags are allowed.


You need to understand the problem, the solution, the meaning of each tag and only output the best tag or tags that match the p
Output a json list of tags separated by commas.

Here are short, concise, precise descriptions for each Codeforces problem tag :
math — Problems that require arithmetic, algebra, combinatorics, or general mathematical reasoning and formulas (proofs, comput
graphs — Problems about vertices and edges: traversals, shortest/longest paths, connectivity, components, cycles, flows, matchi
strings — Problems that focus on sequences of characters: pattern matching, hashing, substring/suffix structures, automata, par
number theory — Problems about integers and their properties: primes, gcd/lcm, modular arithmetic, congruences, divisibility, t
trees — Problems on acyclic connected graphs (rooted/unrooted): tree traversals, LCA, centroid/decomposition, rerooting, subtre
geometry — Problems involving points, lines, polygons, distances, angles, vectors, intersections, areas, and computational geom
games — Problems about combinatorial games and strategies: impartial/partisan games, winning positions, Sprague-Grundy theorem,
probabilities — Problems using chance and expectation: probability calculations, expected value, linearity of expectation, dist

Make sure the JSON is VALID.

Here are a few examples :
PROBLEM_DESCRIPTION : {problem_description_1}
SOURCE_CODE : {source_code_1}
TAGS : {tags_1}

PROBLEM_DESCRIPTION : {problem_description_2}
SOURCE_CODE : {source_code_2}
TAGS : {tags_2}





Label this problem :
PROBLEM_DESCRIPTION : {problem_description}
SOURCE_CODE : {source_code}

"""
```

First iteration : llm prompt that describes the task step by step and include rules to be respected by the llm.

Second iteration : prompt that describes the task step by step, include rules to be respected by the llm but also provides some examples of problems from the training set with their respective labels.

```
def tag_with_llm(client=client, user_prompt=""):
  sleep(1)
  response = client.chat.completions.create(
              model="gpt-4o-mini",
              messages=[
                  {"role": "system", "content": SYSTEM_PROMPT},
                  {"role": "user", "content": user_prompt}
              ],
              response_format={"type": "json_object"},
          )
  return json.loads(response.choices[0].message.content).get('tags')
```

```
# The training phase here is to test the prompt with a few examples
# for speed purposes and improve the prompt each time until finding
# the best prompt (lets try with 1/15 of the train set, less than 200 examples)
X_prompt = X_train[:len(X_train)//15]
y_prompt = y_train[:len(y_train)//15]
```

```
X_prompt.shape , y_prompt.shape
```

```
((132, 4), (132,))
```

First prompt

```
#one example testing
tag_with_llm(user_prompt=USER_PROMPT_1.format(problem_description=X_prompt.iloc[0].problem_description, source_code=X_prompt.il
```

```
['math']
```

```
y_prompt.iloc[0]
```

```
['math']
```

```
y_prompt_predicted = []
for i in range(X_prompt.shape[0]):
  y_prompt_predicted.append(tag_with_llm(user_prompt=USER_PROMPT_1.format(problem_description=X_prompt.iloc[i].problem_descript
```

```
sum([e==None for e in y_prompt_predicted])
```

```
6
```

```
# Re run the model on examples that where not processed correctly by the llm
for i in range(len(y_prompt_predicted)):
  if y_prompt_predicted[i] == None:
    y_prompt_predicted[i] = tag_with_llm(user_prompt=USER_PROMPT_1.format(problem_description=X_prompt.iloc[i].problem_descript
```

```
sum([e==None for e in y_prompt_predicted])
```

```
0
```

```
### We will use 'weighted f1 score' for evaluation, in order not to penalize the model for the smaller classes
mlb = MultiLabelBinarizer()
y_prompt_encoded = mlb.fit_transform(y_prompt)
y_prompt_predicted_encoded = mlb.fit_transform(y_prompt_predicted)

weighted = f1_score(y_prompt_encoded, y_prompt_predicted_encoded, average='weighted')
```

```
print('First prompt f1 score :',weighted)
```

```
First prompt f1 score : 0.6890580209002773
```

Second prompt

```
#one example testing
tag_with_llm(user_prompt=USER_PROMPT_2.format(
  problem_description_1=X_prompt.iloc[-1].problem_description,
  source_code_1=X_prompt.iloc[-1].source_code,
```

```
  tags_1=y_prompt.iloc[-1],

  problem_description_2=X_prompt.iloc[-2].problem_description,
  source_code_2=X_prompt.iloc[-2].source_code,
  tags_2=y_prompt.iloc[-2],

  problem_description=X_prompt.iloc[0].problem_description,
  source_code=X_prompt.iloc[0].source_code))
```

```
['math']
```

```
y_prompt_predicted = []
for i in range(X_prompt.shape[0]):
  y_prompt_predicted.append(tag_with_llm(user_prompt=USER_PROMPT_2.format(
        problem_description_1=X_prompt.iloc[-1].problem_description,
  source_code_1=X_prompt.iloc[-1].source_code,
  tags_1=y_prompt.iloc[-1],

  problem_description_2=X_prompt.iloc[-2].problem_description,
  source_code_2=X_prompt.iloc[-2].source_code,
  tags_2=y_prompt.iloc[-2],


      problem_description=X_prompt.iloc[i].problem_description, source_code=X_prompt.iloc[i].source_code)))

while sum([e==None for e in y_prompt_predicted])>0:
  for i in range(len(y_prompt_predicted)):
    if not y_prompt_predicted[i]:
      y_prompt_predicted[i] = tag_with_llm(user_prompt=USER_PROMPT_2.format(
          problem_description_1=X_prompt.iloc[-1].problem_description,
    source_code_1=X_prompt.iloc[-1].source_code,
    tags_1=y_prompt.iloc[-1],

    problem_description_2=X_prompt.iloc[-2].problem_description,
    source_code_2=X_prompt.iloc[-2].source_code,
    tags_2=y_prompt.iloc[-2],


        problem_description=X_prompt.iloc[i].problem_description, source_code=X_prompt.iloc[i].source_code))
```

```
mlb = MultiLabelBinarizer()
y_prompt_encoded = mlb.fit_transform(y_prompt)
y_prompt_predicted_encoded = mlb.fit_transform(y_prompt_predicted)

weighted = f1_score(y_prompt_encoded, y_prompt_predicted_encoded, average='weighted')
```

```
print('Second prompt f1 score :',weighted)
```

```
Second prompt f1 score : 0.6955657774072096
```

```
print(classification_report(y_prompt_encoded, y_prompt_predicted_encoded))
```

```
              precision    recall  f1-score   support

           0       0.30      0.75      0.43         4
           1       0.71      0.83      0.77        12
           2       0.84      0.59      0.70        27
           3       0.78      0.58      0.67        65
           4       0.60      0.60      0.60        15
           5       0.75      0.60      0.67         5
           6       0.81      0.81      0.81        26
           7       0.91      0.62      0.74        16

   micro avg       0.74      0.65      0.69       170
   macro avg       0.71      0.67      0.67       170
weighted avg       0.77      0.65      0.70       170
 samples avg       0.76      0.69      0.70       170
```

We see a small improvement in the f1 score, We choose the second prompt as our model, and we will run it through the test set to evaluate its performance

```
### RUN ON TEST SET

y_prompt_predicted = []
for i in range(X_test.shape[0]):
  y_prompt_predicted.append(tag_with_llm(user_prompt=USER_PROMPT_2.format(
        problem_description_1=X_prompt.iloc[-1].problem_description,
  source_code_1=X_prompt.iloc[-1].source_code,
```

```
  tags_1=y_prompt.iloc[-1],

  problem_description_2=X_prompt.iloc[-2].problem_description,
  source_code_2=X_prompt.iloc[-2].source_code,
  tags_2=y_prompt.iloc[-2],


      problem_description=X_test.iloc[i].problem_description, source_code=X_test.iloc[i].source_code)))

while sum([e==None for e in y_prompt_predicted])>0:
  for i in range(len(y_prompt_predicted)):
    if y_prompt_predicted[i] == None:
      y_prompt_predicted[i] = tag_with_llm(user_prompt=USER_PROMPT_2.format(
          problem_description_1=X_prompt.iloc[-1].problem_description,
    source_code_1=X_prompt.iloc[-1].source_code,
    tags_1=y_prompt.iloc[-1],

    problem_description_2=X_prompt.iloc[-2].problem_description,
    source_code_2=X_prompt.iloc[-2].source_code,
    tags_2=y_prompt.iloc[-2],


    problem_description=X_test.iloc[i].problem_description, source_code=X_test.iloc[i].source_code)
      )
```

```
mlb = MultiLabelBinarizer()
y_prompt_encoded = mlb.fit_transform(y_test)
y_prompt_predicted_encoded = mlb.fit_transform(y_prompt_predicted)

weighted = f1_score(y_prompt_encoded, y_prompt_predicted_encoded, average='weighted')
```

```
print('F1 Score on test set: ',weighted)
```

```
F1 Score on test set:  0.711880222655802
```

```
print(classification_report(y_prompt_encoded, y_prompt_predicted_encoded))
```

```
              precision    recall  f1-score   support

           0       0.31      1.00      0.47        19
           1       0.63      0.88      0.73        33
           2       0.88      0.62      0.73       156
           3       0.82      0.56      0.67       323
           4       0.62      0.74      0.67        86
           5       0.80      0.70      0.74        23
           6       0.75      0.86      0.80       107
           7       0.88      0.74      0.80        85

   micro avg       0.74      0.68      0.71       832
   macro avg       0.71      0.76      0.70       832
weighted avg       0.79      0.68      0.71       832
 samples avg       0.77      0.72      0.72       832
```

2nd Approach : BERT Classifier

```
labels_to_ids = {j:i for i,j in enumerate(focus_tags)}
ids_to_labels = {i:j for i,j in enumerate(focus_tags)}
```

```
labels_to_ids
```

```
{'math': 0,
 'graphs': 1,
 'strings': 2,
 'number theory': 3,
 'trees': 4,
 'geometry': 5,
 'games': 6,
 'probabilities': 7}
```

```
MAX_LEN = 128
TRAIN_BATCH_SIZE = 16
VALID_BATCH_SIZE = 2
EPOCHS = 1
LEARNING_RATE = 1e-05
tokenizer = BertTokenizerFast.from_pretrained('bert-base-uncased')
```

```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
```

tokenizer_config.json: 100% 48.0/48.0 [00:00<00:00, 1.08kB/s]

vocab.txt: 100% 232k/232k [00:00<00:00, 3.68MB/s]

tokenizer.json: 100% 466k/466k [00:00<00:00, 17.0MB/s]

config.json: 100% 570/570 [00:00<00:00, 21.4kB/s]

```
# Data retriever class, we need to tokenize text and binerize labels
# before feeding the Bert classifier, this class will help us handle
# this part on the fly

class dataset(Dataset):
    def __init__(self, dataframe, tokenizer, max_len):
        self.len = len(dataframe)
        self.data = dataframe
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __getitem__(self, index):

        sentence = self.data.problem_description[index].strip()
        labels = self.data.tags[index]

        encoding = self.tokenizer(sentence,
                                  return_offsets_mapping=True,
                                  padding='max_length',
                                  truncation=True,
                                  max_length=self.max_len)

        labels_holder = np.array([0 for _ in range(len(labels_to_ids))], dtype=np.float32)
        for label in labels:
          labels_holder[labels_to_ids[label]] = 1
        labels = labels_holder[:]

        item = {key: torch.as_tensor(val) for key, val in encoding.items()}
        item['labels'] = torch.as_tensor(labels)
        return item

    def __len__(self):
        return self.len
```

```
# We create an architecture based on a bert model for the embedding phase
# We add a dense layer for classification (we could have added a droupout layer in between)

class ModelClassifier(pl.LightningModule):

  def __init__(self, n_classes: int, model_name: str):
    super().__init__()
    self.bert = BertModel.from_pretrained(model_name, return_dict=True)
    self.classifier = nn.Linear(self.bert.config.hidden_size, n_classes)
    self.criterion = nn.BCELoss()

  def forward(self, input_ids, attention_mask, labels=None):
    output = self.bert(input_ids, attention_mask=attention_mask)
    output = self.classifier(output.pooler_output)
    output = torch.sigmoid(output)
    loss = 0
    if labels is not None:
        loss = self.criterion(output, labels)
    return loss, output

  def training_step(self, batch, batch_idx):
    input_ids = batch["input_ids"]
    attention_mask = batch["attention_mask"]
    labels = batch["labels"]
    loss, outputs = self(input_ids, attention_mask, labels)
    self.log("train_loss", loss, prog_bar=True, logger=True)
    return {"loss": loss, "predictions": outputs, "labels": labels}

  def validation_step(self, batch, batch_idx):
    input_ids = batch["input_ids"]
    attention_mask = batch["attention_mask"]
    labels = batch["labels"]
    loss, outputs = self(input_ids, attention_mask, labels)
```

```
    self.log("val_loss", loss, prog_bar=True, logger=True)
    return loss


  def configure_optimizers(self):
    optimizer = torch.optim.AdamW(params=self.parameters(), lr=LEARNING_RATE)
    scheduler = get_linear_schedule_with_warmup(
      optimizer,
      num_warmup_steps=20,
      num_training_steps=100
    )
    return dict(
      optimizer=optimizer,
      lr_scheduler=dict(
        scheduler=scheduler,
        interval='step'
      )
    )
```

```
train_dataset = data[data.index.isin(X_train.index)]
test_dataset = data.drop(train_dataset.index).reset_index(drop=True)
train_dataset = train_dataset.reset_index(drop=True)

print("FULL Dataset: {}".format(data.shape))
print("TRAIN Dataset: {}".format(train_dataset.shape))
print("TEST Dataset: {}".format(test_dataset.shape))

training_set = dataset(train_dataset, tokenizer, MAX_LEN)
testing_set = dataset(test_dataset, tokenizer, MAX_LEN)
```

```
FULL Dataset: (2656, 5)
TRAIN Dataset: (1992, 5)
TEST Dataset: (664, 5)
```

```
train_params = {'batch_size': TRAIN_BATCH_SIZE,
                'shuffle': True,
                'num_workers': 0
                }

test_params = {'batch_size': VALID_BATCH_SIZE,
                'shuffle': True,
                'num_workers': 0
                }

training_loader = DataLoader(training_set, **train_params)
testing_loader = DataLoader(testing_set, **test_params)
```

```
model = ModelClassifier(len(labels_to_ids),'bert-base-uncased')
#trainer = pl.Trainer(accelerator="cpu", devices=1, max_epochs=3)
#trainer.fit(model, training_loader)
```

model.safetensors: 100% 440M/440M [00:21<00:00, 22.2MB/s]

```
model = ModelClassifier(len(labels_to_ids),'bert-base-uncased')
state_dict = torch.load("model_v1",  weights_only=True, map_location=device)
model.load_state_dict(state_dict)
```

```
<All keys matched successfully>
```

```
THRESHOLD = 0.5
y_pred = []
y_true = []

model.eval()
with torch.no_grad():
  for idx, batch in enumerate(testing_loader):

    ids = batch['input_ids']
    mask = batch['attention_mask']
    labels = batch['labels']

    loss, predictions = model(input_ids=ids, attention_mask=mask, labels=labels)
    predictions = (predictions > THRESHOLD).long()

    y_pred.append(predictions)
    y_true.append(labels)
```

```
metric = MulticlassF1Score(num_classes=len(labels_to_ids), average="weighted")
f1_tensor = metric(predictions, labels)

f1_value = f1_tensor.item() if isinstance(f1_tensor, torch.Tensor) else float(f1_tensor)
print("Weighted multiclass F1:", f1_value)
```

```
Weighted multiclass F1: 0.9281609058380127
```

The bert based model clearly outperforms the one shot LLM approach. This is not surprising since the BERT is trained but the LLM was not.

We will use the bert model for the cli module.

```
!python problem_tagger.py --test true
```

```
2025-10-28 15:34:06.603398: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to register cuFFT factory: Att
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
E0000 00:00:1761665646.628375   41830 cuda_dnn.cc:8579] Unable to register cuDNN factory: Attempting to register factory for plu
E0000 00:00:1761665646.635450   41830 cuda_blas.cc:1407] Unable to register cuBLAS factory: Attempting to register factory for p
W0000 00:00:1761665646.653355   41830 computation_placer.cc:177] computation placer already registered. Please check linkage and
W0000 00:00:1761665646.653402   41830 computation_placer.cc:177] computation placer already registered. Please check linkage and
W0000 00:00:1761665646.653407   41830 computation_placer.cc:177] computation placer already registered. Please check linkage and
W0000 00:00:1761665646.653411   41830 computation_placer.cc:177] computation placer already registered. Please check linkage and
{'TRUE LABELS': ['math'], 'PREDICTED LABELS': ['math']}
```

Improvements

This work was done in 4h approximatively. If more time is to be invested in the project we can explore many approaches/techniques that could improve performance.

DATASET improvements :

- We have an imbalanced dataset, that's the first thing to be approached. Historically techniques that uses synthetic data augmentation (like SMOTE) are the first thing to be tested. But here we are lucky enough to have a real world dataset publically available. So what we can do is simply augment the very small classes with real world codeforces problems. ATTENTION : This does not mean creating a dataset with all classes equally presented, because that's not what the real world is (real world : codeforces problems dataset). So we will try to have a balance between minimum necessary number of samples for the model to learn and real