IFC-Bank of Italy Workshop on "Data science in central banking: enhancing the access to and sharing of data"

17-19 October 2023

Coding time series with machine learning[1]

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[1] This contribution was prepared for the workshop. The views expressed are those of the authors and do not necessarily reflect the views of the Bank of Italy, the BIS, the IFC or the other central banks and institutions represented at the event.

STATISTICS

Coding Time Series With Machine Learning

3RD IRVING FISHER COMMITTEE WORKSHOP ON "DATA SCIENCE IN CENTRAL BANKING"

BANCA D'ITALIA - OCTOBER 18, 2023

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Context

Increasingly available text data

Surveys

Data tables

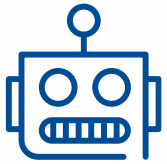
Websites

Challenges and opportunities

Nonstandard terminology

Outdated processes

New technologies

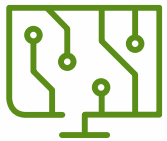


Objectives

Understand the data

Explore new approaches

Design solutions



What is “coding time series”?

- IMF member countries publish economic time series data in their National Summary Data Pages (NDSPs)
- IMF staff map these data to the internal Catalogue of Time Series (CTS) to ingest in IMF database.
- This is referred to as “coding time series.”

DATASTRUCTURE	IMF:ECOFIN_DSD(1.0)	Datastructure
DATASTRUCTURE_NAME	ECOFIN Data Structure Definition	Datastructure Name
DATA_DOMAIN	CGO	Dataset
REF_AREA	KW	Country
COUNTERPART_AREA	_Z	Counterpart area
UNIT_MULT	6	Scale = Million
FREQ	A	Frequency = Annual
COMMENT	Source: https://www.cbk.gov.kw/en/stati	Source / Observation status

Descriptor_Alt	Descriptor	INDICATOR	2009	2010
	General public services and defence			
	Public order and safety			
	Education affairs and services			
	Health affairs and services			
	Social security and welfare affairs and s			
	Housing and community affairs and serv			
	Recreational, cultural and religious affa			
	Fuel and energy affairs and services			
	Agricultural affairs and services			
	Manufacturing affairs and services			
	Transportation and communication affa			
	Other economic affairs and services			
	Expenditures, not classified by function			

Challenges

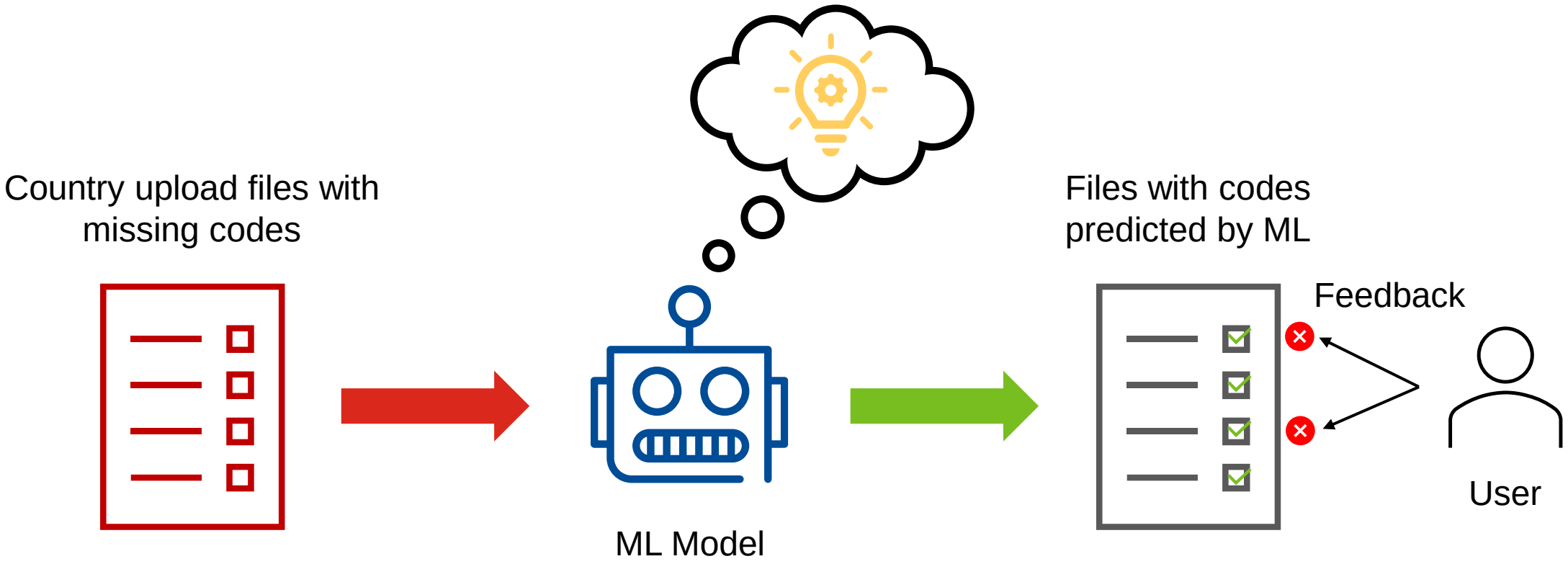
Time consuming and manual.

Finding similarities is not simple
when new wording is used for time series descriptors.

Not always straightforward.
E.g., “Health, affairs and services”:
218 indicators with the word “health”;
32 with the word “service.”

Subject to Human Error

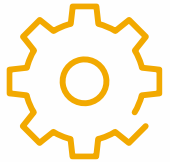
Hypothesis


Country upload files with missing codes
ML Model
Files with codes predicted by ML
Feedback
User

Data processing

~142k coded indicators from 53 countries across 4 macroeconomic sectors

Build a master dataset based on already coded data files to train/test



Light data processing and cleaning approach to allow reproducibility and scalability

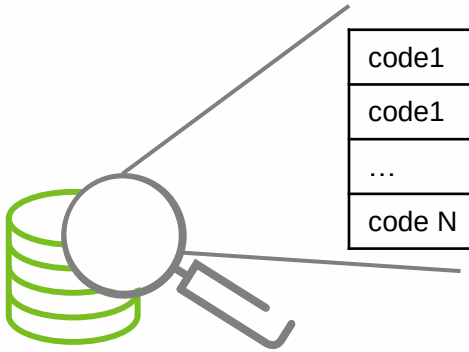
A few data files were in French, Spanish and Portuguese

- **Remove country-specific codes**.
- **Construct descriptors hierarchy.**
- **Keep only alphanumeric characters and remove stop words** (“a”, “the” etc.)
- **Keep available metadata fields** such as data domain, frequency, etc.
- **Train and Test data**: 90/10 split for training and testing/validation

Methodology

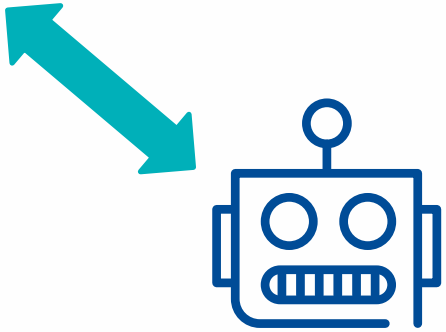
- Our data have specific terminology, a **supervised ML approach** is used.
- Start with proof of concept (PoC) to test the **feasibility and adequacy** of several ML models and feature extraction techniques (TF-IDF, word embeddings, Skip-Gram, logistic regression, etc.)
- Use an open-source text classification library, **fasttext**
- Text classification with Skip-Gram model and 3 n-gram
- Vectors dimension: 100, Epochs: 20

High-level underlying logic

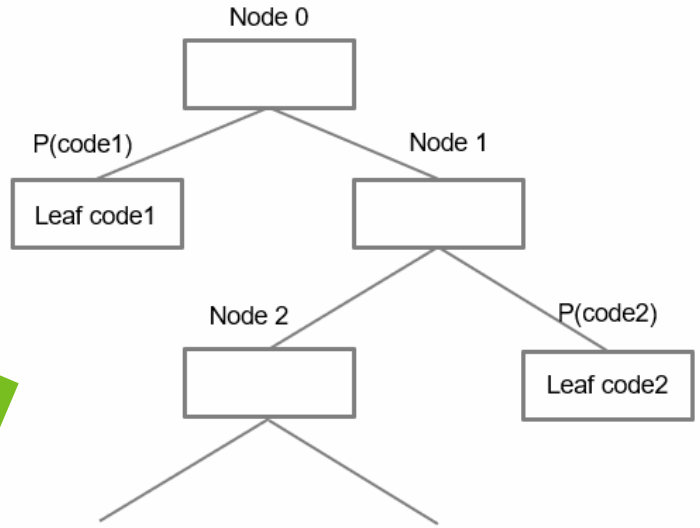


code1	descriptor1
code1	descriptor2
…	…
code N	descriptor M

Constructed hierarchical descriptors with their respective codes



Model learns from training data and creates a decision tree calculating probabilities of codes based on descriptors



Overall process

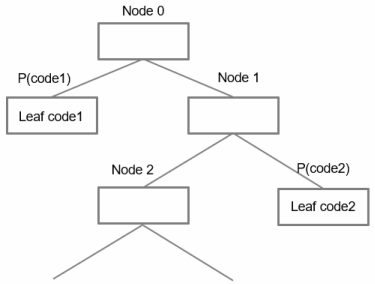
1 Data Processing

Health	Affairs	and	Services

3X

DATA_DOMAIN_CGO	METHODOLOGY_2014_Manual	Health	Affairs	Services

Model 2



3 Rank codes based on their probability

Code N	Probability N
code2	Probability 2
…	…
code 1	Probability 1

4 Returning top 5 codes with highest probability

GEL_G14_CG	Government and Public Sector Finance, Expenditure by COFOG, Central Government, Health [2014 Manual]
…	…
…	…
…	…
…	…

Results

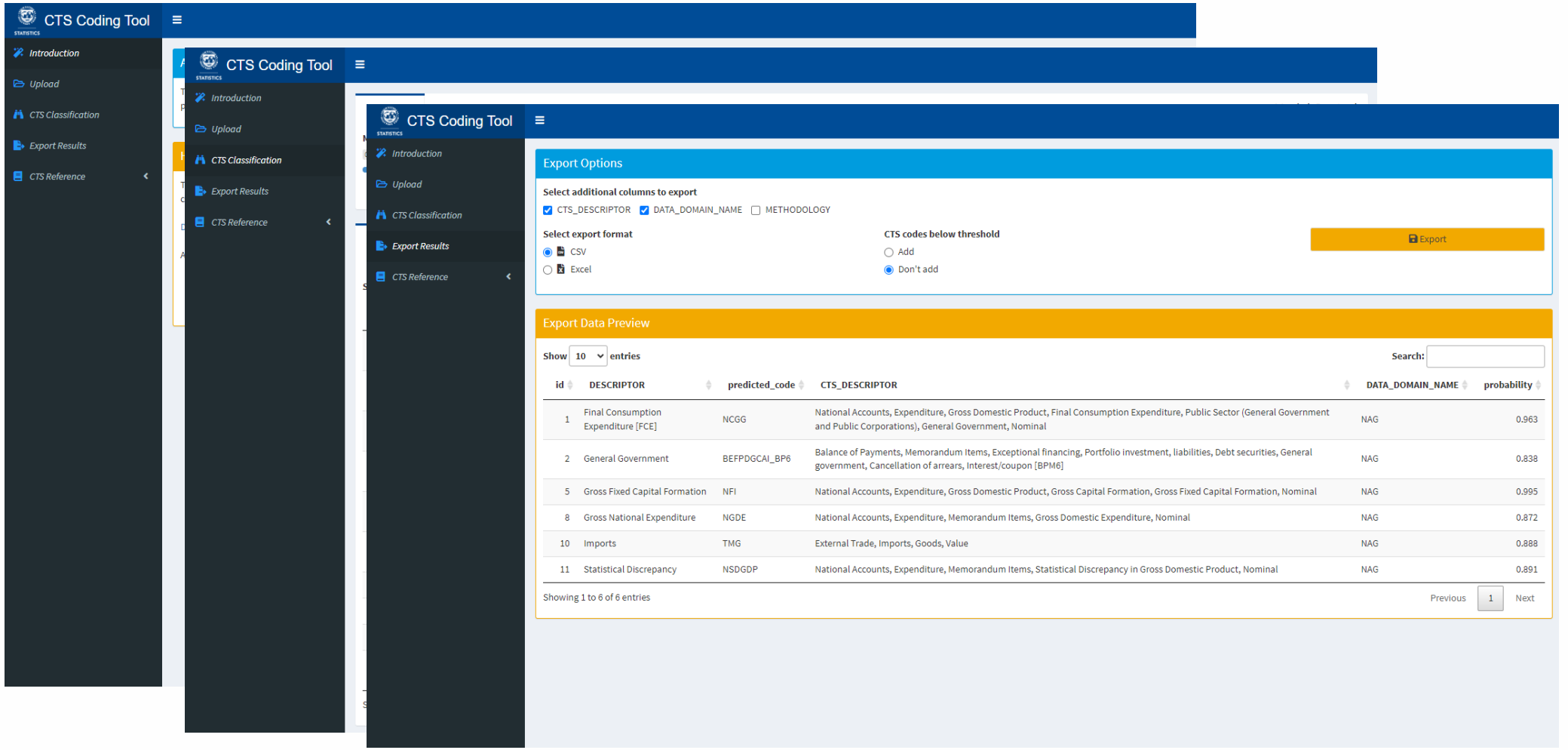
- Precision ranging by data domain, majority of domains precision around 90%
- Recall ranging by data domain, majority of domains recall around 90%
- Cases of low precision and recall due to:
  - Low number of time series for certain domain in training dataset
  - Original data file's structure not allowing to construct full hierarchy indicators
- For a data file with ~500 time series, the model takes about 2 seconds to return predicted codes

Domain	N	precision	recall
balance payments bpm	5,014.0	0.965	0.966
m&b central bank	1,309.0	0.915	0.914
m&b depository corporations	1,293.0	0.92	0.922
international investment position bpm	1,205.0	0.975	0.973
direction trade statistics	771.0	0.966	NA
financial soundness indicators sectoral financial statements	544.0	0.965	0.963
financial soundness indicators institution deposit takers ofcs	533.0	0.32	0.319
national accounts gross domestic product	398.0	0.885	0.872
financial soundness indicators data report form	348.0	0.965	0.963
m&b financial corporations	344.0	0.925	0.924
balance payments	337.0	0.99	0.991
financial access survey	267.0	0.86	0.861
international investment position	247.0	0.98	0.980
merchandise trade	246.0	0.69	0.679
consumer price index	224.0	0.915	0.915

Achievements

- Use open-source tools to build a solution
- Built a specific vocabulary and train the model
- Light data processing allowing reproducibility and scalability of the tool
- Achieved for most domains a high-level Precision and Recall
- Create an **R package** with the documented code available for sharing upon request
- Build an **R-Shiny app** for end users based on received feedback

Shiny App


CTS Coding Tool
Introduction
Upload
CTS Classification
Export Results
CTS Reference
Export Options
Select additional columns to export
CTS_DESCRIPTOR
DATA_DOMAIN_NAME
METHODOLOGY
Select export format
CSV
Excel
CTS codes below threshold
Add
Don't add
Export
Export Data Preview
Show 10 entries
Search:
id
DESCRIPTOR
predicted_code
CTS_DESCRIPTOR
DATA_DOMAIN_NAME
probability
1 Final Consumption Expenditure [FCE] NCGG National Accounts, Expenditure, Gross Domestic Product, Final Consumption Expenditure, Public Sector (General Government and Public Corporations), General Government, Nominal NAG 0.963
2 General Government BEFPDGCAI_BP6 Balance of Payments, Memorandum Items, Exceptional financing, Portfolio investment, liabilities, Debt securities, General government, Cancellation of arrears, Interest/coupon [BPM6] NAG 0.838
5 Gross Fixed Capital Formation NFI National Accounts, Expenditure, Gross Domestic Product, Gross Capital Formation, Gross Fixed Capital Formation, Nominal NAG 0.995
8 Gross National Expenditure NGDE National Accounts, Expenditure, Memorandum Items, Gross Domestic Expenditure, Nominal NAG 0.872
10 Imports TMG External Trade, Imports, Goods, Value NAG 0.888
11 Statistical Discrepancy NSDGDP National Accounts, Expenditure, Memorandum Items, Statistical Discrepancy in Gross Domestic Product, Nominal NAG 0.891
Showing 1 to 6 of 6 entries
Previous
1
Next

Next steps

- Incorporate user feedback into the end-to-end pipeline
- Officially roll out the tool into production and implement monitoring mechanisms
- Test the model and solution for out-of-scope time series
- Make the R package sharable upon request

Lessons learned

- **NLP/ML is a fast-changing field:** methods such as TF-IDF or Random Forest, although still used as baseline, are increasingly challenged by more recent methods such as word embedding, transformers, and other deep learning models.

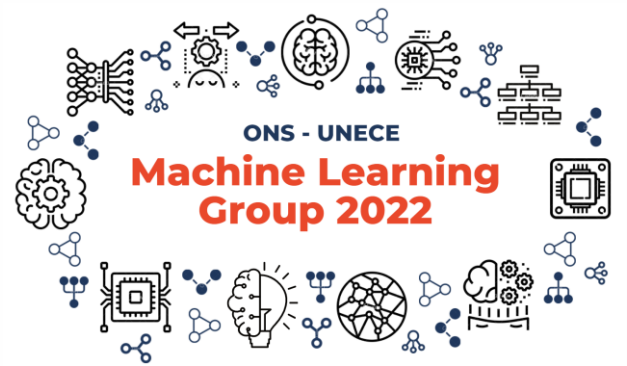
- **Generative AI is changing the landscape of NLP:** considering if it is worth developing in-house solution or opt for off-the-shelf solutions such as ChatGPT.

- **Importance of the maintenance strategy:** Preparing in advance the monitoring and re-training plan is crucial for the sustainability of the model and can increase the acceptance and facilitate the transition from PoC to production.

- **Machine Learning solutions take time to implement to reach robust and high-quality results**.

- **Collaboration and knowledge sharing can have a big impact :** peer organizations can face similar challenges and we believe a solution like ours could be adapted and implemented by others.

Useful References



- Text and classification
  - Model retraining

Measure (2017): use artificial intelligence (AI) to map worker injury to internal coding

Evans et al (2021), “Need for Speed: Using fasttext (Machine Learning) to Code the Labor Force Survey”

Thank You

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