# Sequence-to-Sequence Models for Extracting Information from Registration and Legal Documents 

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## Introduction



Q: What is the state?
A: SP
Q: What is the county?
A: São Paulo
Q: What is the office?
A: 150 Oficial de Registro de Imóveis
Q: What is the private area?
A: $64,020 \mathrm{~m} 2$


Q: What is the full name?
A: (anonymized)
Q: What is the address?
A: (anonymized)
Q: What is the zip code?
A: (anonymized)
Q: What is the identity number?
A: (anonymized)

Current commercial information extraction (IE) systems consist of individual modules controlled by manually defined rules

In production pipelines, the requirements and specifications often change

This leads to higher maintenance costs due to an ever larger number of individual components

## Our Proposal

We study the viability of a framework for information extraction based on a single sequence-to-sequence model for extracting and processing information from legal and registration documents
$\rightarrow$ a single model needs to be trained and maintained
$\rightarrow$ can be shared by multiple projects with different requirements and types of documents

## Our Proposal



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## Questions and Answers

Our method uses questions coupled with contexts as input and answers as output

For consistency, we strive to formulate questions as general as possible

We also format the answers by adding clues for each category of information
$\rightarrow$ important to structure the response
$\rightarrow$ useful for designing compound answers

## Q\&A: Simple QAs

## simple

context: Apartment type no 32, located on the 10th floor of the Central Building, situated at 1208 Santos Dumont St., having a private covered built area of 64,020 square meters, a common covered built area of 44,509 square meters, a total built area of 108,529 square meters...

Q: What is value of the private area?
A: [value]: 64.02

Q: What is the unit of measure of the private area?
A: [unit]: square meters


Some subsets of fields are often closely related or even appear connected

The classical pipeline is cumbersome as it requires the model to analyze each document oftentimes for extracting information of the same scope

By using compound QAs, a set of questions for extracting individual information are replaced by a single question

Q\&A: Compound QAs
context: Apartment type no 32, located on the 10th floor of the Central Building, situated at 1208 Santos Dumont St., having a private covered built area of 64,020 square meters, a common covered built area of 44,509 square meters, a total built area of 108,529 square meters...

```
Q: What is the private area?
A: [value]: 64.02 [unit]: square meters
```



## Q\&A: Sentence IDs

One way to monitor the quality of predictions is to know the location in the input text from which the information was extracted

However, the location cannot be trivially inferred from the output of seq2seq models

To address this limitation, we propose the use of sentinel tokens that allow the generative model to reveal the location of its prediction in the original sequence

## Q\&A: Sentence IDs

## sent

context: Apartment type № 32,
situated at 1208 Santos Dumont St.,
located on the 10th floor of the Central Building, רaving a private covered built area of 64,020 square meters,
a common covered built area of 44,509 square meters,
a total built area of 108,529 square meters...

Q: What is the private area?
A: [value]: 64.02 [unit]: square meters


## Q\&A: Sentence IDs

context: [SENT1] Apartment type no 32, [SENT2] located on the 10th floor of the Central Building, [SENT3] situated at 1208 Santos Dumont St., [SENT4] having a private covered built area of 64,020 square meters, [SENT5] a common covered built area of 44,509 square meters, [SENT6] a total built area of 108,529 square meters...

Q: What is the private area?
A: [value]: 64.02 [unit]: square meters


## Q\&A: Sentence IDs

context: [SENT1] Apartment type no 32, [SENT2] located on the 10th floor of the Central Building, [SENT3] situated at 1208 Santos Dumont St., [SENT4] having a private covered built area of 64,020 square meters, [SENT5] a common covered built area of 44,509 square meters, [SENT6] a total built area of 108,529 square meters...

Q: What is the private area?
A: [SENT4] [value]: 64.02 [SENT4] [unit]: square meters


## Q\&A: Sentence IDs

context: [SENT1] Apartment type no 32, [SENT21 Iocated on the 10th floor of the Central Buildina. ICFNIT21 cituatad at 1208 Santos Dumont St [SENT4]having a private covered built area of 64,020 square meters, [SENT5] a common covered built area of 44,509 square meters, [SENT6] a total built area of 108,529 square meters...

Q: What is the private area?
A: [SENT4] [value]: 64.02 [SENT4] [unit]: square meters


## Q\&A: Canonical format

Often, certain types of information appear in a document in a variety of formats
$\rightarrow 23$ May 2022
$\rightarrow$ 23/05/2022
$\rightarrow$ 23-05-2022
$\rightarrow$ May 23, 2022
$\rightarrow$ 2022/05/23
$\rightarrow$ 2022-05-23

Our IE system is able to directly extract those particular fields in canonical format

However, with canonical formats, the use of sentence IDs may not be enough for locating the extracted information in the original document

## Q\&A: Canonical format

context: [SENT1] Apartment type no 32, [SENT2] located on the 10th floor of the Central Building, [SENT3] situated at 1208 Santos Dumont St., [SENT4] having a private covered built area of 64,020 square meters, [SENT5] a common covered built area of 44,509 square meters, [SENT6] a total built area of 108,529 square meters...

```
Q: What is the private area?
A: [SENT4] [value]: 64.02 [SENT4] [unit]: m2
```



## Q\&A: Canonical format

context: [SENT1] Apartment type no 32, [SENT2] located on the 10th floor of the Central Building, [SENT3] situated at 1208 Santos Dumont St., [SENT4] having a private covered built area of 64,020 square meters, [SENT5] a common covered built area of 44,509 square meters, [SENT6] a total built area of 108,529 square meters...

Q: What is the private area and how does it appear in text?
A: [SENT4] [value]: 64.02 [SENT4] [unit]: m² [text] square meters


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PTT5:
T5-base model pretrained on a large Brazilian Portuguese corpus

PTT5-Legal:
PTT5 pretrained on legal documents in Portuguese

PTT5-QA:
PTT5 pre-finetune on the SQuAD v1.1 dataset

PTT5-Legal-QA:
In-domain pretraining followed by task-aware pre-finetuning

## Datasets

NM-Property:
Property registres (legal domain)

NM-Certificates:
Certificates (legal domain)

NM-Legal:
Legal notices (legal domain)

NM-Forms:
Forms (registration domain)

## Datasets

Table 1: Statistics of the datasets.

| Dataset | Chars/doc | Fields | Train | Valid | Test |
| :--- | :--- | :--- | ---: | ---: | ---: |
| NM-Property | 3011.53 | 17 | 3191 | 799 | 242 |
| NM-Certificates | 4914.39 | 10 | 760 | 191 | 311 |
| NM-Publications | 1895.76 | 3 | 1600 | 401 | 500 |
| NM-Forms | 1917.14 | 25 | 240 | 60 | 282 |
| Total | - | 55 | 5791 | 1451 | 1334 |

## Exact matching (EM): accuracy

F1-measure (F1): token-based harmonic mean of precision and recall

Before computing the metrics, both label and prediction sentences are normalized by converting to lower case, removing double spaces and punctuation

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Results
EM
F1


IAPR (6)

## Results

EM F1


IAPR (6)
PTT5 (En)

Results

The adoption of Portuguese tokenizer provided an error reduction in EM of $70.3 \%$ over the previous experiment that used the same pretraining dataset

Results

Adapting the model for QA on the SQuAD dataset did not provide improvements over the large-scale pretraining


## Results

The unsupervised pretraining brought the best result over the NMProperties dataset, and a minor improvement on the average of the four datasets


T5
PTT5 (En)
PTT5 (Pt)



IIPRR䢧

## Results

## This model achieved the <br> best

average EM and F1


## Results

EM Although superior to results using individual QAs, F1 the average results are comparable

Compound QAs yields better results than using individual QAs, reaching superior performance for three datasets


## Results

F1 The robustness for extracting information on varied types of documents was not affected


This method does not outperform the one without sentence IDs and raw-text extractions

IIPR(

## Comparison with BERT

We compare seq2seq models with the classical named entity recognition

The dataset was filtered out, retaining $38 \%$ of the documents and 42 of the 55 fields.

Table 3: NER ablation results .

| Model | Params | Precision | Recall | F1-score (micro) |
| :--- | :---: | :---: | :---: | :---: |
| BERT-Large | 330 M | 90.2 | 92.9 | 91.5 |
| T5-base (ours) | 220 M | 91.6 | 89.6 | 90.6 |

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We validated the use of a single seq2seq model for extracting information from four different classes of legal and registration documents in Portuguese

The model is trained end-to-end to output structured text, thus replacing parts of rule-based normalization and post-processing steps of a classical pipeline

Language (Portuguese) pretraining and tokenization are the most important adaptations to increase effectiveness

Pretraining on in-domain (legal) text and pre-finetuning on a large questionanswering dataset marginally improve results

## Sentence IDs and Canonical

## Sentence IDs

We propose a method to align answers with the input text, thus allowing seq2seq models to be more easily monitored and audited in IE pipelines

## Canonical Format

The model is capable of extracting canonical formats for dates that can originally appear in the document in various formats

```
[SENT14] [Issue Date]: 14/01/2020
```

[text] 14 days of the month of August of the year 2020

## Sentence IDs and Canonical




## Questions?


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https://github.com/neuralmind-ai/information-extraction-t5

