

# Oncology Use Cases

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### **Agenda**

- 1. Introduction
- 2. Case Study Samples
- 3. Problem Description
- 4. Solution Steps
- 5. Coding



# John Snow Labs Provides State-of-the-Art Medical Language Models

### 100+ million

Downloads on PyPI.

"Most Widely Used NLP
Library in the Enterprise."

O'Reilly Media

### **59% share**

of Healthcare NLP teams use John Snow Labs

**Gradient Flow** 

### **#1 Accuracy**

on 25 benchmarks in peer-reviewed papers

**Papers with Code** 



### Peer-Reviewed, State-of-the-Art Accuracy

John Snow Labs Peer-Reviewed Papers

## **Deeper Clinical Document Understanding Using Relation Extraction**

#### New state-of-the-art accuracy on:

2019 Phenotype-Gene Relations dataset

2018 n2c2 Posology Relations dataset

2012 Adverse Drug Events Drug-Reaction dataset

2012 i2b2 Clinical Temporal Relations challenge

2010 i2b2 Clinical Relations challenge

## **Biomedical Named Entity Recognition in Eight Languages with Zero Code Changes**

#### New state-of-the-art accuracy on:

LivingNER dataset using a single model architecture in English, French, Italian, Portuguese, Galatian, Catalan & Romanian

#### Mining Adverse Drug Reactions from Unstructured Mediums at Scale

#### **New state-of-the-art accuracy on:**

ADE benchmark
SMM4H benchmark
CADEC entity recognition dataset
CADEC relation extraction dataset

## **Accurate Clinical and Biomedical Named Entity Recognition at Scale**

#### New state-of-the-art accuracy on:

2018 n2c2 medication extraction 2014 n2c2 de-identification 2010 i2b2/VA clinical concept extraction 8 different Biomedical NLP benchmarks



### **Oncology Case Studies from the NLP Summit**



A Real-time NLP-Based Clinical Decision Support Platform for Psychiatry and Oncology



Accelerating Biomedical Innovation by Combining NLP and Knowledge Graphs



Large Language Models to Facilitate Building of Cancer Data Registries



Leveraging Healthcare NLP Models in Regulatory Grade Oncology Data Curation



Applying Natural Language Processing to Cancer Genomics



"Be Like Water" - NLP and GenAl Opportunities and Challenges in Healthcare



### Real-World Oncology Use Case-I

### ICD-10-CM Code Selection for Billing in an Oncology Hospital

**PROBLEM:** An oncology hospital needs to accurately select billable ICD-10-CM codes for insurance reimbursement. This process involves identifying the patient's current diagnoses, extracting the corresponding ICD-10-CM codes, and verifying that these codes are eligible for billing. Currently, this task is performed manually by medical coders, which is timeconsuming, error-prone, and susceptible to human error.





### Real-World Oncology Use Case-I

### ICD-10-CM Code Selection for Billing in an Oncology Hospital

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### **Real-World Oncology Use Case**



### **Solution Steps**



Entity Extraction (NER)

Create a robust NER pipeline and extract oncological entities and body parts.



Assertion Status Detection

Check the assertion status of the detected oncological entities.



**Relation Extraction** 

Extract relations between the oncological entities and body parts.



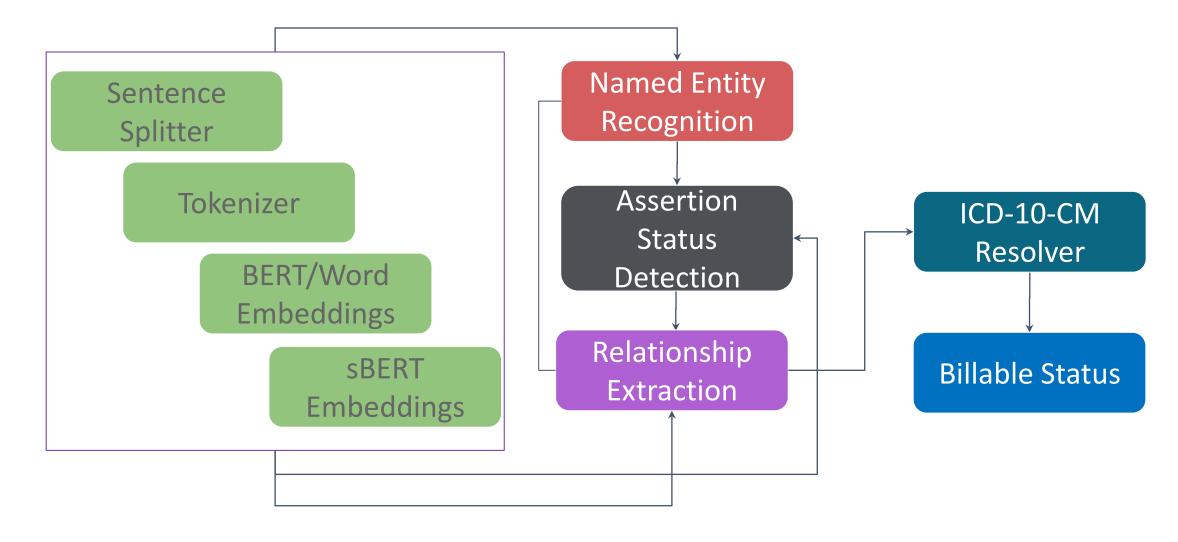
Code Mapping & Billing Status

Map the entities to their corresponding ICD-10-CM codes and check their billable status.



### **Real-World Oncology Use Case**





(Resolvers can be mapped to each other using the pretrained mapper module or resolved from scratch using the same sBert Embeddings)



## **Out-of-the-Box Oncology NLP Models**

#### **Medical NER Models**

ner_oncology_langtest	ner_biomarker
ner_oncology_limited_80p_for_benchmarks	ner_biomarker_langtest
ner_oncology_posology	ner_oncology
ner_oncology_posology_langtest	ner_oncology_anatomy_general
ner_oncology_response_to_treatment	ner_oncology_anatomy_general_healthcare
ner_oncology_response_to_treatment_langtest	ner_oncology_anatomy_general_langtest
ner_oncology_test	ner_oncology_anatomy_granular
ner_oncology_test_langtest	ner_oncology_anatomy_granular_langtest
ner_oncology_therapy	
ner_oncology_therapy_langtest	ner_oncology_biomarker
ner_oncology_tnm	ner_oncology_biomarker_healthcare
ner_oncology_tnm_langtest	ner_oncology_biomarker_langtest
ner_oncology_unspecific_posology	ner_oncology_demographics
ner_oncology_unspecific_posology_healthcare	ner_oncology_demographics_langtest
ner_oncology_unspecific_posology_langtest	ner_oncology_diagnosis
	ner_oncology_diagnosis_langtest
	ner_oncology_emb_clinical_large

ner oncology emb clinical medium

### Relation Extraction Models

re\_oncology
re\_oncology\_biomarker\_result
re\_oncology\_granular
re\_oncology\_location
re\_oncology\_size
re\_oncology\_temporal
re\_oncology\_test\_result

#### Relation Extraction DL Models

redl\_oncology\_biobert

redl\_oncology\_biomarker\_result\_biobert

redl\_oncology\_granular\_biobert

redl\_oncology\_location\_biobert

redl\_oncology\_size\_biobert

redl\_oncology\_temporal\_biobert

redl\_oncology\_test\_result\_biobert

### **Assertion Status Detection Models**

assertion\_oncology
assertion\_oncology\_demographic\_binary
assertion\_oncology\_family\_history
assertion\_oncology\_problem
assertion\_oncology\_response\_to\_treatment
assertion\_oncology\_smoking\_status
assertion\_oncology\_test\_binary
assertion\_oncology\_treatment\_binary

### **Sequence Classification Models**

bert\_sequence\_classifier\_biomarker bert\_sequence\_classifier\_response\_to\_treatment

- **32** NER Models
- **7** Relation Extraction Models
- **7** Relation Extraction DL Models
- Assertion Status Detection Models
- **2** Sequence Classification Models



## **Out-of-the-Box Oncology NLP Models**



#### Explore Oncology Notes with Spark NLP Models

This demo shows how oncological terms can be detected using Spark NLP Healthcare NER, Assertion (...)







Identify Anatomical and Oncology entities related to different Treatments and Diagnosis from Clinical Texts

This demo shows how to extract more than 40 Oncology-related entities including those related (...)







### Identify Tests, Biomarkers, and their Results

This demo shows how to extract entities Pathology Tests, Imaging Tests, mentions of Biomarkers, (...)







#### Identify Demographic Information from Oncology Texts

This demo shows how to extract Demographic information, Age, Gender, and Smoking status fro (...)







### Detect Assertion Status from Clinics Entities

This demo shows how to detect the assertion status of entities related to oncology (including diagnoses, (...)







#### Detect Relation Extraction between different Oncological entity types

This demo shows how to identify relations between Clinical entities, Tumor mentions, Anatomical (...







#### Resolve Oncology terminology using the ICD-O taxonomy

This model maps oncology terminology to ICD-O codes using Entity Resolvers.



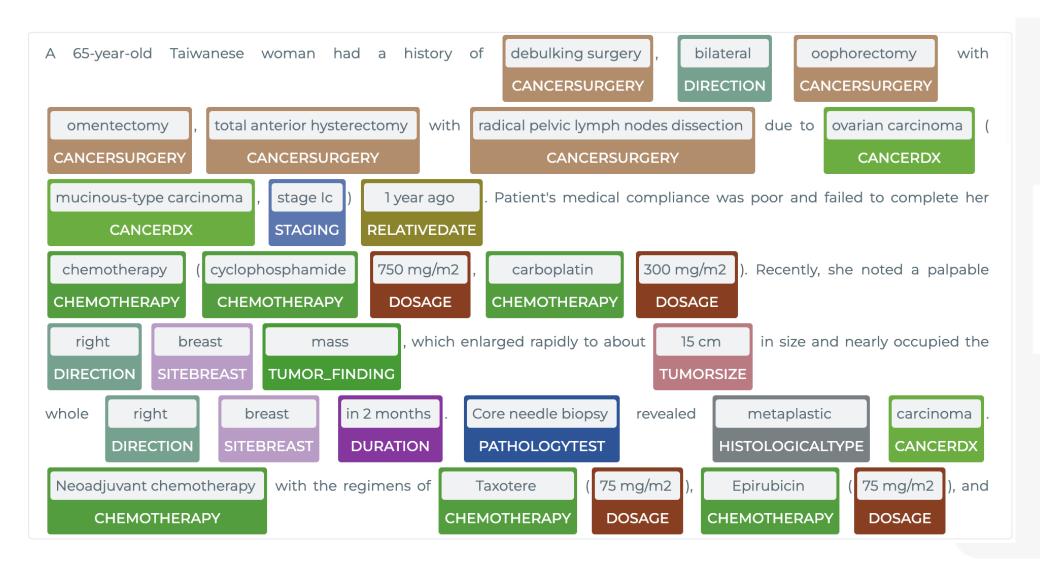


https://nlp.johnsnowlabs.com/oncology



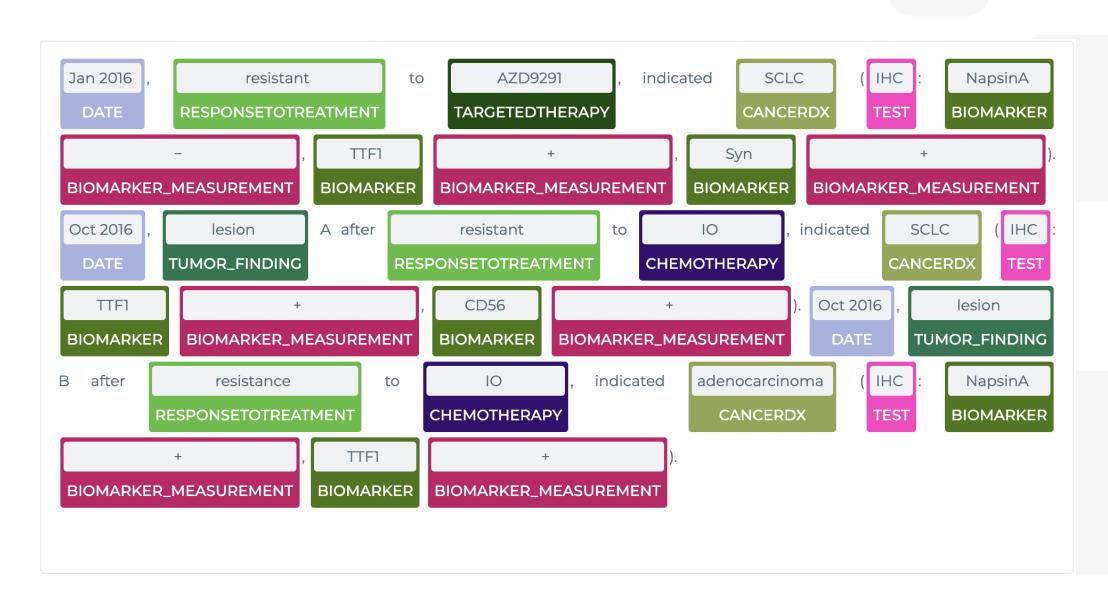
## **Pre-trained Entity Recognition - Oncology**

#### Text annotated with identified Named Entities





# **Pre-trained Entity Recognition - Biomarkers**





### **Assertion Status Detection**

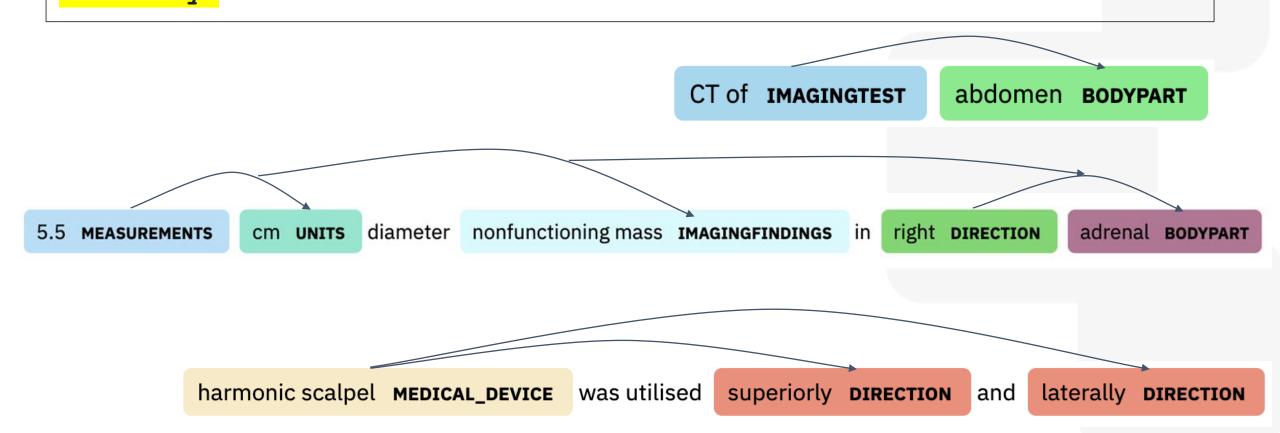
"Mother with a lung cancer, a patient is diagnosed as breast cancer in 1991 and then admitted to Mayo Clinic in Oct 2000, went under chemo for 6 months, discharged in April 2001 with a prescription of 2 mg metformin 3x per day. No sign of gynecological disorder but she suffers from acute cramps if she doesn't take her drug."

Chunk	Entity	Assertion
lung cancer	Oncological	Family
breast cancer	Oncological	Past
chemo	Treatment	Past
gynecological disorder	Disorder	Absent
acute cramps	Disorder	Conditional



### **Relation Extraction**

"This is a 52-year-old inmate with a 5.5 cm diameter nonfunctioning mass in his right adrenal shown by CT of abdomen. During the umbilical hernia repair, the harmonic scalpel was utilised superiorly and laterally."





### **Entity Resolution to Standard Terminologies**

This is a 52-year-old **AGE** inmate with a 5.5 MEASUREMENTS nonfunctioning mass **SYMPTOM** diameter cm units right **DIRECTION** adrenal **BODYPART** CT of **IMAGINGTEST** his **GENDER** shown by abdomen **BODYPART** . During the umbilical hernia repair **PROCEDURE** harmonic scalpel **MEDICAL\_DEVICE** was utilised superiorly **DIRECTION** , the and laterally **DIRECTION** .

# **Entity Resolution**

ICD10CM, Snomed,

RxNorm, CPT-4,

ICD10CPS, RXCUI, ICDO,

UMLS, ATC, HPO,

	Term	Vocab	Code	Explanation (ground truth)
	СТ	CPT-4	76497	Unlisted computed tomography procedure
	CT of <mark>abdomen</mark>	CPT-4	74150	Computed tomography, abdomen; without contrast material
),	umbilical hernia repair	CPT-4	49587	Repair <mark>umbilical hernia</mark> , age <mark>5 years or older</mark> ; incarcerated or strangulated
	nonfunctioning mass, right adrenal	ICD10CM	D35.01	Benign <mark>neoplasm</mark> of <mark>right adrenal gland</mark>



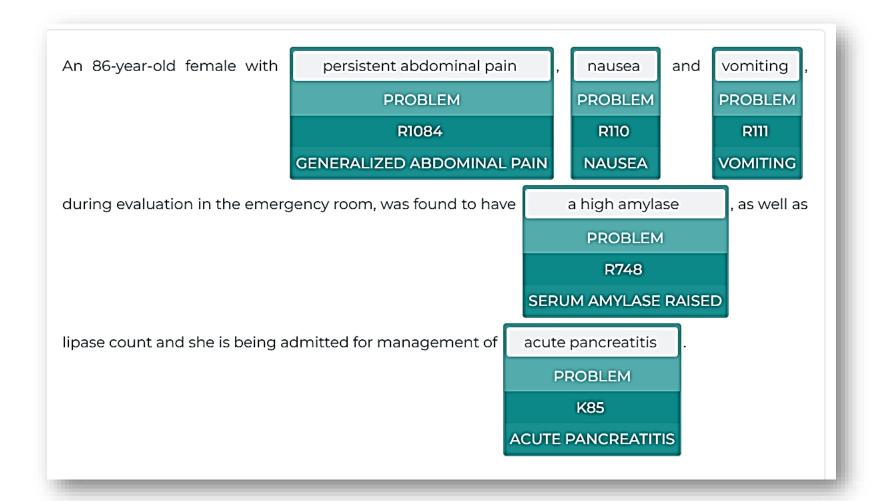
## 4-6x Fewer Errors than AWS, Azure, & GCP

www.johnsnowlabs.com/comparison-of-key-medical-nlp-benchmarks-spark-nlp-vs-aws-google-cloud-and-azure/



### **Benchmark: Extracting ICD-10-CM Codes**

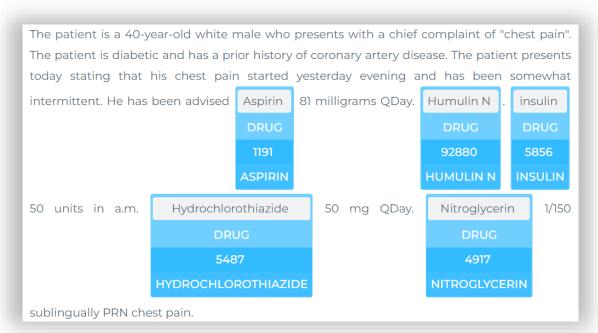


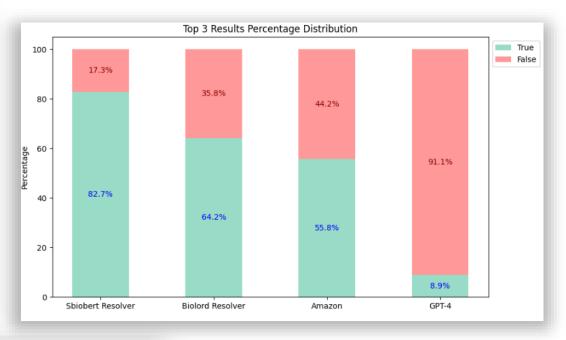


Extracting ICD-10-CM codes is done with a 76% success rate vs. 26% for GPT-3.5 and 36% for GPT-4.

### **Benchmark: Extracting RxNorm Codes**







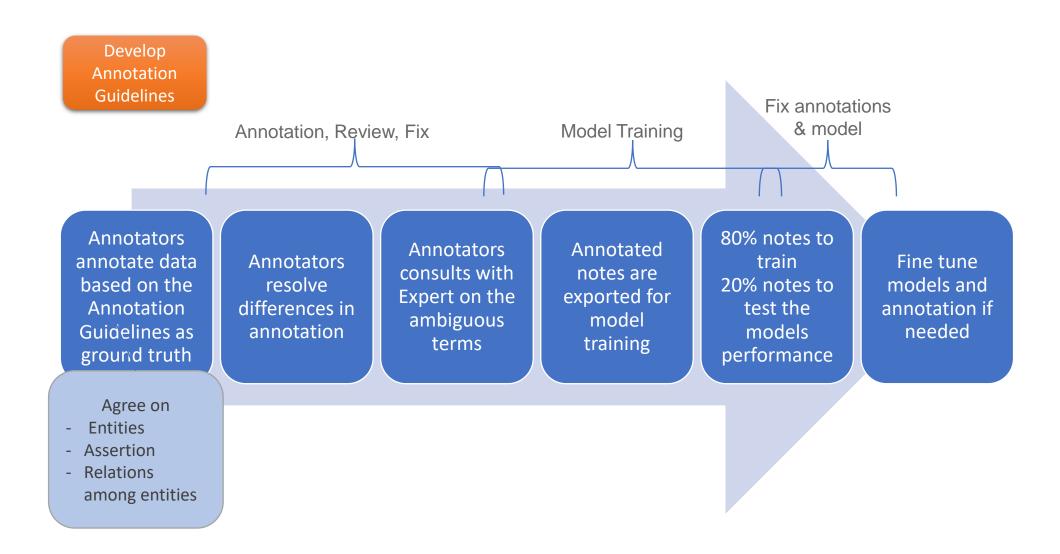
	Top-3 Accuracy	Top-5 Accuracy	Cost
Healthcare NLP	82.7%	84.6%	\$4,500
Amazon Comprehend Medical	55.8%	56.2%	\$24,250
GPT-4 (Turbo)	8.9%	8.9%	\$44,000
GPT-40	8.9%	8.9%	\$22,000

Extracting RxNorm codes is done with a 82.7% success rate vs. 55.8% for Amazon and 8.9% for GPT-4.

Also 5x times cheaper!

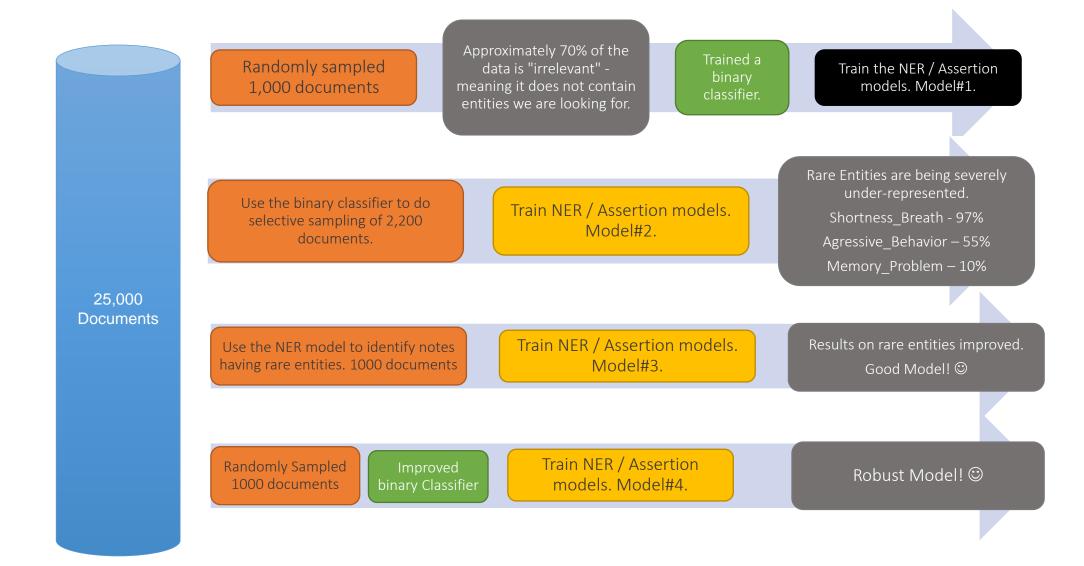


### **Model Training Process overview**





### **Model Training and Evaluation Process**

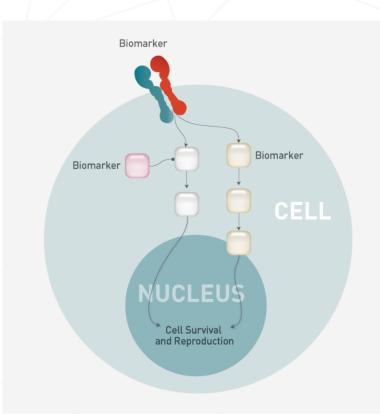




### Real-World Oncology Use Case-II

# Biomarker and Biomarker Result Table Generation from Oncology Notes

**PROBLEM:** Oncology researchers require a method to efficiently extract and organize biomarker and biomarker result information specifically from sections within oncology notes dedicated to biomarker analysis. This information is crucial for data analysis and biomarker research. Currently, manually extracting this data from extensive oncology notes is timeconsuming, labor-intensive, and susceptible to human error.

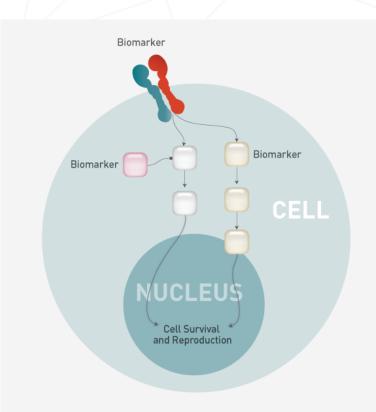




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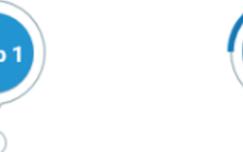
### Real-World Oncology Use Case-II



### **Solution Steps**



Sequence Classification



Entity Extraction (NER)

Step 2

Create a robust NER pipeline and extract biomarker and biomarker result entities from the sequences related to biomarker.



**Relation Extraction** 

the biomarker and biomarker results.

Classify the sequences to determine whether they are related to the biomarker or not.





# Let's code!

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