Prediction of Variables from Cancer Reports

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May 31, 2021

Introduction

Tuscany cancer reports

- Doctors write reports after **oncological visits**
- **ISPRO collects reports** in Tuscany
- Experts extract **variables** from reports

Variables

- describe the **progress of the pathology**
- used to ensure that patients are receving the **correct care**

Problem

Reports are analyzed with some **years of delay** ($\sim$ 5 years)

Prediction of variables

Objective

Predict variables to **speedup** the analyses of reports

This thesis

Study the **predictability** of these variables for breast cancer reports

Previous work [1]

Dataset with all cancer types, prediction of **primary site** and **morphology**

[1] S. Martina, L. Ventura and P. Frasconi, “Classification of Cancer Pathology Reports: A Large-Scale Comparative Study”

Breast cancer dataset

Example of report

field	value
notizie	
macroscopia	Q.I.C. mammella sn (cm 12x8x5):\nT1-4) neoplasia (mm 23), distanza dai margini >mm 10; MS) margine superiore; MI) margine inferiore; MM) margine mediale; ML) margine laterale; MP) margine profondo; CU) margine cutaneo. \n(eseguita colorazione ematossilina-eosina e valutazione parametri biologici con controllo di qualitï¿½).
diagnosi	CARCINOMA DUTTALE INFILTRANTE (N.O.S.) (G2) DELLA MAMMELLA CON ASSOCIATE ESPRESSIONI INTRADUTTALI DI BASSO GRADO (T1-4)\nNON EVIDENTE PERMEAZIONE NEOPLASTICA VASCOLARE \n NESSUNA PROLIFERAZIONE CANCERIGNA NEI MARGINI DI SEZIONE CHIRURGICA (MS, MI, ML, MM, MP), NELLLA CUTE (CU), NEL LINFONODO SENTINELLA (vedi es.B 10508/12).\n(p T2 N0(OSNA -))* \n*(TNM, VIIï¿½ ed., 2009)\nParametri biologici: ER: + 90% ; PGR: + 60% ; ki67: + 10% ; Her 2: - .

field	value
id_paz	5******
anno_diagnosi	2012
sede_icdo3	C509
morfologia_icdo3	85003
dimensioni	23
tipo_T	P
metastasi	
modalita_T	E
modalita_N	E
stadio_T	2
stadio_N	0SN
recettori_estrogeni	90
recettori_progestin	60
numero_sentinella_asportati	1
numero_sentinella_positivi	0
mib1	
cerb	0
ki67	10
grading	2
anno_referto	2012
id_isto	5******

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Some variables

- **grading**: difference between cancer cells and healthy ones
- **tumor stage**: extension of the primary tumor
- **lymph nodes stage**: involvement of lymph nodes
- **ki67**: marker of tumor cells proliferation speed
- **removed lymph nodes**: how many lymph nodes was removed
- **positive lymph nodes**: how many lymph nodes had malignant cells
- **size**: size of the primary tumor

Dataset info

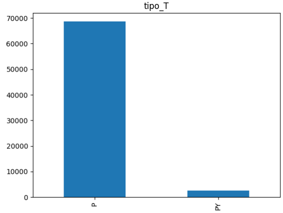
- breast cancer
- $\sim$ 25k patients
- $\sim$ 115k reports
- more than 10 variables

Dataset info

- breast cancer
- $\sim$ 25k patients $\rightarrow$ labeled from 2003 to 2015
- $\sim$ 115k reports
- more than 10 variables $\rightarrow$ many missing values

Types of variables

binary variable



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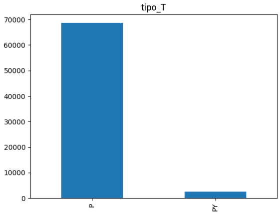
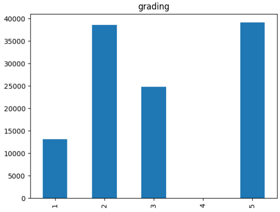


multi-class



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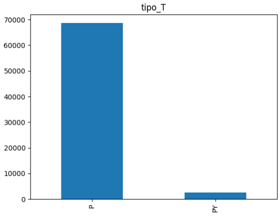

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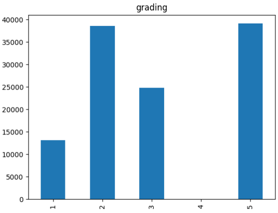
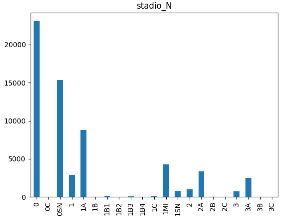


with subclasses



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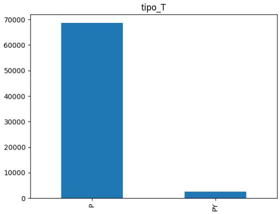

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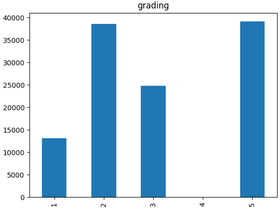

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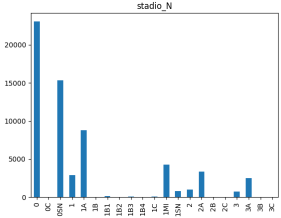
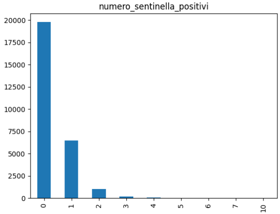


with missing values



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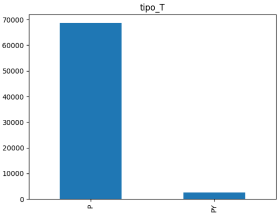
binary variable



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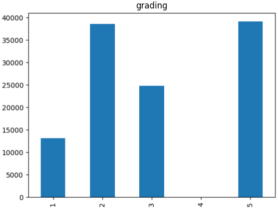
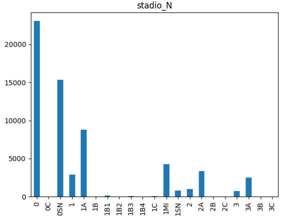


with subclasses



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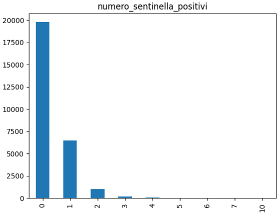
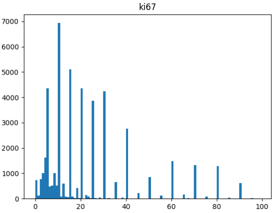
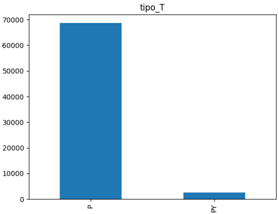


percentages



Types of variables

binary variable



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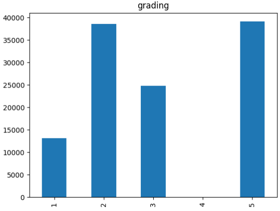

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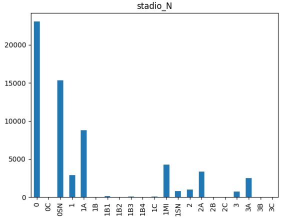

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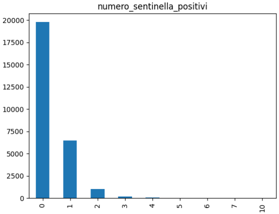

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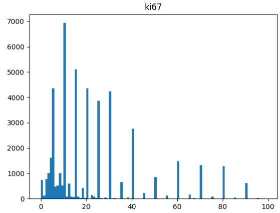
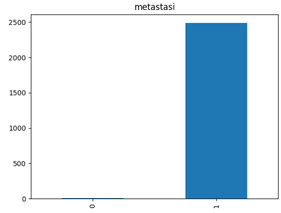


unpredictable



Methods and models

Question we want to answer

Question

Is it possible to **predict variables** from these reports?

There are no previous references to compare

Approach

Different strategies for different variables:

1. **classification**

   Examples:

   - "*carcinoma duttale infiltrante nos* **g3**"
   - "*nessuna proliferazione neoplastica nel linfonodo sentinella*"

2. **segmentation**

   Examples:

   - "*Ki67 (clone MIB1):* **80%**"
   - "*neoplasia (***mm 23***), distanza dai margini >mm 10;*"

Approach

Different strategies for different variables:

1. **classification** → **machine learning models**

   Examples:

   - "*carcinoma duttale infiltrante nos* **g3**"
   - "*nessuna proliferazione neoplastica nel linfonodo sentinella*"

2. **segmentation** → **regex-based algorithm**

   Examples:

   - "*Ki67 (clone MIB1):* **80%**"
   - "*neoplasia (***mm 23***), distanza dai margini >mm 10;*"

Classifications: preparation steps

report → preprocess → tokenize → tokens

Example:

“CARCINOMA DUTTALE INFILTRANTE (NOS) DELLA MAMMELLA. Grado 3 secondo Elston- Ellis.”

↓ **preprocess**

“carcinoma duttale infiltrante (nos) della mammella . g3 secondo elston - ellis .”

↓ **tokenize**

[“carcinoma”, “duttale”, “infiltrante”, “(”, “nos”, “)”, “della”, “mammella”, “.”, “g3”, “secondo”, “elston”, “-”, “ellis”, “.”]

Classifications: models

- Transformer
- MLP
- Decision Tree
- Random Forest
- XGBoost
- Linear SVM

Transformer, MLP $\rightarrow$ Neural Networks

Random Forest, XGBoost $\rightarrow$ Trees ensemble

Transformer

- at the base of state-of-the-art in many NLP tasks
- usually take advantage of large amounts of unlabeled data...
- ...but we do not investigate this path due to the nature of the dataset.

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Segmentations

Example:
"CARCINOMA DUTTALE INFILTRANTE NOS G3, MULTIFOCALE. INVASIONE VASCOLARE ...
TNM 2010 VII edizione: pT1c (m), pN1 mi (sn). PARAMETRI BIOLOGICI: ER (clone SP1): POSITIVO 100% INTENSITA' DELLA COLORAZIONE: MARCATA PgR (clone 1E2): POSITIVO 70% INTENSITA' DELLA COLORAZIONE: MARCATA Ki67 (clone MIB1): 30% c-erbB-2 (policlonale A 0485): POSITIVO > 10% INTENSITA' DELLA COLORAZIONE: MODERATA. SCORE 2+."

Steps:

1. find a marker of the variable — `ki67\s?.{,10} :`
2. take a window of characters
3. cut after a foreign marker — `cerb|pgr|\ser\s|progest|estrog`
4. find a number in the window — `(\d?\d?\d)%`

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Results

Results for multi-class classification variables

Accuracy					
	Grading	**Stadio N**	**Stadio T**	**Sentinella Asportati**	**Sentinella Positivi**
Decision Tree	92.3%	95.3%	89.6%	75.6%	87.6%
Random Forest	**94.8%**	**97.6%**	97.0%	83.5%	**92.2%**
XGBoost	94.2%	97.2%	**97.6%**	**84.6%**	90.7%
SVM	93.4%	96.8%	94.4%	83.9%	91.1%
MLP	91.6%	93.1%	94.0%	71.7%	86.8%
Transformer	94.0%	93.4%	94.6%	70.1%	86.8%
num classes	3	5	5	4	3

Observations

- *Grading*, *Stadio-N*, *Stadio-T* are easier
- *Random Forest* and *XGBoost* have the best results

Results for binary classification variables

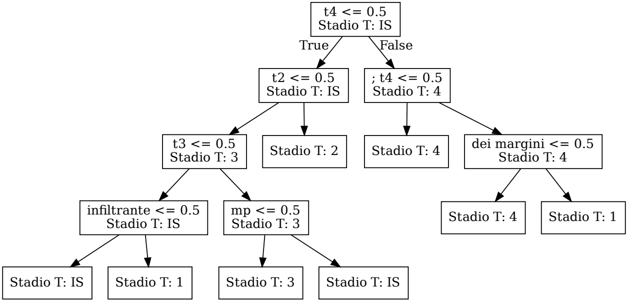
Tipo-T variable

	Accuracy	Precision	Recall	F1
Decision Tree	96.5%	48.2%	70.2%	57.1%
Random Forest	96.5%	47.8%	**77.2%**	**59.1%**
XGBoost	96.4%	46.1%	61.4%	52.6%
SVM	96.4%	47.1%	71.9%	56.9%
MLP	**96.9%**	**53.1%**	45.6%	49.1%
Transformer	95.6%	40.2%	68.4%	50.6%

Observations

- Highly unbalanced classification
- Random Forest has the best results

Predictions interpretability: example tree



Observations

- trees were greedily constructed...
- ... but learned trees are very compact

Segmentations results

Metrics

- Extracted: % of predictions on the total
- Accuracy on extracted
- Hit: % of correct predictions on the total

	Extracted	Acc. on extracted	Hit
recettori estrogeni	96.3%	71.3%	68.7%
recettori progestin	96.8%	89.9%	87.0%
mib1	100%	18.2%	18.2%
cerb	96.1%	83.6%	80.4%
ki67	97.7%	81.9%	80.0%
dimensioni	76.9%	73.7%	56.7%

Problems

- *mib1* has very few labels
- *dimensioni* has different unit of measure

Conclusions

Answering the question

Question

Is it possible to **predict variables** from these reports?

Answer

It's possible to predict them with high accuracy in most cases.

Whether these accuracies are enough can be verified only using these models in practice.

Recap

- *RF* and *XGBoost* are **good classifiers** for some variables
- *NN* do not obtain better results
- in [1] complex models were not much better than simpler ones
- regex-based algorithm is a **good baseline** for many variables
- further **improvements** are possible

[1] S. Martina, L. Ventura and P. Frasconi, "Classification of Cancer Pathology Reports: A Large-Scale Comparative Study"

Conclusions

Considerations

- the aim is not to replace human experts
- **two registers** that proceed at different speed

Future works

- predict **presence** of the variable
- access to **similar datasets**
- numbers extraction as a **learning** problem
- focus on **interpretable** models

Thank you for the attention.
Are there any questions?

Macro F1 on the test set for the multi-class classification variables.

Macro F1					
	Grading	**Stadio N**	**Stadio T**	**Sentinella Asportati**	**Sentinella Positivi**
Decision Tree	91.5%	92.3%	84.5%	66.3%	75.5%
Random Forest	**94.1%**	**96.5%**	93.3%	73.1%	80.4%
XGBoost	93.5%	95.9%	**94.4%**	**77.2%**	81.2%
SVM	92.5%	95.3%	89.8%	75.4%	**82.0%**
MLP	90.6%	87.7%	82.8%	62.6%	69.0%
Transformer	93.3%	89.7%	91.6%	64.3%	72.8%
num classes	3	5	5	4	3

Important tokens for Random Forest

	Grading	Stadio N	Stadio T
1	g2	n1	t2
2	g3	n0	p t2
3	g1	n1 a	p t1
4	nos g3	n2 a	t1
5	(g2	n2	ptis
6	scarsamente differenziato	p n1	t1 c
7	scarsamente	p n1 a	p t1 c
8	infiltrante nos g3	n3 a	: p t2
9	(g3	n0 (	t2 ,
10	moderatamente differenziato	n3	infiltrante

Data format

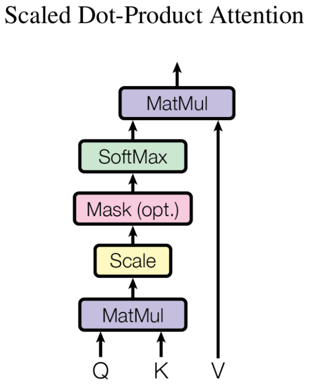
Transformer:

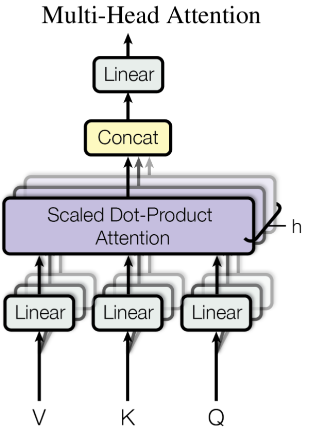
- tokens indices
- vector of integers

Other models:

- bag of *n*-grams of tokens
- vector of booleans

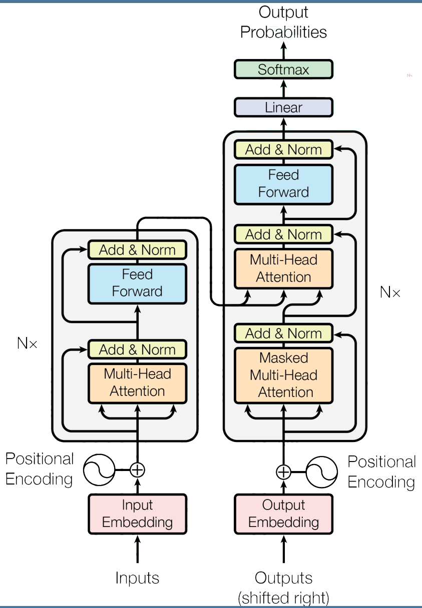
Attention


Scaled Dot-Product Attention
MatMul
SoftMax
Mask (opt.)
Scale
MatMul
Q
K
V

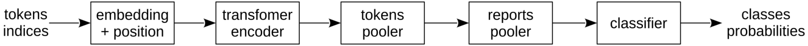

Multi-Head Attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q

Transformer architecture

- we use only the left part (encoder)



Pipeline of Transformer-based model



Numbers segmentation as position regression

Ground truth location can be ambiguous