



# **Lost in Labels**: an Ongoing Quest to Optimize Text-to-Text Label Selection for Classification

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**Open Issue**: Few works have investigated the importance of the string representation of classes in T2T classification tasks.

**Our Contribution**: We present an investigation on the <u>importance of</u> <u>string representations for model performances</u>, and on the relationship between the classes and the strings that represent them.

## Introduction



# **Dataset dimension**: 13.553 posts formed the training dataset and 5055 the test dataset.

**Task:** We focused on the Topic Classification Task, which is a multilabel classification tasks with **eleven classes**.

Categories	# Data	# Training	# Test
Anime	3,972	2,894	1,078
Auto-Moto	3,783	2,798	985
Bikes	520	365	155
Celebrities	1,115	754	361
Entertainment	469	354	115
<b>Medicine-Aesthetics</b>	447	310	137
Metal-Detecting	1,382	1,034	348
Nature	516	394	122
Smoke	1,478	1,101	377
Sports	4,790	3,498	1,292
Technology	136	51	85
All	18,608	13,553	5,055

#### TAG-IT Dataset (Cimino et al., 2020)



**Model:** IT5 (Sarti e Nissim, 2022), an encoder-decoder architecture based on T5 and trained on the italian sentences cleaned and retrieved from the mC4 corpus.

Idea: <u>Finding a meaningful relationship between the classes</u> and their string representation to do **label representation** selection. In particular, we tried to see whether the *cosine distances* between the class and its string representation are correlated to the model's performance on that class.





Original Classes Translated

 $\begin{array}{l} c_1 = \text{Anime} \rightarrow \text{Anime} \\ c_2 = \text{Auto-Moto} \rightarrow \text{Automobilismo} \\ c_3 = \text{Bikes} \rightarrow \text{Bicicletta} \\ c_4 = \text{Celebrities} \rightarrow \text{Celebrità} \\ c_5 = \text{Entertainment} \rightarrow \text{Intrattenimento} \\ c_6 = \text{Medicine-Aesthetics} \rightarrow \text{Medicina} \end{array}$ 

 $\begin{array}{l} c_7 = \text{Metal-Detecting} \rightarrow \textit{Metal Detector} \\ c_8 = \text{Nature} \rightarrow \textit{Natura} \\ c_9 = \text{Smoke} \rightarrow \textit{Fumo} \\ c_{10} = \text{Sports} \rightarrow \textit{Sport} \\ c_{11} = \text{Technology} \rightarrow \textit{Tecnologia} \end{array}$ 

These representations of the original classes have been used to calculate the *cosine similarities* between the **classes** and the **candidate representations.** 





We have 100 representations: the original class translated + 10 manually selected from the class **synonyms** + 90 **randomically chosen noun** between the most frequent in the ItWac Corpus (Baroni et al., 2009)





The 100 representation have been ranked by the *cosine similarity* between the original class translated and the candidate representation. The similarity is computed between the **IT5 embedding vectors** that represent the strings









**Fine-Tuning**: After creating the 100 sets of representation  $S_1, ..., S_{99}$  we fine-tuned 100 IT5 models on each of this sets of label representations.





**Overall results**: we can observe how the choice of string representation <u>has a</u> <u>considerable impact on the models performances</u>. However, no correlation was found between the **representation' ranks** and the **model weighted F-score**.





**Per-class analysis:** <u>The way the classes are represented is especially important for</u> <u>lower-frequency classes</u> where the f-score variations are greater. In some of the least frequent classes the f-score ranges from zero to acceptable performances.



	NATURE	META	L-DETECT	ING MEDIC	NE-AESTH	ETICS EN	TERTAINMENT	
organizzatore -	0.56	artigiano -	0.52	acuto -	0.71	quarto -	0.43	
arbitro -	0.56	sussistenza -	0.51	retta -	0.7	colpevolezza -	0.42	
velo -	0.56	vibrazione -	0.51	benessere -	0.69	concessione -	0.42	
infiammazione -	0.55	portatore -	0.5	medicina -	0.69	ballo -	0.41	0 0 0
dinosauro -	0.55	effettivo -	0.49	sensibilità -	0.68	pianista -	0.41	
polmone -	0.54	tregua -	0.49	croato -	0.68	quota -	0.41	representation
prigionia -	0.53	moneta -	0.48	incrocio -	0.68	musica -	0.41	
filone -	0.53	operato -	0.48	dottoressa -	0.68	vernice -	0.4	bv t-score
foresta -	0.52	esplosione -	0.48	ordinamento -	0.67	spirale -	0.4	J
curiosità -	0.51	costituente -	0.48	documentare -	0.67	approdo -	0.39	
	NATURE	MET	DETECT					
55077050		META	AL-DETECT	ING MEDIC	NE-AESTH	ETICS EN	TERTAINMENT	
SCOZZESE -	0.31	deputato -	0.35	ING MEDIC produrre -	NE-AESTH 0.37	ETICS EN <sup>-</sup> cinema -	0.086	
dirigenza -	0.31 0.29	deputato - sfumatura -	0.35 0.34	ING MEDIC produrre - sposo -	NE-AESTH 0.37 0.35	ETICS EN <sup>-</sup> cinema - fucile -	TERTAINMENT 0.086 0.079	
dirigenza - maratona -	0.31 0.29 0.28	deputato - sfumatura - ambizione -	0.35 0.34 0.33	ING MEDIC produrre - sposo - progettista -	NE-AESTH 0.37 0.35 0.34	ETICS EN cinema - fucile - piatto -	TERTAINMENT 0.086 0.079 0.05	Morst 10
dirigenza - maratona - venditore -	0.31 0.29 0.28 0.28	deputato - sfumatura - ambizione - astronauta -	0.35 0.34 0.33 0.32	ING MEDIC produrre - sposo - progettista - semiare -	NE-AESTH 0.37 0.35 0.34 0.31	ETICS EN cinema - fucile - piatto - sitcom -	TERTAINMENT 0.086 0.079 0.05 0.034	Worst 10
dirigenza - maratona - venditore - diga -	0.31 0.29 0.28 0.28 0.25	deputato - sfumatura - ambizione - astronauta - cross -	0.35 0.34 0.33 0.32 0.31	ING MEDIC produrre - sposo - progettista - semiare - industria -	NE-AESTH 0.37 0.35 0.34 0.31 0.22	ETICS EN cinema - fucile - piatto - sitcom - prosa -	TERTAINMENT 0.086 0.079 0.05 0.034 0.033	Worst 10
dirigenza - maratona - venditore - diga - paradigma -	0.31 0.29 0.28 0.28 0.25 0.23	deputato - sfumatura - ambizione - astronauta - cross - urina -	0.35 0.34 0.33 0.32 0.31 0.3	ING MEDIC produrre - sposo - progettista - semiare - industria - suolo -	NE-AESTH 0.37 0.35 0.34 0.31 0.22 0.19	ETICS EN cinema - fucile - piatto - sitcom - prosa - marchesato -	TERTAINMENT 0.086 0.079 0.05 0.034 0.033 0.016	Worst 10 representation
dirigenza - maratona - venditore - diga - paradigma - testimonial -	0.31 0.29 0.28 0.28 0.25 0.23 0.22	deputato - sfumatura - ambizione - astronauta - cross - urina - dio -	0.35 0.34 0.33 0.32 0.31 0.3 0.29	ING MEDIC produrre - sposo - progettista - semiare - industria - suolo - infortuno -	NE-AESTH 0.37 0.35 0.34 0.31 0.22 0.19 0.13	ETICS EN cinema - fucile - piatto - sitcom - prosa - marchesato - lasso -	TERTAINMENT 0.086 0.079 0.05 0.034 0.033 0.016 0	Worst 10 representation
dirigenza - maratona - venditore - diga - paradigma - testimonial - banca -	0.31 0.29 0.28 0.28 0.25 0.23 0.22 0.19	deputato - sfumatura - ambizione - astronauta - cross - urina - dio - trasmissione -	0.35 0.34 0.33 0.32 0.31 0.3 0.29 0.26	ING MEDIC produrre - sposo - progettista - semiare - industria - suolo - infortuno - dotazione -	NE-AESTH 0.37 0.35 0.34 0.31 0.22 0.19 0.13 0.042	ETICS EN cinema - fucile - piatto - sitcom - prosa - marchesato - lasso - posa -	TERTAINMENT 0.086 0.079 0.05 0.034 0.033 0.016 0 0	Worst 10 representation by f-score
dirigenza - maratona - venditore - diga - paradigma - testimonial - banca - professore -	0.31 0.29 0.28 0.25 0.23 0.22 0.19 0.13	deputato - sfumatura - ambizione - astronauta - cross - urina - dio - trasmissione - esempo -	0.35 0.34 0.33 0.32 0.31 0.3 0.29 0.26 0.26	ING MEDIC produrre - sposo - progettista - semiare - industria - suolo - infortuno - dotazione - geologo -	NE-AESTH 0.37 0.35 0.34 0.31 0.22 0.19 0.13 0.042 0.028	ETICS EN cinema - fucile - piatto - sitcom - prosa - marchesato - lasso - posa - pulizia -	TERTAINMENT 0.086 0.079 0.05 0.034 0.033 0.016 0 0 0 0	Worst 10 representation by f-score

**Per-class analysis:** looking at the classes with the **highest f-score variance** <u>there is no</u> <u>clear indication to which representations work better.</u>



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dirigenza -	0.29	sfumatura -	0.34	sposo -	0.35	fucile -	0.079	
maratona -	0.28	ambizione -	0.33	progettista -	0.34	piatto -	0.05	M/orst 10
venditore -	0.28	astronauta -	0.32	semiare -	0.31	sitcom -	0.034	00013110
diga -	0.25	cross -	0.31	industria -	0.22	prosa -	0.033	representation
paradigma -	0.23	urina -	0.3	suolo -	0.19	marchesato -	0.016	representation
testimonial -	0.22	dio -	0.29	infortuno -	0.13	lasso -	0	hy f-score
banca -	0.19	trasmissione -	0.26	dotazione -	0.042	posa -	0	By I SCOIC
professore -	0.13	esempo -	0.26	geologo -	0.028	pulizia -	0	
ninfa -	0.12	rivisitazione -	0.23	proprio -	0	aioco -	0	

**Per-class analysis:** looking at the classes with the **highest f-score variance** there is no clear indication to which representations work better. <u>The placement of in-domain words</u> in the f-score ranking doesn't indicate that those words work better.



**Internal similarity**: we calculated Spearman correlation between the f-score and the *internal similarity score* of a set.

The *internal similarity score* of a set S was defined as the **average cosine distance between all possible distinct combination of representation couples in a set**.

The score varied considerably between sets, however, when we calculated Spearman between:

- the **100 internal similarity scores** (one for each representations sets);
- the **100 f-score** (one for each model fine-tuned on the representations set);

We found a **Spearman of 0.01** with a **p-value of 0.9**, indicating no apparent correlation between how semantically similar are the representation between themselves in a set, and how the model performs.

#### Results - Label Selection Strategies (1)



**Representation frequencies**: we calculated the Spearman correlation per-class between the **f-scores** and the **absolute frequency** of the representation in the mC4 training corpus of IT5.

_	Categories	Spearman	p-value
_	Medicine-Aesthetics	0.13	0.20
	Nature	0.06	0.54
	Sports	0.04	0.66
	Bikes	0.01	0.94
	Technology	-0.02	0.88
า	Anime	-0.02	0.84
	Entertainment	-0.03	0.75
	Auto-Moto	-0.05	0.62
	Metal-Detecting	-0.06	0.57
$\backslash$	Celebrities	-0.06	0.54
	Smoke	-0.25	0.01 *

#### Results - Label Selection Strategies (2)



The only statistically significant results was on Smoke.

**Representations are important**: our results indicate that for tasks such as Topic classification where lexical information are important, <u>the choice of label representation</u> <u>is critical to model performance</u>, especially for low-frequency classes where the classification f-score can vary from 0 to competitive results, <u>but we didn't find out why</u>.





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**Representation similarity is not that important**: we found that <u>how similar the</u> <u>representation is to the original class doesn't seem to affect the classification results</u>. This, however, could be attributed to poor choice of the initial class name for the category or *cosine similarity* not being an effective measure of semantic similarity for this purpose.





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**Representation choice is not trivial**: finding class representation in T2T classification scenarios **is not trivial** and we couldn't find a simple and effective way to choose them in a way that maximise the performances. <u>We propose to call the task of finding the best</u> <u>class representation in a T2T classification scenario</u> **Automatic Class Label Selection**, and future research should focus on developing an effective way to solve it.

## Conclusion



# Thank you for your attention!

#### Contacts

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#### **Semantic Similarity**: we calculated <u>Spearman correlation per-class between the</u> <u>f-score of a model trained with a specific representation, and the representation's</u> <u>cosine similarity with its class</u>.

We found 6 had statistically significant correlation, with most of the correlation being negative, implying that to a **higher similarity** between the representation and the class name **corresponds a lower f-score**.

Categories	Spearman	p-value
Entertainment	0.29	0.003 *
Auto-Moto	0.05	0.62
<b>Medicine-Aesthetics</b>	-0.02	0.85
Bikes	-0.05	0.61
Anime	-0.10	0.37
Technology	-0.12	0.21
Smoke	-0.20	0.04 *
Sports	-0.22	0.03 *
Nature	-0.25	0.01 *
Metal-Detecting	-0.35	0.00 *
Celebrities	-0.45	0.00 *

#### Results - Label Selection Strategies (3)

