

# Oncology Research And Treatment With Healthcare NLP

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# Agenda

1. Introduction
2. Case Study Samples
3. Use Case I - Analysis Based On Cancer Types
4. Use Case II - Biomarker Table Generation
5. Coding

# Healthcare AI Expert - 10 Year Growth

**120+**  
million

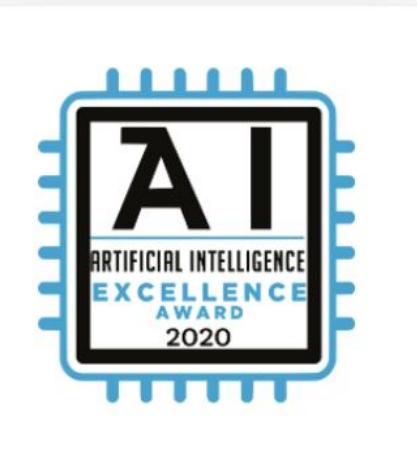
downloads on PyPI. “Most Widely Used NLP Library in the Enterprise.”  
**O'Reilly Media**

**54%**  
share

of GenAI in Healthcare projects at large companies 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

## 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

## 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, Galician, Catalan & Romanian

## 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



National Cancer  
Centre Singapore  
SingHealth

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



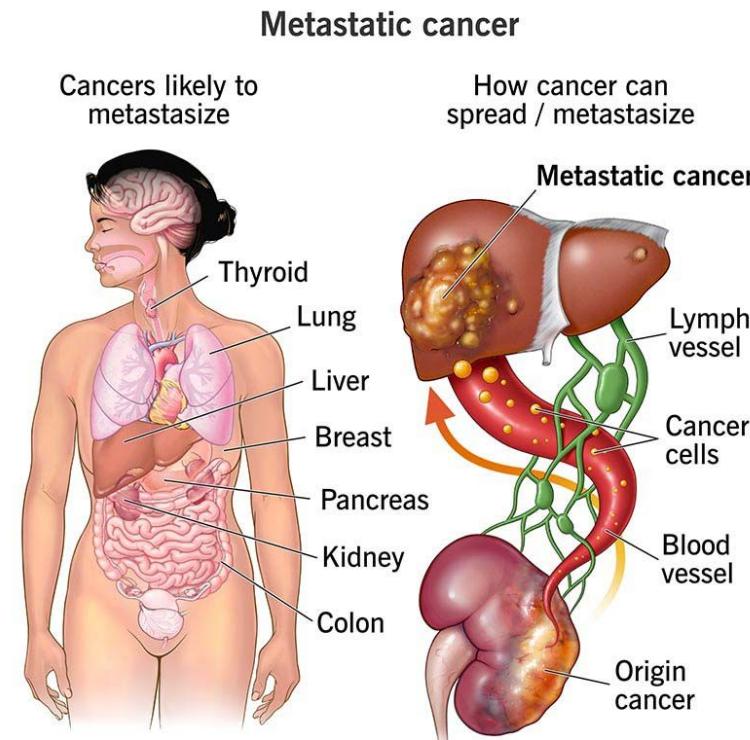
Fred Hutch  
Cancer Center

"Be Like Water" – NLP and GenAI Opportunities and Challenges in Healthcare

# Use Case I - Analysis Based On Cancer Types

## Analyzing Oncological Entities and Disease Progression

To assess **disease progression** and identify cases where cancer has **metastasized** beyond its primary site, clinical documents can be filtered for mentions of **metastasis**. Analyzing oncological entities within these documents, along with their associations to specific **body parts**, offers critical insights into **cancer spread patterns**. This information can support more accurate staging and guide personalized **treatment planning**.



# Real-World Oncology Use Case

## Solution Steps

01



### Document Filtering

Filter the documents which contain “metastasis” entity.

02



### Entity Extraction (NER)

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

03



### Assertion Status Detection

Check the assertion status of the detected oncological entities.

04



### Relation Extraction

Extract relations between the oncological entities and body parts.

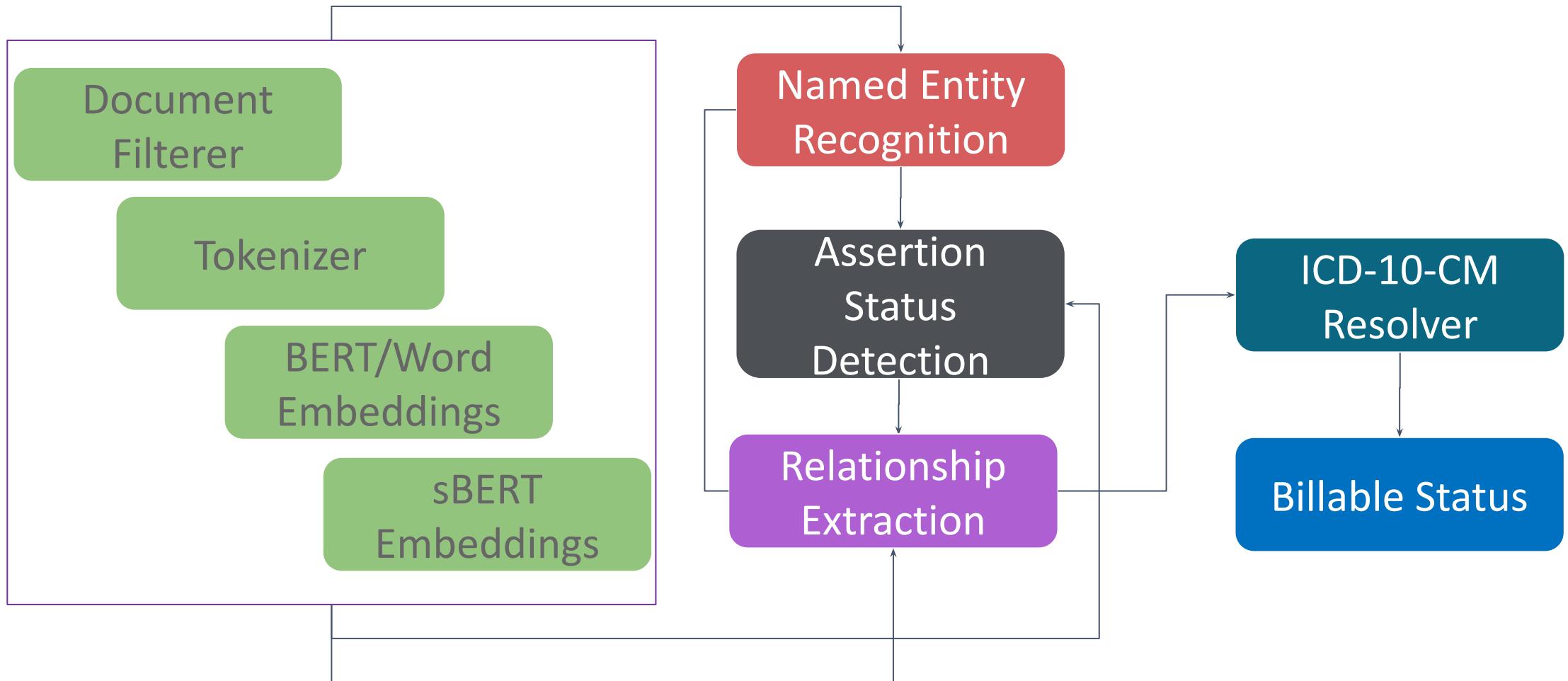
05



### Entity Resolution

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)*

# Oncology NLP Models

## Medical NER Models

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

## Relation Extraction Models

re_oncology	redl_oncology_biobert
re_oncology_biomarker_result	redl_oncology_biomarker_result_biobert
re_oncology_granular	redl_oncology_granular_biobert
re_oncology_location	redl_oncology_location_biobert
re_oncology_size	redl_oncology_size_biobert
re_oncology_temporal	redl_oncology_temporal_biobert
re_oncology_test_result	redl_oncology_test_result_biobert

## Sequence Classification

bert_sequence_classifier_biomarker
bert_sequence_classifier_response_to_treatment

## 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

**35 NER Models**

**7 Relation Extraction Models**

**7 Relation Extraction DL Models**

**8 Assertion Status Detection Models**

**2 Sequence Classification Models**

# Entity Extraction

Adenopathy	Leukemia_Type
Age	Leukemia
Anatomical_Site	Line_Of_Therapy
Biomarker	Lymph_Node
Biomarker_Measurement	Lymph_Node_Modifier
Biomarker_Quant	Lymphoma_Type
Biomarker_Result	Melanoma
Body_Site	Metastasis
CNS_Tumor_Type	Oncogene
CancerDx	Other_Tumors
CancerModifier	Pathology_Result
Cancer_Score	Pathology_Test
Cancer_Surgery	Performance_Status
Cancer_Therapy	Predictive_Biomarkers
Carcinoma_Type	Prognostic_Biomarkers
Chemotherapy	RNA
Cycle_Count	Radiation_Dose
Cycle_Day	Radiological_Test
Cycle_Number	Radiological_Test_Result
DNA	Radiotherapy
Date	Response_To_Treatment
Death_Entity	Route
Direction	Sarcoma_Type
Dosage	Smoking_Status
Drug	Staging
Duration	Size_Trend
Ethnicity	Targeted_Therapy
Frequency	Test
Gender	Test_Result
Grade	Tumor
Histological_Type	Tumor_Size
Hormonal_Therapy	cell_line
Imaging_Test	cell_type
Immunotherapy	...

A	65 year old	woman	had a history of	debulking surgery	,	bilateral	oophorectomy	with	omentectomy	,
	AGE	GENDER		CANCER_SURGERY		DIRECTION	CANCER_SURGERY		CANCER_SURGERY	
	total anterior hysterectomy	with	radical pelvic lymph nodes dissection	due to	ovarian carcinoma	(	mucinous-type		carcinoma	)
	CANCER_SURGERY		CANCER_SURGERY		CANCER_DX	(	HISTOLOGICAL_TYPE		CANCER_DX	)
	stage Ic	)	1 year ago	. Patient's medical compliance was poor and failed to complete	her	chemotherapy	(	cyclophosphamide		
	STAGING		RELATIVE_DATE		GENDER	CHEMOTHERAPY	(	CHEMOTHERAPY		)
	750 mg/m2	,	carboplatin	300 mg/m2	). Recently,	she	noted a palpable	right	breast	mass
	DOSAGE		CHEMOTHERAPY	DOSAGE		GENDER		DIRECTION	SITE_BREAST	TUMOR_FINDING
	15 cm	in size which nearly occupied the whole			right	breast	in 2 months		Core needle biopsy	revealed
	TUMOR_SIZE				DIRECTION	SITE_BREAST	RELATIVE_DATE		PATHOLOGY_TEST	
	metaplastic	carcinoma	.	Neoadjuvant chemotherapy	with the regimens of	Taxotere	(	75 mg/m2	),	Epirubicin
	HISTOLOGICAL_TYPE	CANCER_DX		CHEMOTHERAPY		CHEMOTHERAPY	(	DOSAGE	),	CHEMOTHERAPY
	75 mg/m2	Dosage), and	Cyclophosphamide	(	500 mg/m2	) was given for	6 cycles	with	poor response	, followed by a
	DOSAGE		CHEMOTHERAPY		DOSAGE		CYCLE_COUNT		RESPONSE_TO_TREATMENT	

```

labels = ["Adenopathy", "Age", "Biomarker", "Biomarker_Result", "Body_Part", "Cancer_Dx", "Cancer_Surgery",
          "Cycle_Count", "Cycle_Day", "Date", "Death_Entity", "Direction", "Dosage", "Duration", "Frequency",
          "Gender", "Grade", "Histological_Type", "Imaging_Test", "Invasion", "Metastasis", "Oncogene", "Pathology_Test",
          "Race_Ethnicity", "Radiation_Dose", "Relative_Date", "Response_To_Treatment", "Route", "Smoking_Status",
          "Staging", "Therapy", "Tumor_Finding", "Tumor_Size"]

pretrained_zero_shot_ner = PretrainedZeroShotNER().pretrained("zeroshot_ner_oncology_medium", "en", "clinical/models")\
    .setInputCols("sentence", "token")\
    .setOutputCol("ner")\
    .setPredictionThreshold(0.5)\n    .setLabels(labels)

```

# Assertion Status Detection

## 13 Assertion Status Labels

Present  
 Past  
 Present\_Or\_Past  
 Absent  
 Someone\_Else  
 Family  
 Family\_History  
 Hypothetical  
 Hypothetical\_Or\_Absent  
 Possible  
 Patient  
 Medical\_History  
 Other

Chest CT revealed pulmonary lesions in the right upper lobe, and peripheral lung cancer. Multiple metastases of the thoracic vertebrae, sternum, and ribs were seen, which were similar to previous CT images. Chemotherapy was recommended.

The patient is a 50-year-old white gentleman, heavy smoker, with recent diagnosis of lung cancer. Family history is positive for

lung cancer in his father and his brother. A CT scan was performed to rule out metastases.

A 53-year-old man with diagnosis of colorectal carcinoma was admitted with loss of consciousness. His sister was diagnosed with ovarian cancer when she was 50 y.o., and his mother died of breast cancer at age 40.

AGE OTHER CANCER\_DX OTHER DEATH\_ENTITY FAMILY\_HISTORY CANCER\_DX FAMILY\_HISTORY AGE FAMILY\_HISTORY

# Relation Extraction

## 5 Relation Extraction Labels

is\_date\_of  
is\_finding\_of  
is\_location\_of  
is\_related\_to  
is\_size\_of

A 47-year-old female patient was treated by **breast conserving surgery** CANCER SURGERY in **2008** DATE.

At that time a **3 cm** TUMOR\_SIZE **tumor** TUMOR\_FINDING was found in her left **breast** SITE\_BREAST. Her tumor is **positive** BIOMARKER\_RESULT and **positive** BIOMARKER\_RESULT.

In 2018, cystoscopy revealed a 10-mm sessile **tumor** TUMOR\_FINDING on the right **bladder wall** SITE\_OTHER\_BODY\_PART.

In 2018, cystoscopy revealed a **10-mm** TUMOR\_SIZE **sessile** **tumor** TUMOR\_FINDING on the right bladder wall.

# Entity Resolution to Standard Terminologies

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

## Entity Resolution

ICD10CM, Snomed,  
RxNorm, CPT-4,  
ICD10CPS, RxCUI, ICDO,  
UMLS, ATC, HPO, ...

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

# Out-of-the-Box Oncology NLP Models

 John Snow LABS

Home Docs Learn Models **Demo**   

## Oncology - Clinical NLP Demos & Notebooks

**Demos Categories**

- [Spark NLP: English](#) 
- [Spark NLP: World Languages](#) 
- [Clinical NLP](#) 

  - De-Identification
  - Diagnoses & Procedures
  - Drugs & Adverse Events
  - Labs, Tests, and Vitals
  - Analyze Clinical Notes
  - Radiology
  - Oncology**
  - Resolve Entities to Terminology Codes
  - Databricks Solution Accelerators
  - Social Determinants of Health
  - Risk Factors
  - LangTest
  - Explore Healthcare NLP Models

### Oncology - Live Demos & Notebooks

 Explore Oncology Notes with Spark NLP Models

This demo shows how oncological terms can be detected using Spark NLP Healthcare NER, Assertion Status, and Relation Extraction [\(...\)](#)

 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 to Cancer diagnosis, Staging information, [\(...\)](#)

 Identify Tests, Biomarkers, and their Results

This demo shows how to extract entities Pathology Tests, Imaging Tests, mentions of Biomarkers, and their results from clinical t [\(...\)](#)

 Identify Demographic Information from Oncology Texts

This demo shows how to extract Demographic information, Age, Gender, and Smoking status from oncology texts. [\(...\)](#)

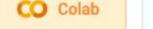
 Detect Assertion Status from Clinics Entities

This demo shows how to detect the assertion status of entities related to oncology (including diagnoses, therapies, and tests), and if a [\(...\)](#)

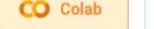
 Detect Relation Extraction between different Oncological entity types

This demo shows how to identify relations between Clinical entities, Tumor mentions, Anatomical entities, Tests, Biomarkers, [\(...\)](#)

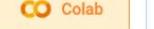
 Resolve Oncology terminology using the ICD-O taxonomy

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

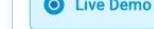
 Bert For Sequence Classification (Biomarker)

This model is a sentence classification system based on BioBERT that is capable of identifying if clinical sentences contain terms associa [\(...\)](#)

 Oncological Response to Treatment for Classification

This model is intended to detect oncological responses to treatments in clinical notes.

 Classify Complaints about Healthcare Facilities

This demo classifies google reviews of various healthcare facilities.

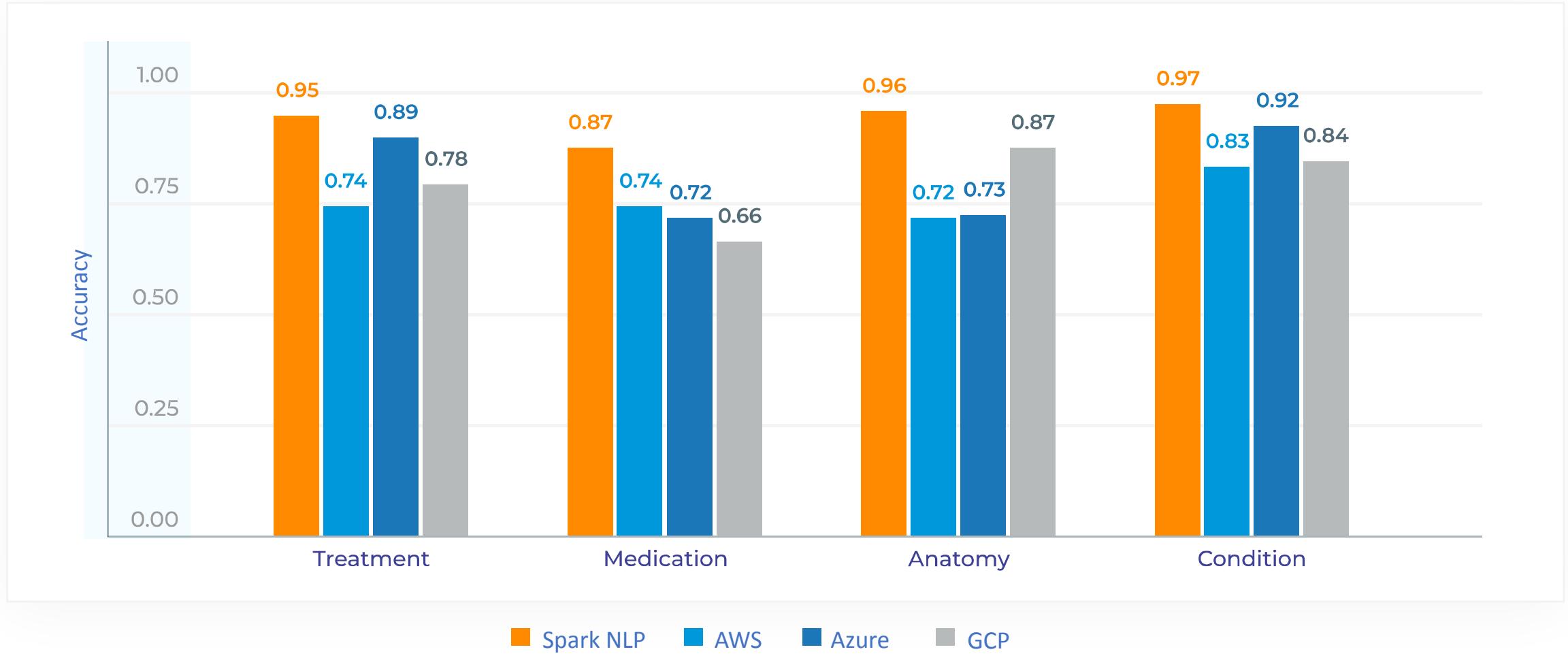
 Multilabel Classification For Hallmarks of Cancer

This demo semantically classifies an article based on its abstract, specifically related to the hallmarks of cancer. [\(...\)](#)

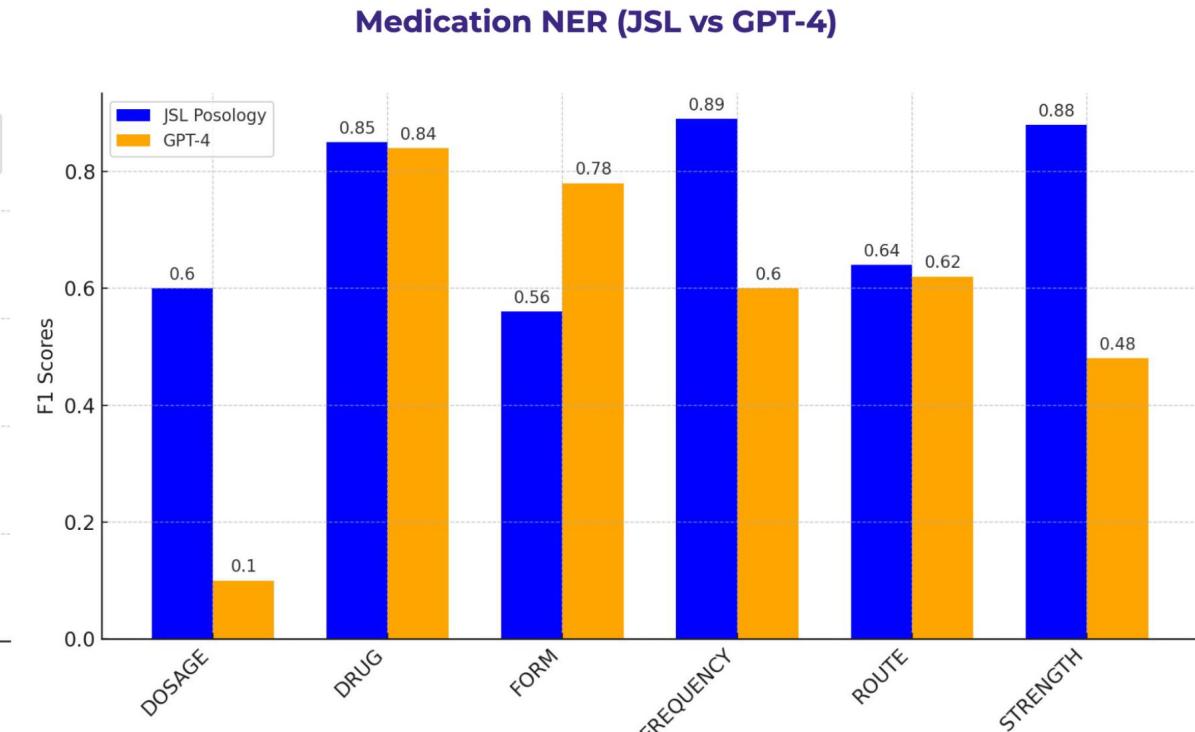
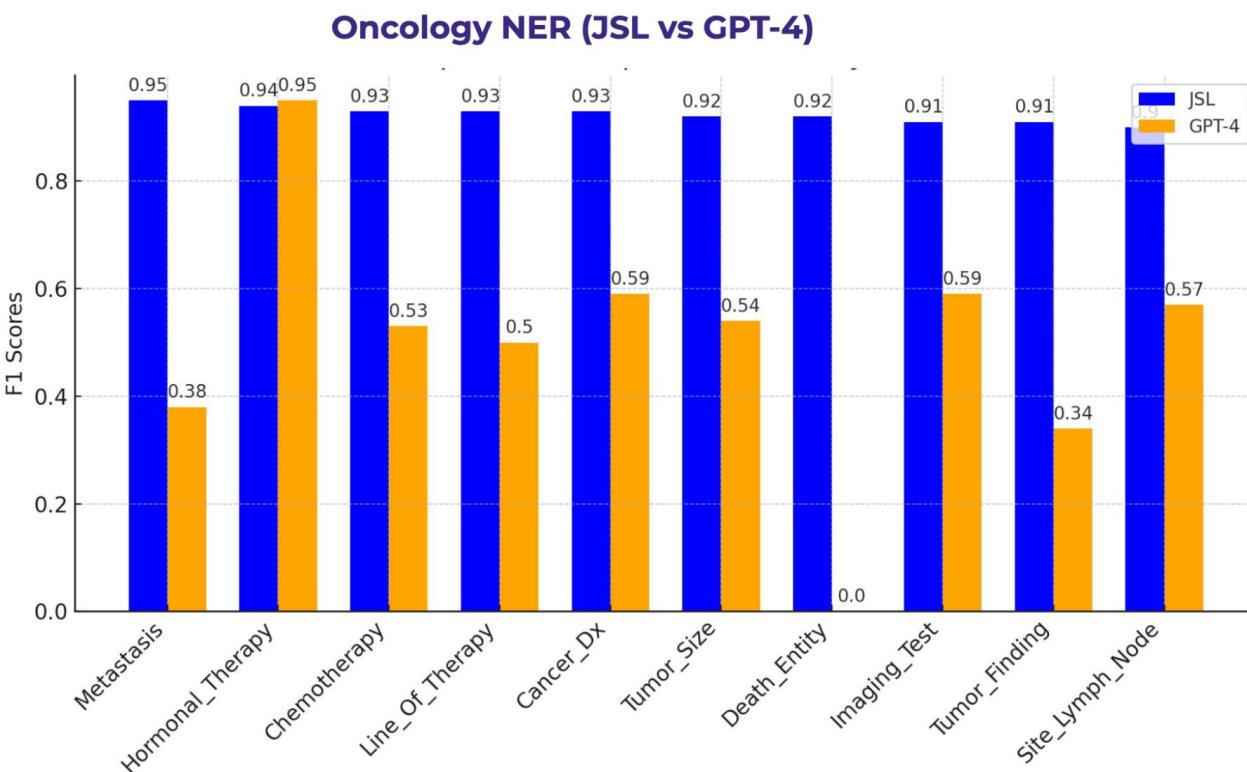
 

# 4-6x Fewer Errors than AWS, Azure, & GCP

[www.johnsnowlabs.com/comparison-of-key-medical-nlp-benchmarks-spark-nlp-vs-aws-google-cloud-and-azure/](http://www.johnsnowlabs.com/comparison-of-key-medical-nlp-benchmarks-spark-nlp-vs-aws-google-cloud-and-azure/)



# Benchmark: NER Metrics



Spark NLP Clinical Models			AWS Medical Comprehend			GCP Healthcare API				
Entity	Sample	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Problem	4891	0.726	0.585	<b>0.648</b>	0.539	0.478	0.507	0.850	0.516	0.642
Test	5903	0.782	0.662	<b>0.717</b>	0.594	0.703	0.644	0.576	0.461	0.512
Drug	10284	0.946	0.882	0.913	0.815	0.910	0.860	0.962	0.885	<b>0.922</b>
Avg. F1			<b>0.759</b>			0.670			0.692	

# Benchmark: Extracting ICD-10-CM Codes



An 86-year-old female with persistent abdominal pain, nausea and vomiting,

**PROBLEM**

R1084

**GENERALIZED ABDOMINAL PAIN**

nausea

**PROBLEM**

R110

**NAUSEA**

vomiting

**PROBLEM**

R111

**VOMITING**

during evaluation in the emergency room, was found to have a high amylase, as well as

**PROBLEM**

R748

**SERUM AMYLASE RAISED**

lipase count and she is being admitted for management of acute pancreatitis.

acute pancreatitis

**PROBLEM**

K85

**ACUTE PANCREATITIS**

**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



The patient is a 40-year-old white male who presents with a chief complaint of "chest pain". The patient is diabetic and has a prior history of coronary artery disease. The patient presents today stating that his chest pain started yesterday evening and has been somewhat intermittent. He has been advised

Aspirin	81 milligrams QDay.
DRUG	
1191	.insulin
ASPIRIN	

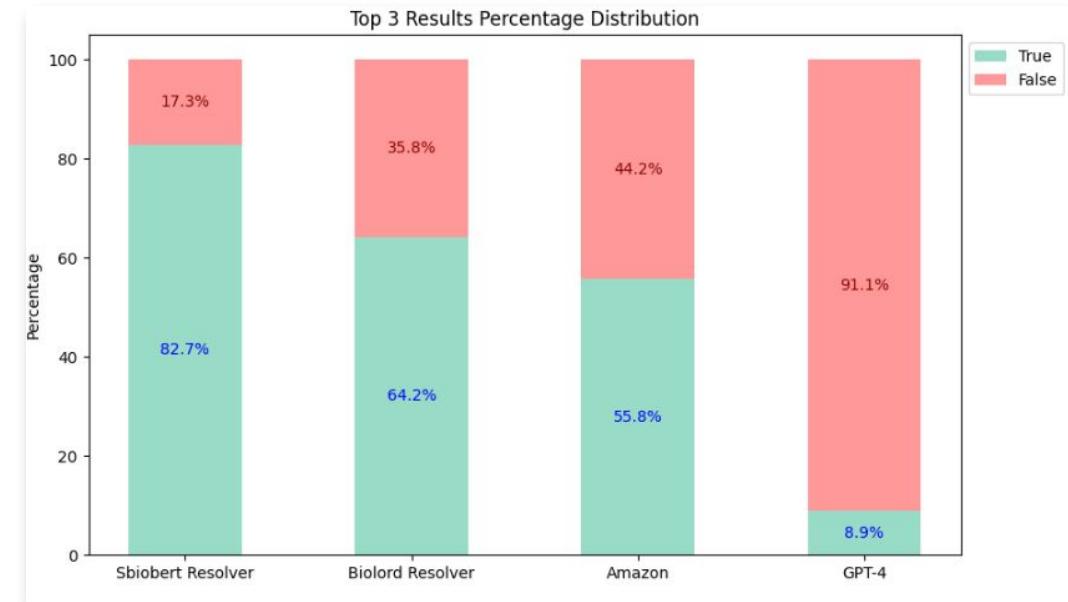
Humulin N	
DRUG	
92880	5856
HUMULIN N	INSULIN

50 units in a.m. Hydrochlorothiazide 50 mg QDay. Nitroglycerin 1/150

Hydrochlorothiazide	DRUG
5487	
HYDROCHLOROTHIAZIDE	

Nitroglycerin	DRUG
4917	
NITROGLYCERIN	

sublingually PRN chest pain.

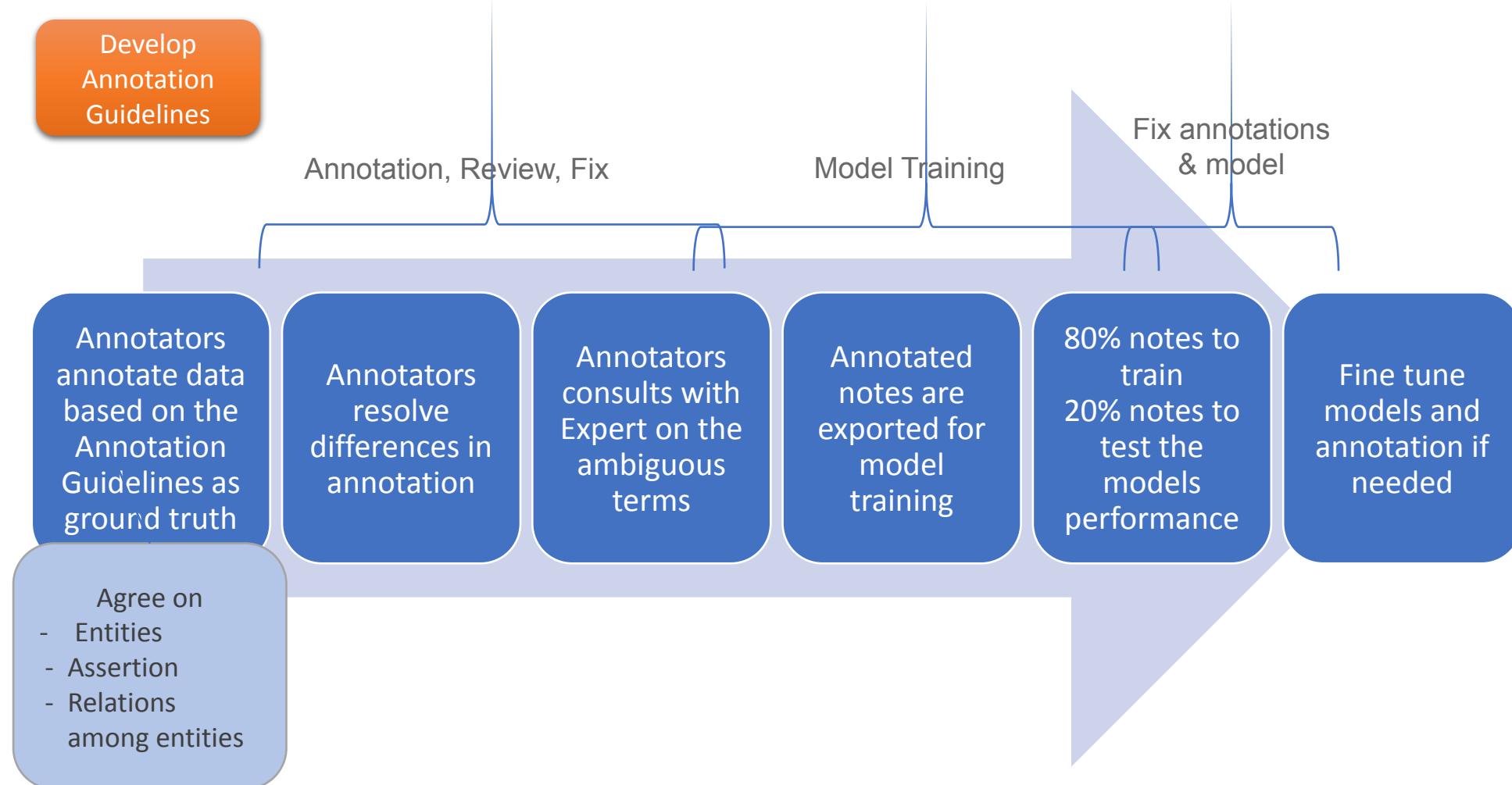


	Top-3 Accuracy	Top-5 Accuracy	Cost
Healthcare NLP	82.7%	84.6%	\$4,500
Amazon Comprehend Medical	55.8%	56.2%	\$24,250
GPT-4 (Turbo)	8.9%	8.9%	\$44,000
GPT-4o	8.9%	8.9%	\$22,000

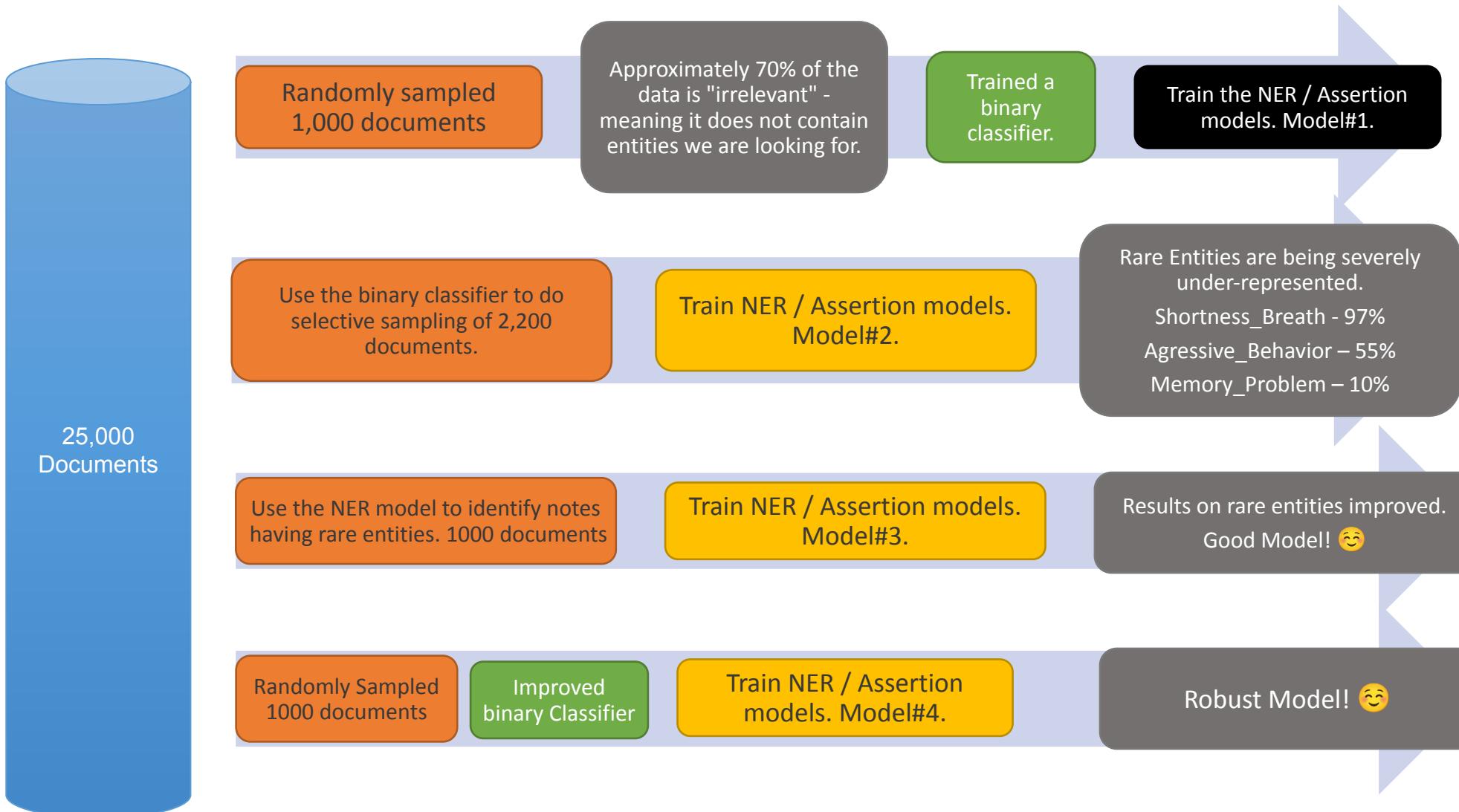
Extracting RxNorm codes is done with a **82.7% success rate vs. 55.8% for Amazon and 8.9% for GPT-4.**

Also **5x times cheaper!**

# Model Training Process overview



# Model Training and Evaluation Process

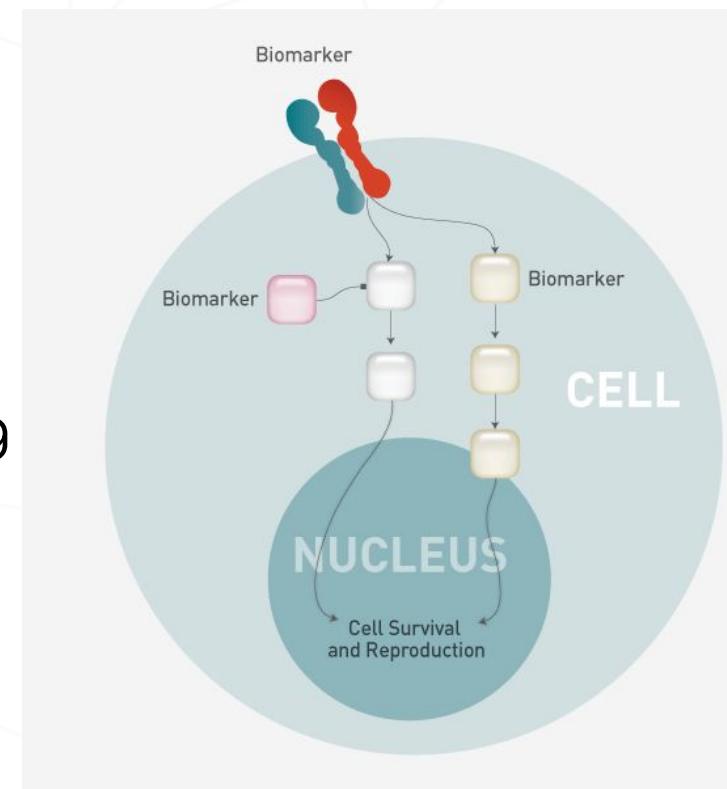


# Use Case II - Biomarker Table Extraction

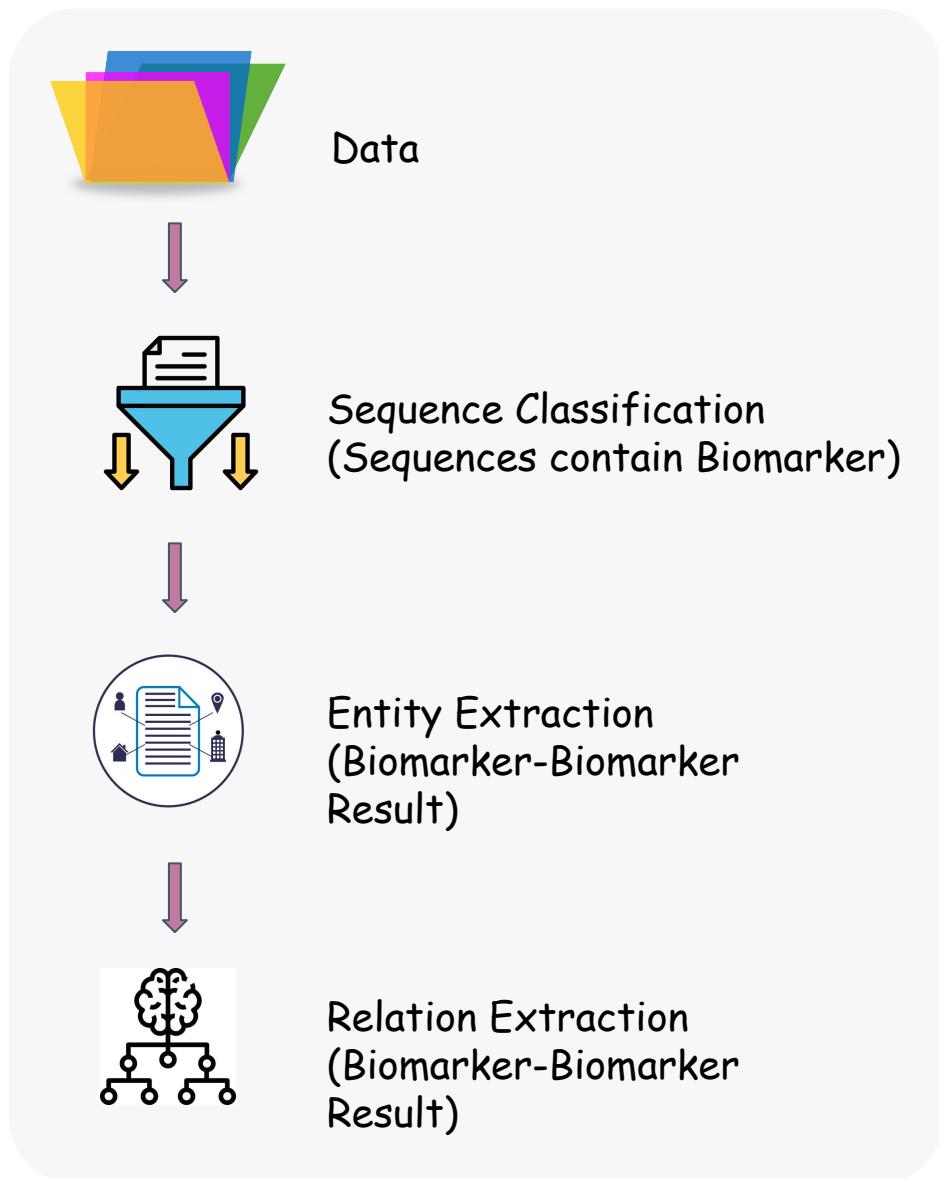


## Biomarker and Biomarker Result Table Generation from Oncology Notes

Oncology researchers often need an efficient approach to extract and organize **biomarker** and **biomarker result** information from specific sections of oncology notes focused on biomarker analysis. This data is essential for both research and analysis. However, manually retrieving this information from lengthy oncology notes is time-consuming, labor-intensive, and prone to human error.



# Use Case II - Biomarker Table Extraction



## Patient

Name: Patient, Test  
 Date of Birth: XX/Mon/19XX  
 Sex: Male  
 Case Number: TN19-XXXXXX  
 Diagnosis: Mucinous adenocarcinoma

## Specimen Information

Primary Tumor Site: Transverse colon  
 Specimen Site: Liver  
 Specimen ID: ABC-1234-XYZ  
 Specimen Collected: XX-Mon-2019  
 Completion of Testing: XX-Mon-2019

## Ordered By

Ordering Physician, MD  
 Cancer Center  
 123 Main Street  
 Springfield, XY 12345, USA  
 1 (123) 456-7890

## High Impact Results

Biomarker	Method	Result	Therapy Association		Biomarker Level*
Mismatch Repair Status	IHC	Deficient	BENEFIT	nivolumab, nivolumab/ipilimumab combination, pembrolizumab	Level 1
MSI	NGS	High	BENEFIT	Irinotecan + [cetuximab or panitumumab] + vemurafenib	Level 2
BRAF	NGS	Mutated, Pathogenic Exon 15   p.V600E	LACK OF BENEFIT	vemurafenib/dabrafenib monotherapy	Level 3A
ERBB2 (Her2/Neu)	CISH	Amplified	BENEFIT	lapatinib, pertuzumab, trastuzumab	Level 3A

\* Biomarker reporting classification: Level 1 - highest level of clinical evidence and/or biomarker association included on the drug label; Level 2 - strong evidence of clinical significance and is endorsed by standard clinical guidelines; Level 3 - potential clinical significance (3A - evidence exists in patient's tumor type, 3B - evidence exists in another tumor type).

## Important Note

This patient has a potential NCI-MATCH Trial-eligible result. Please see Clinical Trial see page 6

## Additional Results

CANCER TYPE RELEVANT BIOMARKERS		
Biomarker	Method	Result
NTRK1	RNA-Seq	Fusion Not Detected
NTRK2	RNA-Seq	Fusion Not Detected
NTRK3	RNA-Seq	Fusion Not Detected
Tumor Mutational Burden		High   121 Mutations/Mb
ERBB2 (Her2/Neu)	NGS	Amplified
KRAS	NGS	Mutation Not Detected
NRAS	NGS	Mutation Not Detected
PIK3CA	NGS	Mutation Not Detected

CANCER TYPE RELEVANT BIOMARKERS (cont)		
Biomarker	Method	Result
PTEN	IHC	Positive   1+, 55%
OTHER FINDINGS (see page 2 for additional results)		
PD-L1	SP142 IHC	Positive   2+, 5%
FBXW7	NGS	Mutated, Pathogenic Exon 10   p.R479Q
TSC1	NGS	Mutated, Pathogenic Exon 12   p.N891fs
CCNE1	NGS	Amplified

relations	entity1_begin	entity1_end	chunk1	entity1	entity2_begin	entity2_end	chunk2	entity2
is_finding_of	968	975	negative	Biomarker_Result	981	1010	thyroid transcription factor-1	Biomarker
is_finding_of	968	975	negative	Biomarker_Result	1016	1023		napsin A Biomarker
is_finding_of	1040	1047	positive	Biomarker_Result	1053	1054		ER Biomarker
is_finding_of	1040	1047	positive	Biomarker_Result	1060	1061		PR Biomarker
is_finding_of	1068	1075	negative	Biomarker_Result	1081	1084		HER2 Biomarker

# Let's code!