Building a Spanish/Catalan Health Records Corpus with Very Sparse Protected Information Labelled

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Salvador Medina and Jordi Turmo

Universitat Politècnica de Catalunya
Talp Research Center

Carrer de Jordi Girona, 1-3, 08034 Barcelona
{smedina, turmo}@cs.upc.edu

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Overview

About this project

- Build Health Record Corpora with labeled Protected Health Information
  - Unstructured health notes
  - High sparsity of Protected Health Information
  - Multilingual: Spanish and Catalan
- Identification based on manual rules
  - Rules defined by non-programmers
  - Rules can be understood by health experts
  - Implemented using Augmented Transition Networks
- Iterative and interactive process:
  - Inspired by active learning
  - Expert evaluator defines new rules each iteration
  - The algorithm selects relevant examples to build such rules

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Motivation

Available Corpora

Several Electronic Health Record (EHR) corpora for Protected Health Information (PHI) can be retrieved from multiple sources:

- Shared Tasks
  - 2006 and 2014 *i2b2* Challenges [Uzuner et al., 2007] [Stubbs and Uzuner, 2015]
  - 2016 CEGS N-GRID Shared Tasks [Stubbs et al., 2017]
- Re-purposed EHR corpora
  - Intelligent Monitoring for Intensive Care (MIMIC-II) [Neamatullah et al., 2008]

$\Rightarrow$ Most corpora is in **English**, multi-lingual corpora is needed

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Regulations and directives

- Different countries have different regulations:
  - **Spain:** *Ley Orgánica de Protección de Datos*
- Legislation imposes restrictions to
  - Who can access non-anonyzed EHR
  - The kinds of entities that must be anonymized
  - The level of protection of different kinds of EHR

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Manual labelling costs

- Health notes usually have a very density of PHI
  - In our corpus, $\sim 0.4\%$ of tokens are people's names
- PHI classes are very unbalanced
  - In our corpus, $< 0.01\%$ of telephone numbers vs $\sim 1\%$ of locations
- Labelling has to be done by experts
- Labels should be consensuated among various evaluators

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Basic ideas about the method

- Potential PHI in EHR are identified by using a set of rules
- Rules are implemented using Augmented Transition Networks (ATN)
- The rule set is iteratively updated
  - New rules are added
  - Existing ones are updated and grow in complexity
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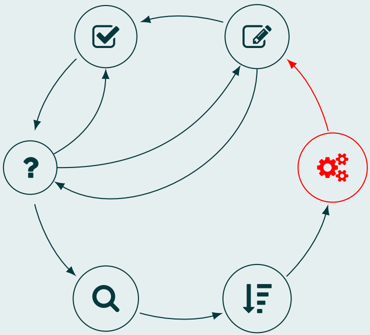

1. Run against C_{tr}
2. Define new rule so that $F_1'(C_{tr}) \geq F_1(C_{tr})$
3. Evaluate against C_{val}
4. Repeat from 2 unless
   - $r' \leq r$ and $F_1' < F_1 \Rightarrow$ Discard rule
   - $p' < p$ and $F_1' < F_1 \Rightarrow$ Update rule ($p' > p$)
5. Run against C_{unl}
6. Rank and select $f(C_{unl})$

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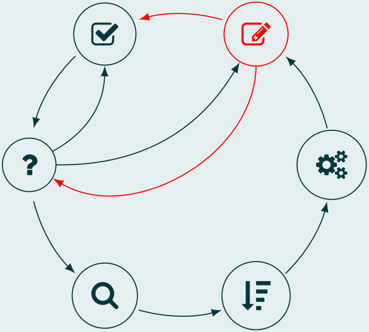

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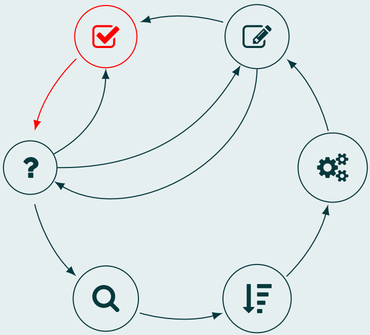

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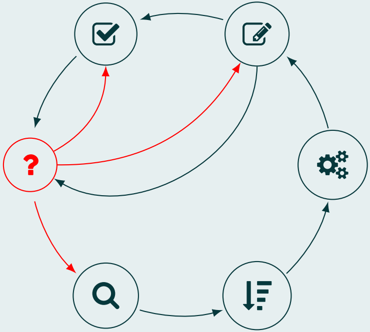

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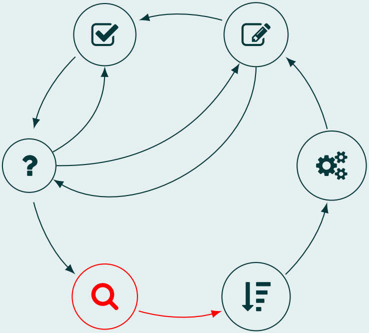

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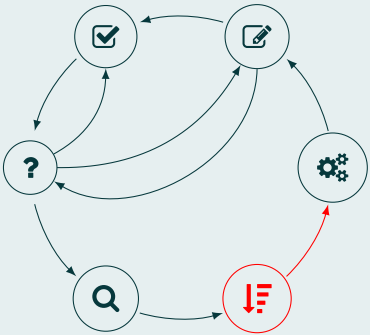

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Ranking and selection of EHR

$$f(d) = \sum_{i \epsilon K} N_i(d) * (1 - F_1(i)) * (1 - p_i)$$

$$p_i = \frac{\sum_{t \epsilon T} N_i(t)}{\sum_{i \epsilon K} \sum_{t \epsilon T} N_i(t)} \quad (1)$$

of Documents: Elbow Criterion

Threshold score is the one that corresponds to the *elbow* point of the curve defined by the document's scores sorted in decreasing order

The Iterative Method

Observations

- Prioritizes rules that increase *recall* while F_1 is not decreased
- F_1 increases monotonically
- Can be applied indefinitely
- Entities of uncommon classes are prioritized
- Documents with no entities are not selected

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Evaluation Framework

Direct and Indirect Evaluation

Direct Evaluation

Goal: Optimize the manual labeling process

- Evaluate using F_1 score achieved by the rule set
- Partial evaluation for boundary identification

Indirect Evaluation

Goal: Optimize the resulting corpus

- Evaluate using F_1 score achieved by a tagger trained using the resulting corpus
- Strict evaluation for boundary identification

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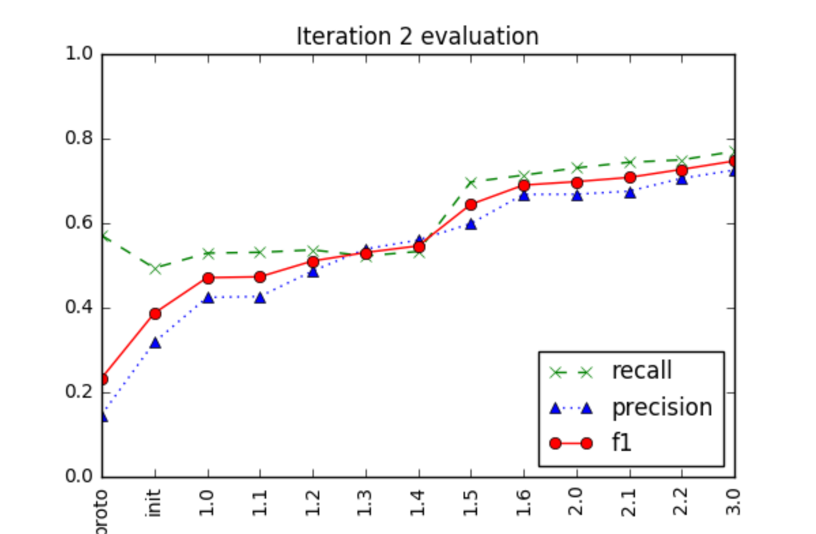
Evaluation Results

Direct evaluation over each Iteration



Evaluation Results

Final direct Evaluation

	Eval.	NERC	initial	final
ALL	Recall	0.052	0.147	0.702
	Prec.	0.494	0.208	0.489
	F_1	0.094	0.172	0.576
PERSON	Recall	0.436	0.676	0.772
	Prec.	0.023	0.196	0.445
	F_1	0.044	0.304	0.564
LOCATION	Recall	0.517	0.013	0.371
	Prec.	0.064	0.127	0.809
	F_1	0.114	0.024	0.509

Table: Evaluation results in the test set for the general-purpose *Freeling* NERC module, and for the initial and final sets of hand-crafted rules.

Evaluation Results

Final indirect evaluation

	Eval.	Cross-Val.	Res. Corpus
ALL	Recall	0.721 (0.027)	0.699 (0.042)
	Prec.	0.839 (0.026)	0.769 (0.047)
	F_1	0.774 (0.017)	0.732 (0.039)
PERSON	Recall	0.784 (0.064)	0.759 (0.093)
	Prec.	0.909 (0.041)	0.730 (0.061)
	F_1	0.840 (0.025)	0.744 (0.057)
LOCATION	Recall	0.695 (0.040)	0.676 (0.056)
	Prec.	0.812 (0.022)	0.783 (0.061)
	F_1	0.748 (0.037)	0.726 (0.052)

Table: Mean *recall*, *precision* and F_1 score obtained by a CRF model trained using the labelled corpus obtained after 3 iterations of the method (1051 health records) compared to the *8-fold* cross validation of the test corpus (4350 health records) for the 8 testing partitions. Standard deviation is shown between brackets.

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Thank you for your attention!

Questions?