John Snow LABS

# Spark NLP for Healthcare Data Scientists

**July 20-21, 2022**

**Veysel Kocaman**
**Head of Data Science**
**veysel@johnsnowlabs.com**

# Agenda

| Day | Dur. | Topic | Host |
|---|---|---|---|
| Day-1 | 50 min | - Intro to John Snow Labs and Spark NLP<br>- Healthcare NLP in Spark NLP | Veysel |
| | 50 min | - Clinical Named Entity Recognition *(nb 1, 1.5 and 7)* | Veysel |
| | 50 min | - Clinical Pretrained Pipelines *(nb 1, 1.5 and 7)* | Veysel |
| | 50 min | - Clinical Assertion Status Model *(nb 2)* | Hasham |
| Day-2 | 50 min | - Clinical Entity Resolution *(nb 3, 3.1, 13, 13.1)* | Veysel |
| | 50 min | - Clinical Entity Resolution *(nb 3, 3.1, 13, 13.1)*<br>- Misc *(ADE, ChunkMerger, ChunkMapper, ChunkKeyPhraseExtractor, ChunkSentenceSplitter, Generic Clf, Gender Clf)* *(nb 8, 9, 18, 16, 21)* | Veysel |
| | 50 min | - Clinical Relation Extraction Model *(nb 10, 10.1, 10.2, 10.3)* | Hasham |
| | 50 min | - De-Identification and Obfuscation of PHI *(nb 4)* | Luca |

# Colab Notebooks

**spark-nlp==4.0.0**
**spark-nlp-jsl==4.0.0**

Open in Colab

master · spark-nlp-workshop / tutorials / Certification_Trainings / Healthcare / · Go to file · Add file · ···

**RUNNING CODE:**
https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/Certification_Trainings/Healthcare
[How to set up Google Colab]

**BOOKMARK:**
https://nlp.johnsnowlabs.com/models
https://nlp.johnsnowlabs.com/docs/en/quickstart
spark-nlp.slack.com

### Clinical Named Entity Recognition

1.Clinical_Named_Entity_Recognition_Model.ipynb
1.2.Contextual_Parser_Rule_Based_NER.ipynb
1.3.prepare_CoNLL_from_annotations_for_NER.ipynb
1.4.Resume_MedicalNer_Model_Training.ipynb
1.5.BertForTokenClassification_NER_SparkNLP_with_Transformers.ipynb
7.Clinical_NER_Chunk_Merger.ipynb
16.Adverse_Drug_Event_ADE_NER_and_Classifier.ipynb

### Clinical Assertion

2.Clinical_Assertion_Model.ipynb
2.1.Scope_window_tuning_assertion_status_detection.ipynb

### Clinical Entity Resolution

3.Clinical_Entity_Resolvers.ipynb
3.1.Calculate_Medicare_Risk_Adjustment_Score.ipynb
3.2.Sentence_Entity_Resolvers_with_EntityChunkEmbeddings.ipynb
13.Snomed_Entity_Resolver_Model_Training.ipynb
13.1.Finetuning_Sentence_Entity_Resolver_Model.ipynb
22.CPT_Entity_Resolver.ipynb
24.Improved_Entity_Resolvers_in_SparkNLP_with_sBert.ipynb
24.1.Improved_Entity_Resolution_with_SentenceChunkEmbeddings.ipynb

### Clinical Relation Extraction

10.Clinical_Relation_Extraction.ipynb
10.1.Clinical_Relation_Extraction_BodyParts_Models.ipynb
10.2.Clinical_RE_Knowledge_Graph_with_Neo4j.ipynb
10.3.ZeroShot_Clinical_Relation_Extraction.ipynb

### Clinical De-identification

4.Clinical_DeIdentification.ipynb
4.1.Clinical_Deidentification_in_German.ipynb
4.2.Clinical_Deidentification_in_Spanish.ipynb
4.3.Clinical_Deidentification_SparkNLP_vs_Cloud_Providers_Comparison.ipyn
4.4.Clinical_Deidentification_SparkNLP_vs_SpaCy_Comparison.ipynb
4.5.Clinical_Deidentification_in_French.ipynb
4.6.Clinical_Deidentification_in_Italian.ipynb

### Optical Character Recognition with Spark OCR

5.Spark_OCR.ipynb
5.1.Spark_OCR_Multi_Modals.ipynb
5.2.Spark_OCR_Deidentification.ipynb

### Clinical Pipelines

11.Pretrained_Clinical_Pipelines.ipynb
11.1.Healthcare_Code_Mapping.ipynb
11.2.Pretrained_NER_Profiling_Pipelines.ipynb

### Classifiers

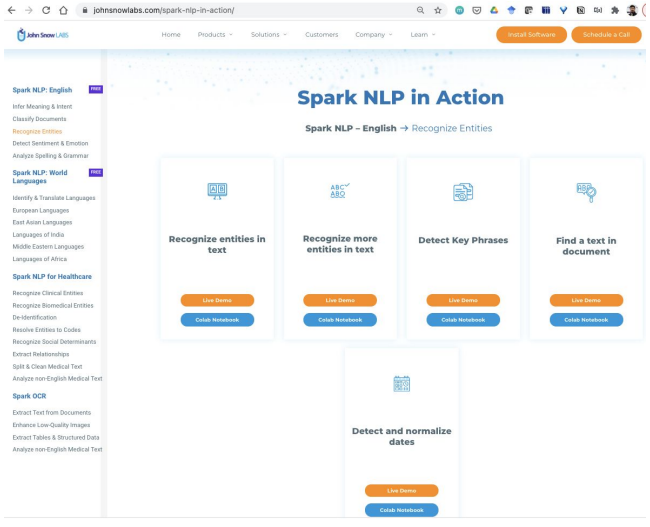
8.Generic_Classifier.ipynb
21.Gender_Classifier.ipynb

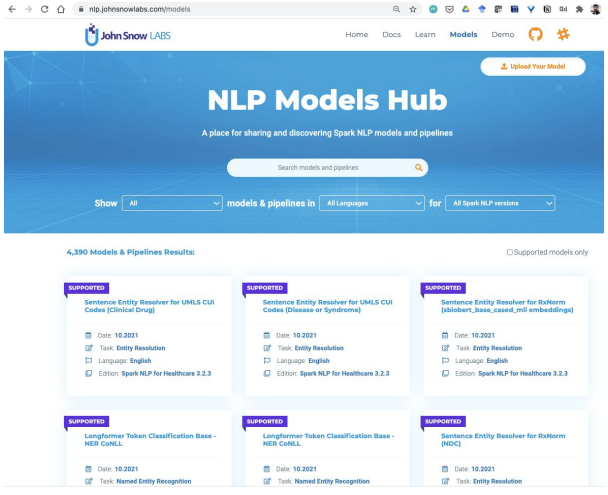
### Normalizers

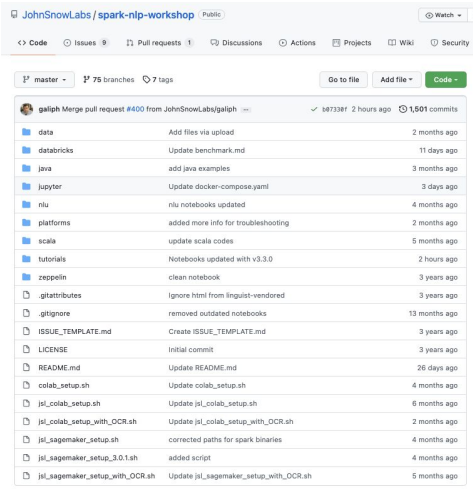
23.Drug_Normalizer.ipynb
25.Date_Normalizer.ipynb

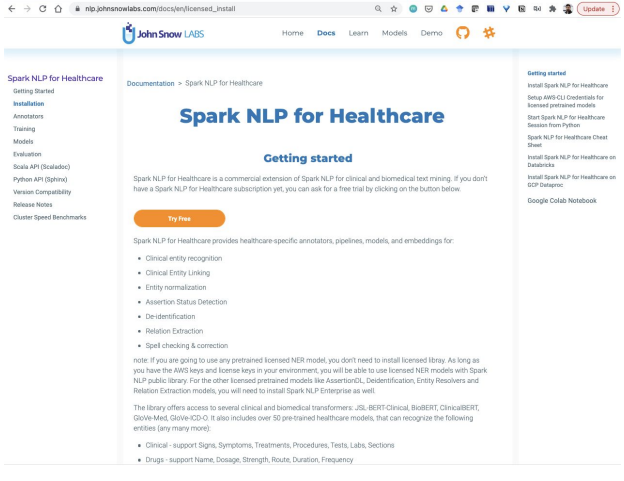
### Auxillary Notebooks

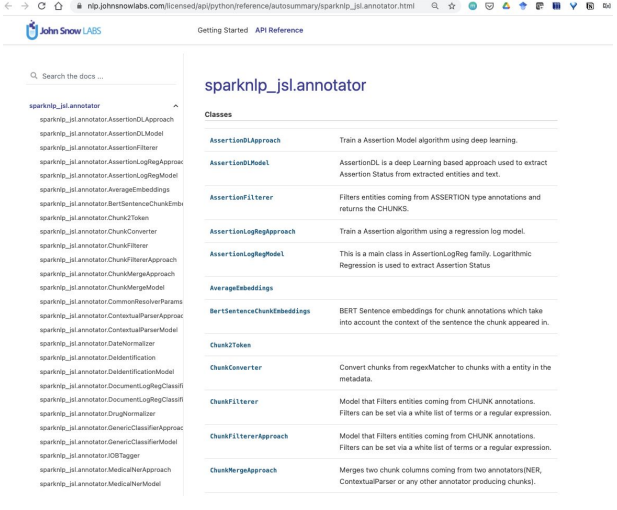
6.Clinical_Context_Spell_Checker.ipynb
9.Chunk_Key_Phrase_Extraction.ipynb
12.Named_Entity_Disambiguation.ipynb
14.German_Healthcare_Models.ipynb
15.German_Licensed_Models.ipynb
17.Graph_builder_for_DL_models.ipynb
18.Chunk_Sentence_Splitter.ipynb
19.Financial_Contract_NER.ipynb
20.SentenceDetectorDL_Healthcare.ipynb
26.Chunk_Mapping.ipynb

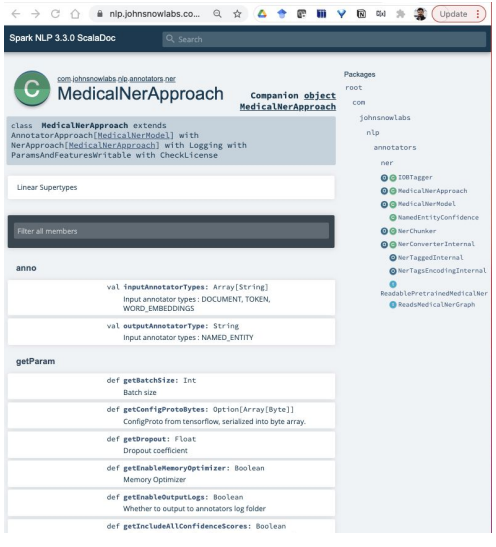

johnsnowlabs.com/spark-nlp-in-action/
Spark NLP in Action
Spark NLP – English → Recognize Entities
Recognize entities in text
Recognize more entities in text
Detect Key Phrases
Find a text in document
Detect and normalize dates
Live Demo
Colab Notebook


nlp.johnsnowlabs.com/models
NLP Models Hub
A place for sharing and discovering Spark NLP models and pipelines
Upload Your Model
4,390 Models & Pipelines Results:
SUPPORTED
Sentence Entity Resolver for UMLS CUI Codes (Clinical Drug)
Sentence Entity Resolver for UMLS CUI Codes (Disease or Syndrome)
Sentence Entity Resolver for RxNorm (sbiobert_base_cased_mli embeddings)
Longformer Token Classification Base - NER CoNLL
Sentence Entity Resolver for RxNorm (NDC)


JohnSnowLabs / spark-nlp-workshop
Public
Code
Issues
Pull requests
Discussions
Actions
Projects
Wiki
Security
master
75 branches
7 tags
Go to file
Add file
Code
1,501 commits
data
databricks
java
jupyter
nlu
platforms
scala
tutorials
zeppelin
.gitattributes
.gitignore
ISSUE_TEMPLATE.md
LICENSE
README.md
colab_setup.sh
jsl_colab_setup.sh
jsl_colab_setup_with_OCR.sh
jsl_sagemaker_setup.sh
jsl_sagemaker_setup_3.0.1.sh
jsl_sagemaker_setup_with_OCR.sh


nlp.johnsnowlabs.com/docs/en/licensed_install
Spark NLP for Healthcare
Getting Started
Installation
Annotators
Training
Models
Evaluation
Scala API (Scaladoc)
Python API (Sphinx)
Version Compatibility
Release Notes
Cluster Speed Benchmarks
Documentation > Spark NLP for Healthcare
Spark NLP for Healthcare
Getting started
Try Free
Spark NLP for Healthcare provides healthcare-specific annotators, pipelines, models, and embeddings for:
Clinical entity recognition
Clinical Entity Linking
Entity normalization
Assertion Status Detection
De-identification
Relation Extraction
Spell checking & correction
Getting started
Install Spark NLP for Healthcare
Setup AWS-CLI Credentials for licensed pretrained models
Start Spark NLP for Healthcare Session from Python
Spark NLP for Healthcare Cheat Sheet
Install Spark NLP for Healthcare on Databricks
Install Spark NLP for Healthcare on GCP Dataproc
Google Colab Notebook


nlp.johnsnowlabs.com/licensed/api/python/reference/autosummary/sparknlp_jsl.annotator.html
Getting Started
API Reference
Search the docs ...
sparknlp_jsl.annotator
sparknlp_jsl.annotator.AssertionDLApproach
sparknlp_jsl.annotator.AssertionDLModel
sparknlp_jsl.annotator.AssertionFilterer
sparknlp_jsl.annotator.AssertionLogRegApproac
sparknlp_jsl.annotator.AssertionLogRegModel
sparknlp_jsl.annotator.AverageEmbeddings
sparknlp_jsl.annotator.BertSentenceChunkEmb
sparknlp_jsl.annotator.Chunk2Token
sparknlp_jsl.annotator.ChunkConverter
sparknlp_jsl.annotator.ChunkFilterer
sparknlp_jsl.annotator.ChunkFiltererApproach
sparknlp_jsl.annotator.ChunkMergeApproach
sparknlp_jsl.annotator.ChunkMergeModel
sparknlp_jsl.annotator.CommonResolverParams
sparknlp_jsl.annotator.ContextualParserApproac
sparknlp_jsl.annotator.ContextualParserModel
sparknlp_jsl.annotator.DateNormalizer
sparknlp_jsl.annotator.Deidentification
sparknlp_jsl.annotator.DeidentificationModel
sparknlp_jsl.annotator.DocumentLogRegClassifi
sparknlp_jsl.annotator.DocumentLogRegClassifi
sparknlp_jsl.annotator.DrugNormalizer
sparknlp_jsl.annotator.GenericClassifierApproac
sparknlp_jsl.annotator.GenericClassifierModel
sparknlp_jsl.annotator.IOBTagger
sparknlp_jsl.annotator.MedicalNerApproach
sparknlp_jsl.annotator.MedicalNerModel
sparknlp_jsl.annotator
Classes
AssertionDLApproach
Train a Assertion Model algorithm using deep learning.
AssertionDLModel
AssertionDL is a deep Learning based approach used to extract Assertion Status from extracted entities and text.
AssertionFilterer
Filters entities coming from ASSERTION type annotations and returns the CHUNKS.
AssertionLogRegApproach
Train a Assertion algorithm using a regression log model.
AssertionLogRegModel
This is a main class in AssertionLogReg family. Logarithmic Regression is used to extract Assertion Status
AverageEmbeddings
BertSentenceChunkEmbeddings
BERT Sentence embeddings for chunk annotations which take into account the context of the sentence the chunk appeared in.
Chunk2Token
ChunkConverter
Convert chunks from regexMatcher to chunks with a entity in the metadata.
ChunkFilterer
Model that Filters entities coming from CHUNK annotations. Filters can be set via a white list of terms or a regular expression.
ChunkFiltererApproach
Model that Filters entities coming from CHUNK annotations. Filters can be set via a white list of terms or a regular expression.
ChunkMergeApproach
Merges two chunk columns coming from two annotators(NER, ContextualParser or any other annotator producing chunks).


nlp.johnsnowlabs.co...
Update
Spark NLP 3.3.0 ScalaDoc
Search
com.johnsnowlabs.nlp.annotators.ner
MedicalNerApproach
Companion object MedicalNerApproach
class MedicalNerApproach extends AnnotatorApproach[MedicalNerModel] with NerApproach[MedicalNerModel] with Logging with ParamsAndFeaturesWritable with CheckLicense
Linear Supertypes
Filter all members
anno
val inputAnnotatorTypes: Array[String]
Input annotator types : DOCUMENT, TOKEN, WORD_EMBEDDINGS
val outputAnnotatorType: String
Input annotator types : NAMED_ENTITY
getParam
def getBatchSize: Int
Batch size
def getConfigProtoBytes: Option[Array[Byte]]
ConfigProto from tensorflow, serialized into byte array.
def getDropout: Float
Dropout coefficient
def getEnableMemoryOptimizer: Boolean
Memory Optimizer
def getEnableOutputLogs: Boolean
Whether to output to annotators log folder
def getIncludeAllConfidenceScores: Boolean
Packages
root
com
johnsnowlabs
nlp
annotators
ner
IOBTagger
MedicalNerApproach
MedicalNerModel
NamedEntityConfidence
NerChunker
NerConverterInternal
NerTaggedInternal
NerTagsEncodingInternal
ReadablePretrainedMedicalNer
ReadsMedicalNerGraph

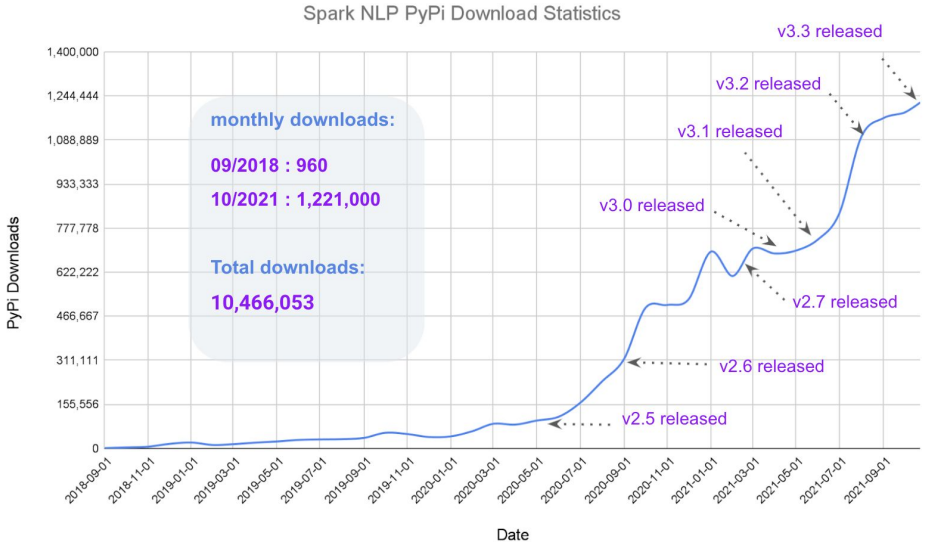
# Part - I

- Overview and key concepts in Spark NLP
- NLP basics & review
- Common medical NLP use cases
- Clinical named entity recognition

# Introducing Spark NLP

Daily ~ 80K
Monthly ~ 2.3M

| | |
|---|---|
| PyPI link | https://pypi.org/project/spark-nlp |
| Total downloads | 30,067,117 |
| Total downloads - 30 days | 2,331,332 |
| Total downloads - 7 days | 543,740 |




- Spark NLP is an open-source natural language processing library, built on top of Apache Spark and Spark ML. (initial release: Oct 2017)
  - A single unified solution for all your NLP needs
  - Take advantage of transfer learning and implementing the latest and greatest **SOTA** algorithms and models in NLP research
  - The most widely used NLP library in industry (3 yrs in a row)
  - Delivering a mission-critical, enterprise grade NLP library (used by multiple Fortune 500)
  - Full-time development team (a new release every other week)

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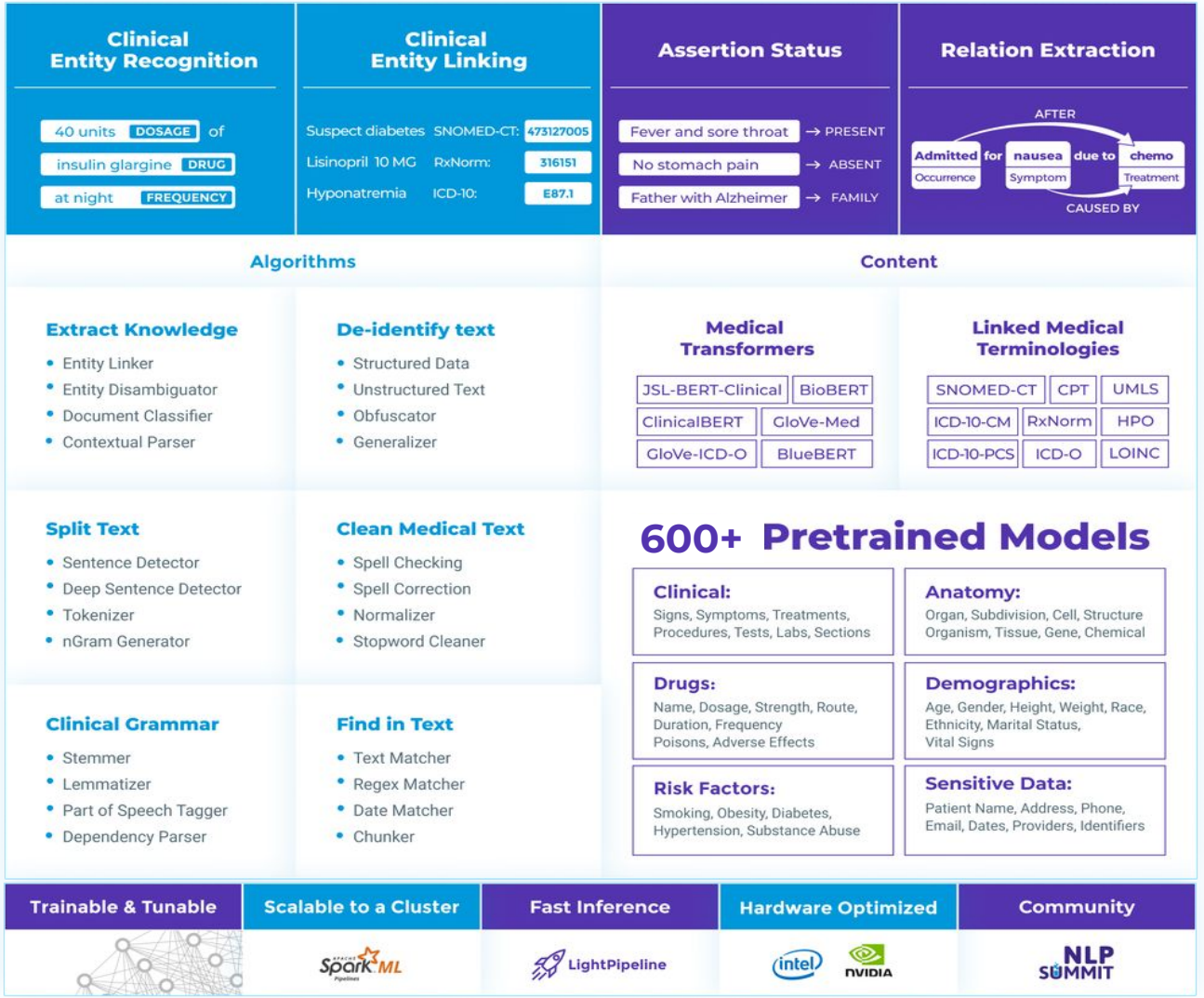
# Spark NLP for Healthcare

Spark NLP for Healthcare provides

- accurate,
- scalable,
- private,
- tunable,
- modular

software library that helps healthcare & pharma organizations build longitudinal patient records and knowledge graphs on real-world EHR data.



# Academic Activities & Benchmarks

John Snow LABS

nature COMMUNICATIONS

Stanford University

**Preparing for the Next Pandemic: Transfer Learning from Existing Diseases via Hierarchical Multi-Modal BERT Models to Predict COVID-19 Outcomes**

Khushbu Agarwal[1], Sutanay Choudhury*[1], Sindhu Tipirneni[2], Pritam Mukherjee[3], Colby Ham[1], Suzanne Tamang[4], Matthew Baker[5], Siyi Tang[3], Veysel Kocaman[7], Olivier Gevaert[3,4], Robert Rallo[1], and Chandan K Reddy[2]

[1]Pacific Northwest National Laboratory, Richland, 99354, USA
[2]Department of Computer Science, Virginia Tech, Arlington, 22203, USA
[3]Stanford Center for Biomedical Informatics Research, Department of Medicine, School of Medicine, Stanford University, Stanford, 94305, USA
[4]Department of Biomedical Data Science, Stanford University, Stanford, 94305, USA
[5]Department of Electrical Engineering, Stanford University, Stanford, 94305, USA
[6]Division of Immunology and Rheumatology, Department of Medicine, Stanford University, Stanford, 94305, USA
John Snow Labs, Delaware City, 19958, USA
*sutanay.choudhury@pnnl.gov

Journal of Biomedical Semantics

SOFTWARE

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

Veysel Kocaman* and David Talby

*Correspondence: veysel@johnsnowlabs.com
John Snow Labs, Lewes, DE, USA
Full list of author information is available at the end of the article

Scientific Document Understanding (SDU) at AAAI

**Deeper Clinical Document Understanding Using Relation Extraction**

Hasham Ul Haq, Veysel Kocaman, David Talby
John Snow Labs Inc.
16192 Coastal Highway
Lewes, DE , USA 19958
{hasham, veysel, david} @ johnsnowlabs.com

**Abstract**

The surging amount of biomedical literature & digital clinical records presents a growing need for text mining techniques that can not only identify but also semantically ...

publications and literature are growing rapidly, there still lacks structured knowledge that can be easily processed by computer programs. Relation Extraction becomes even more pertinent in biomedical research as it can provide the criti-

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

Health Intelligence (W3PHIAI-22) at AAAI

Hasham Ul Haq, Veysel Kocaman, David Talby
John Snow Labs Inc.
16192 Coastal Highway
Lewes, DE , USA 19958
{hasham, veysel, david} @ johnsnowlabs.com

ADR's has been estimated to cost $136 billion each year in the United States alone (van Der Hooft et al. 2006).

Finding all ADR's of a drug before it is marketed is not practical for several reasons. First, The number of human subjects going through clinical trials is often too small to detect rare ADR's. Second, many clinical trials are short-lasting while some ADR's take time to manifest. Third,

**New State-of-the-art (SOTA) Benchmarks**

AMIA

INFORMATICS PROFESSIONALS. LEADING THE WAY.

American Medical Informatics Association

**Tracking the Evolution of COVID-19 via Temporal Comorbidity Analysis from Multi-Modal Data**

Sutanay Choudhury[1], Khushbu Agarwal[1], Colby Ham[1], Pritam Mukherjee[2], Siyi Tang[2], Sindhu Tipirneni[3], Chandan Reddy[3], Suzanne Tamang[2], Robert Rallo[1], Veysel Kocaman[4]
[1]Pacific Northwest National Laboratory; [2]Stanford University; [3]Virginia Tech.; [4]John Snow Labs

**Introduction**

We aim to characterize the evolution in the effectiveness of treatment for different patient groups over the course of the COVID-19 pandemic. In contrast to most existing studies[1], we study the evolution of patient trajectories based on unique sets of frequent comorbid conditions discovered from the data. Further, we study the association between frequent co-morbid conditions to the length of stay (LOS) as a measure of treatment efficacy, for poor COVID-19 related outcomes.

- ✓ 6 academic publications & events and 1 patent application, 20+ medium blogposts
- ✓ new SOTA benchmarks on Clinical NER challenges (i2b2 2010 Clinical, i2b2 2014 Deid, n2c2 2018 Medication)
- ✓ new SOTA benchmarks on Adverse Drug Reaction NER datasets (ADE, CADEC, SMM4H )
- ✓ new SOTA benchmarks on Adverse Drug Reaction classification datasets (ADR, CADEC)
- ✓ new SOTA benchmarks on Clinical Relation Extraction datasets (i2b2, temporal, ADE, Posology, PGR – 5 out of 7)

# TRUSTED BY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intel


IBM


databricks


verizon


indeed


CapitalOne


viacom


McKESSON


MERCK


Roche


selectdata


UiPath
Reboot Work.


ASCO
CANCER·LINQ
DISCOVERY


cnrs

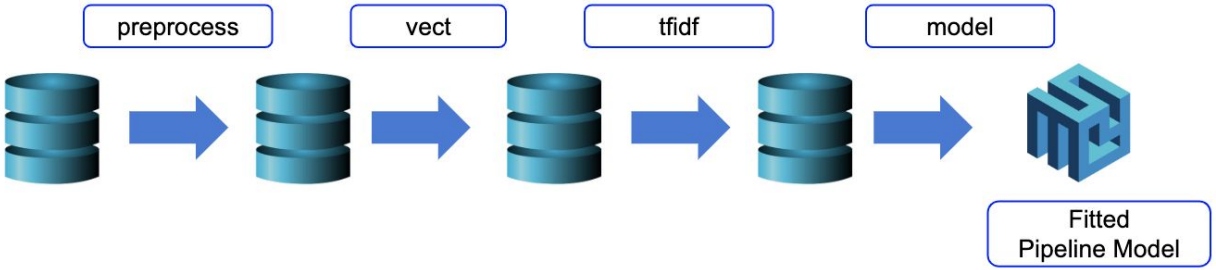

Imperial College
London


Georgia
Tech

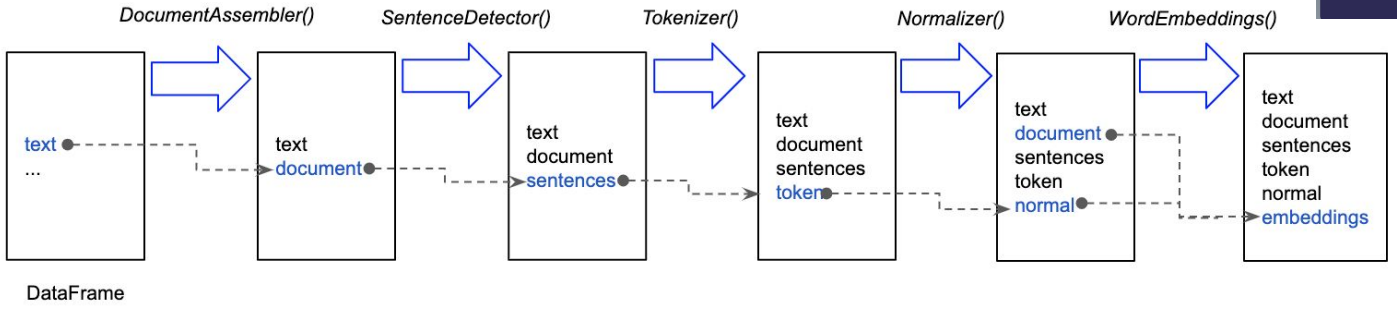

STANFORD
UNIVERSITY

# Introducing Spark NLP

## Pipeline of annotators




```
from pyspark.ml import Pipeline

document_assembler = DocumentAssembler()\
 .setInputCol("text")\
 .setOutputCol("document")

sentenceDetector = SentenceDetector()\
 .setInputCols(["document"])\
 .setOutputCol("sentences")

tokenizer = Tokenizer() \
 .setInputCols(["sentences"]) \
 .setOutputCol("token")

normalizer = Normalizer()\
 .setInputCols(["token"])\
 .setOutputCol("normal")

word_embeddings=WordEmbeddingsModel.pretrained()\
 .setInputCols(["document","normal"])\
 .setOutputCol("embeddings")

nlpPipeline = Pipeline(stages=[
 document_assembler,
 sentenceDetector,
 tokenizer,
 normalizer,
 word_embeddings,
 ])

nlpPipeline.fit(df).transform(df)
```



# Introducing Spark NLP

Spark is like a locomotive racing a bicycle. The bike will win if the load is light, it is quicker to accelerate and more agile, but with a heavy load the locomotive might take a while to get up to speed, but it's going to be faster in the end.

Faster inference

```
from sparknlp.base import LightPipeline
LightPipeline(someTrainedPipeline).annotate(someStringOrArray)
```

**LightPipelines** are Spark ML pipelines converted into a single machine but multithreaded task, becoming more than 10x times faster for smaller amounts of data (small is relative, but 50k sentences is roughly a good maximum).

# Spark NLP in Healthcare

Clean & structured data

Raw & unstructured data

Healthcare data

- Less than 50% of the structured data and less than 1% of the unstructured data is being leveraged for decision making in companies (HBR). This is even worse in healthcare.
- NLP is ultra domain specific, so train your own models.

# Why is language understanding hard?

## Human Language is:

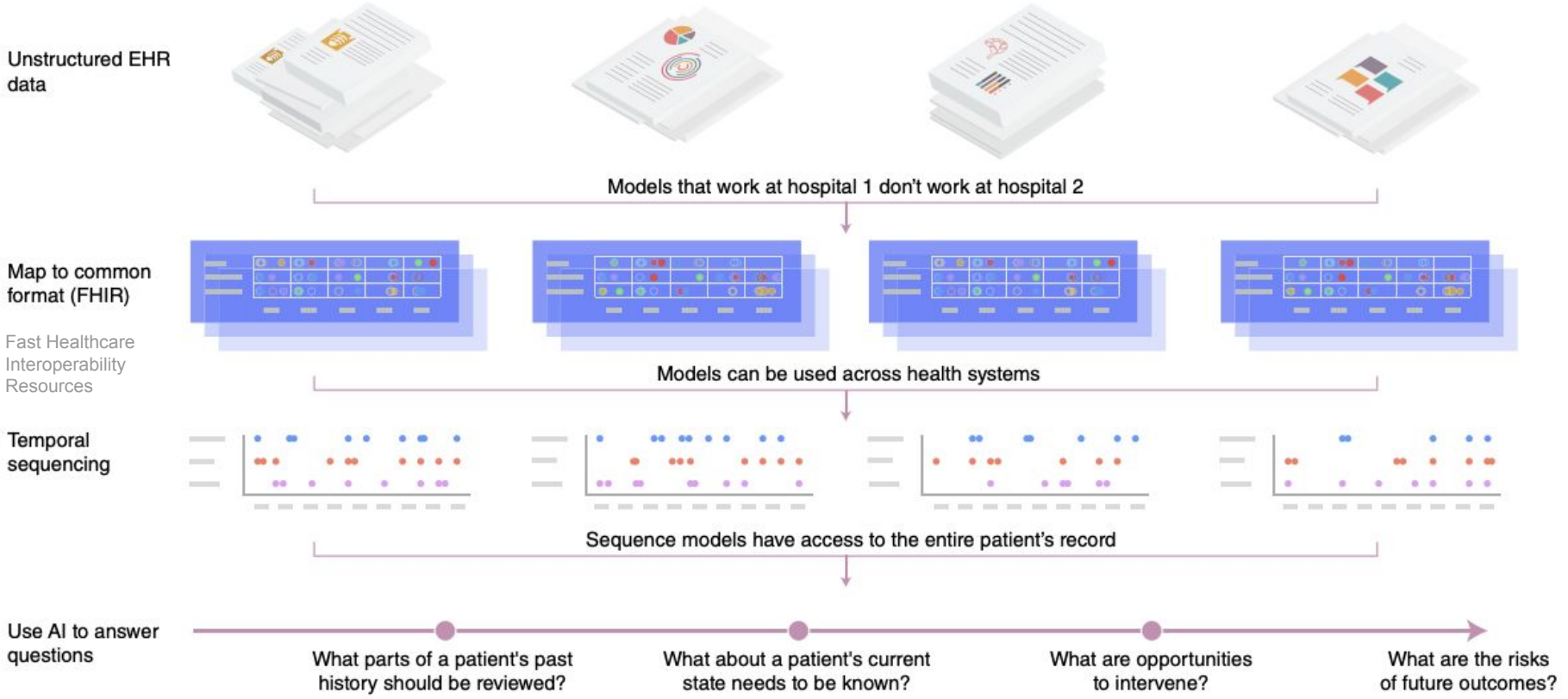
- Nuanced
- Fuzzy
- Contextual
- Medium specific
- Domain specific

## Healthcare specific needs:

1. Core Annotators
   Part of speech, spell checking, …
2. Vocabulary
   Ontologies, relationships, word embeddings, …
3. ML & DL Models
   Named entity recognition, entity resolution, …

| ED Triage Notes |
| --- |
| states started last night, upper abd, took alka seltzer approx 0500, no relief. nausea no vomiting |
| Since yeatreday 10/10 "constant Tylenol 1 hr ago. +nausea. diaphoretic. Mid abd radiates to back |
| Generalized abd radiating to lower x 3 days accompanied by dark stools. Now with bloody stool this am. Denies dizzy, sob, fatigue. Visiting from Japan on business." |

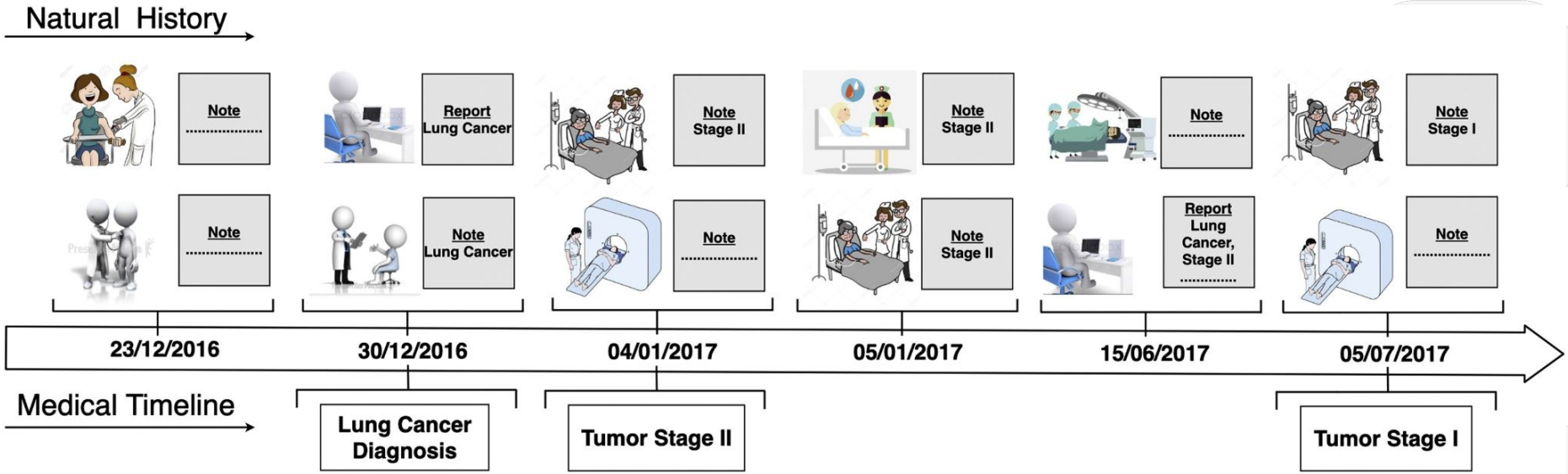
| Features | |
| --- | --- |
| Type of Pain | Symptoms |
| Intensity of Pain | Onset of symptoms |
| Body part of region | Attempted home remedy |



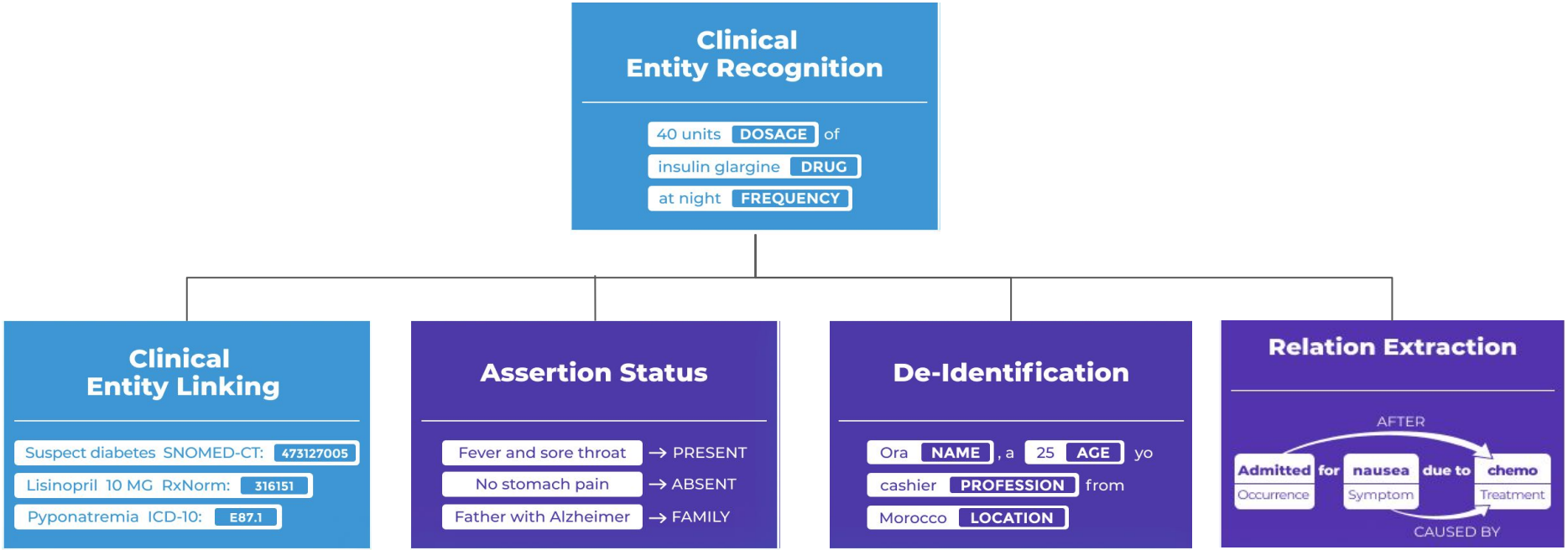

NLP SUMMIT

**"Systems used to generate health data are designed for operations, not to organize data effectively for research or analytics."**

# Putting the clinical facts on a timeline



# NLP in Healthcare



# Spark NLP for Healthcare

Named Entity Recognition

ICD10 Resolver

Snomed Resolver

UMLS Resolver

Assertion Status Detection

Risk Adj. Module

RxNorm Resolver

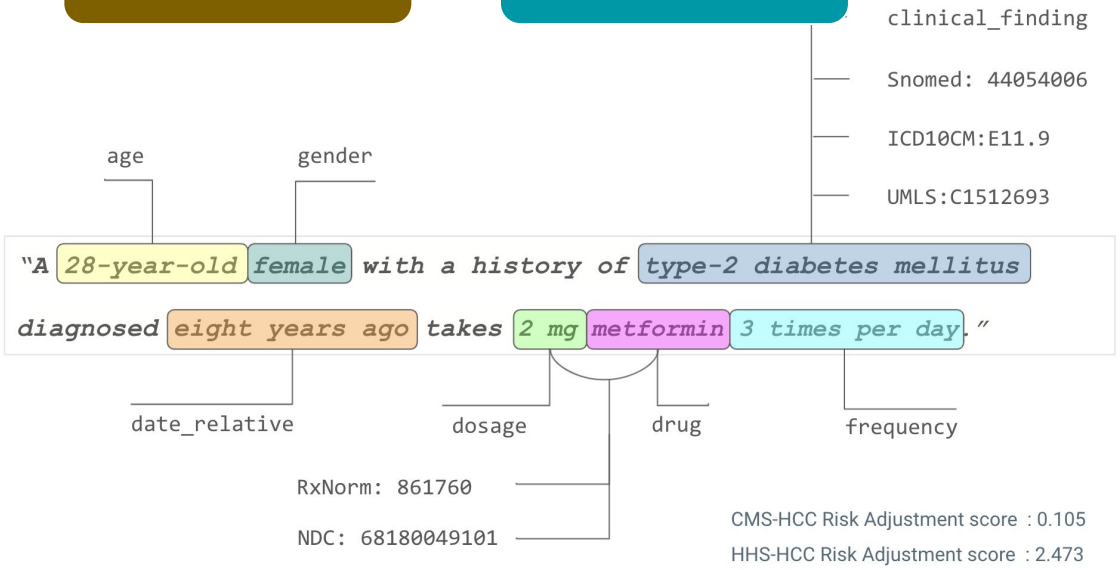
Relationship Extraction

Sentence Splitter

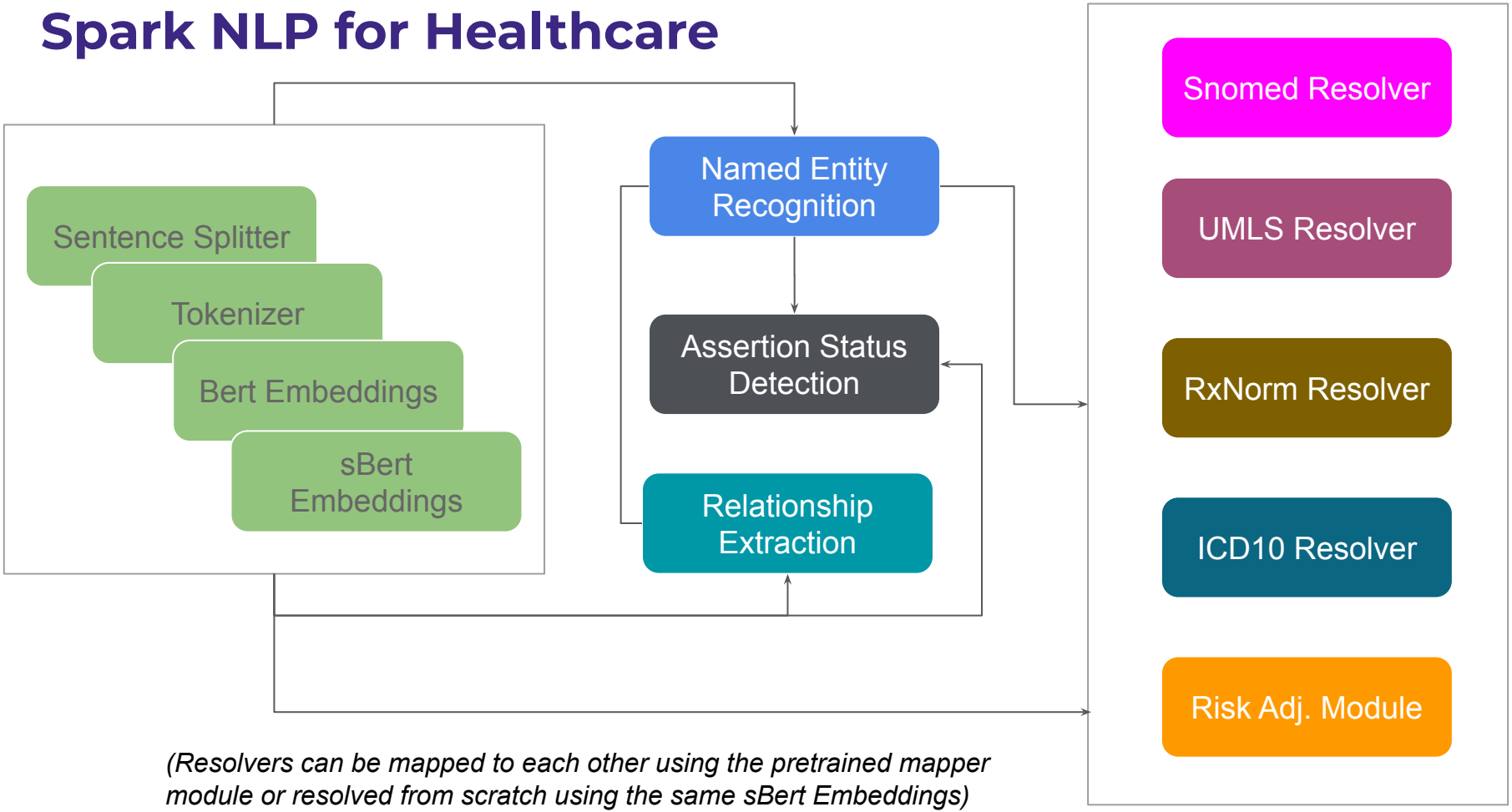
Tokenizer

Bert Embeddings

sBert Embeddings

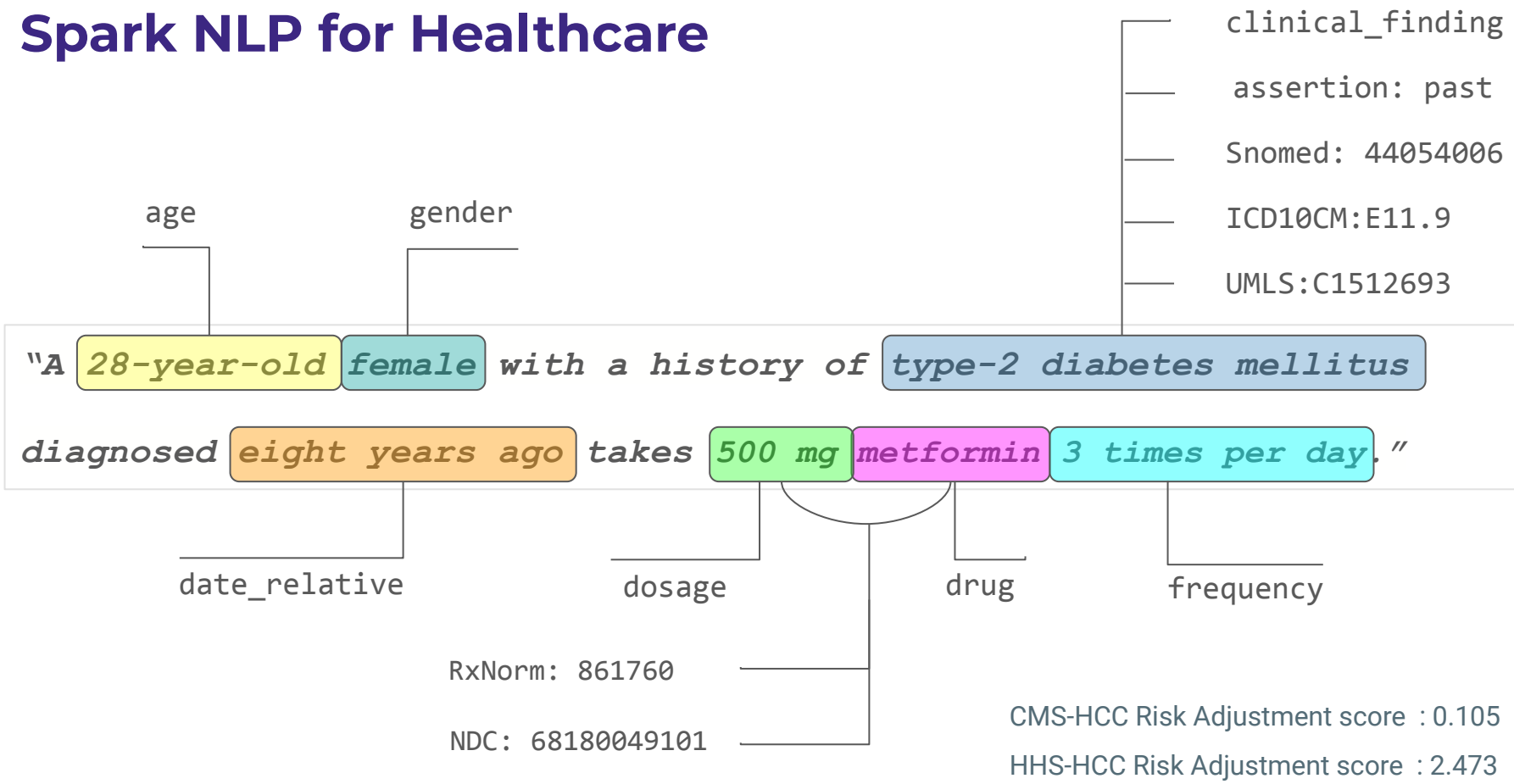


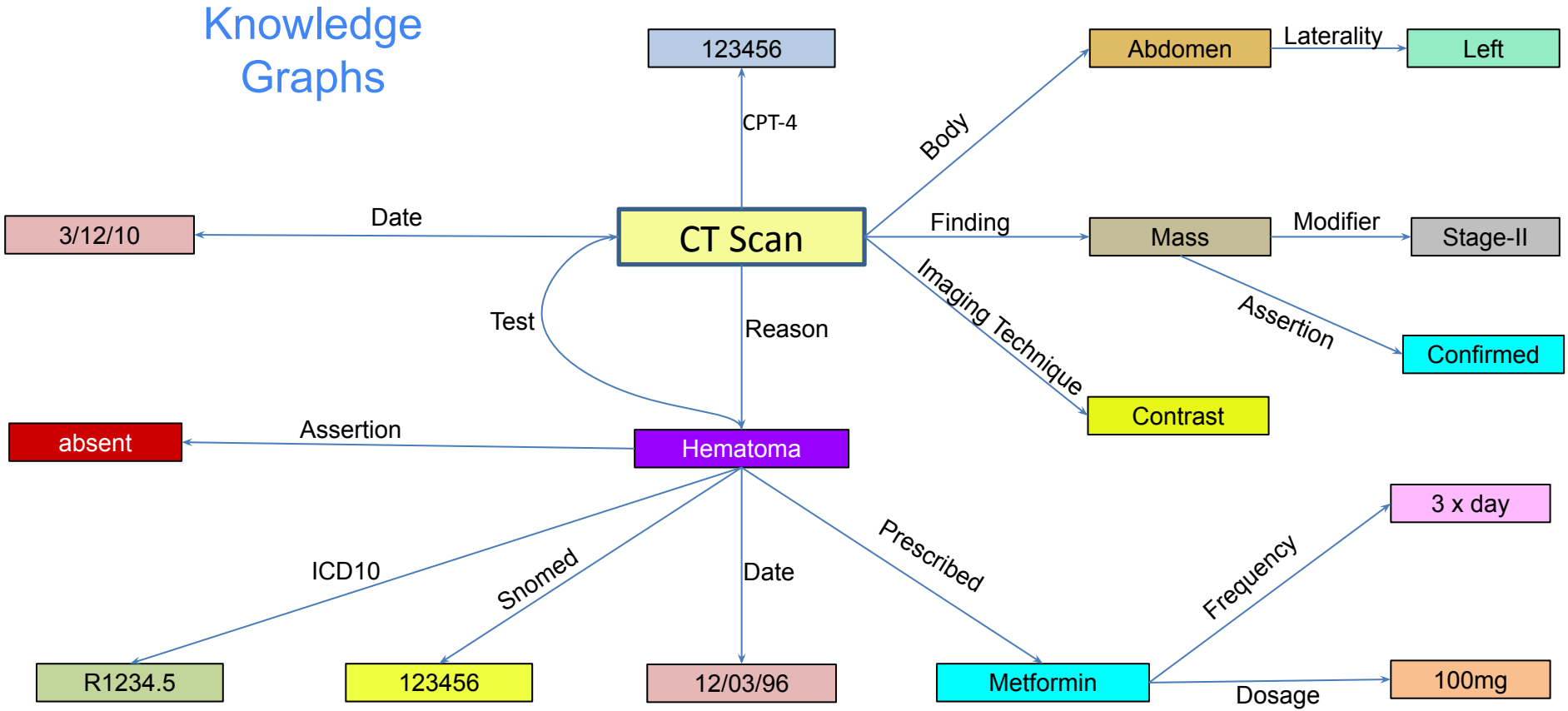
# Spark NLP for Healthcare




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

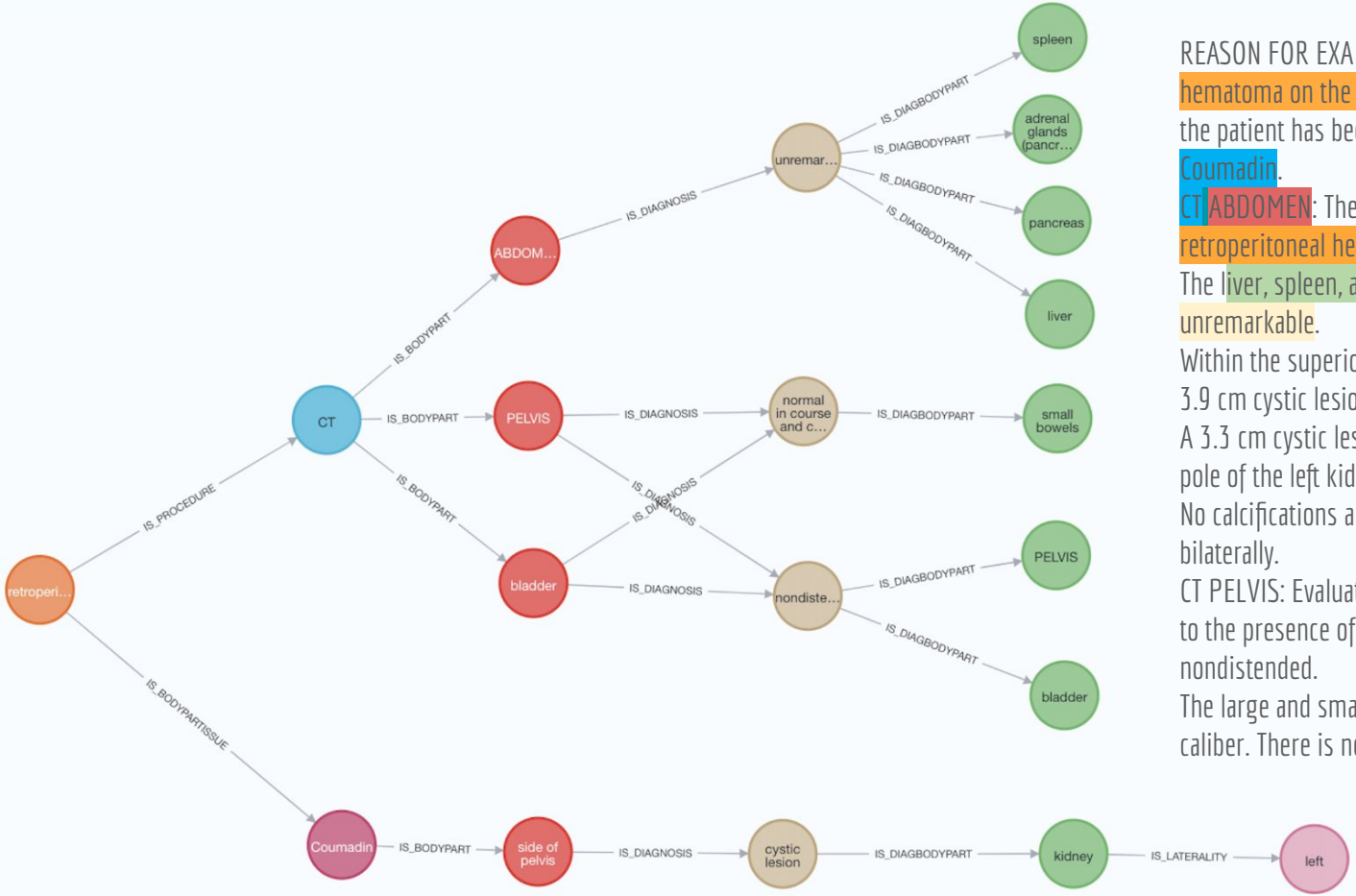
# Spark NLP for Healthcare




Knowledge Graphs
123456
CPT-4
Abdomen
Laterality
Left
Body
3/12/10
Date
CT Scan
Finding
Mass
Modifier
Stage-II
Test
Reason
Assertion
Confirmed
Imaging Technique
Contrast
absent
Assertion
Hematoma
ICD10
Snomed
Date
Prescribed
3 x day
Frequency
R1234.5
123456
12/03/96
Metformin
Dosage
100mg

*(20) Exam(1) Procedure(1) BodyPart(4) Diagnosis(4) DiagnosisBodyPart(8) BodyPartIssue(1) Laterality(1)

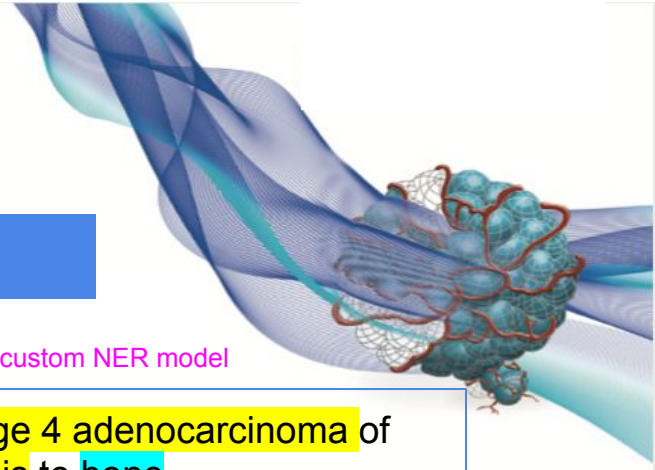
*(21) IS_BODYPARTISSUE(1) IS_PROCEDURE(1) IS_BODYPART(4) IS_DIAGNOSIS(6) IS_DIAGBODYPART(8) IS_LATERALITY(1)



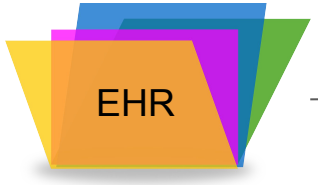

REASON FOR EXAM: Evaluate for retroperitoneal hematoma on the right side of pelvis,
the patient has been following, is currently on Coumadin.
CT ABDOMEN: There is no evidence for a retroperitoneal hematoma.
The liver, spleen, adrenal glands, and pancreas are unremarkable.
Within the superior pole of the left kidney, there is a 3.9 cm cystic lesion.
A 3.3 cm cystic lesion is also seen within the inferior pole of the left kidney.
No calcifications are noted. The kidneys are small bilaterally.
CT PELVIS: Evaluation of the bladder is limited due to the presence of a Foley catheter, the bladder is nondistended.
The large and small bowels are normal in course and caliber. There is no obstruction.

neo4j

# NLP in Healthcare



**Case:** Predicting if a patient would develop a metastasis on certain sites.




*Extract metastasis related sentences with mets-classifier*

Annotate your own data and train a custom NER model

Recently diagnosed, stage 4 adenocarcinoma of both lungs with metastasis to bone.
CT scan shows no indication of mets on brain.

*Extract named entities with Spark NLP NERDL and assign assertion statuses with AssertionDL model*

Feature extraction & engineering

- *The frequency of clinical visits using document dates*
- *The number of positive site (organ) entities (hits by window)*
- *The number of Radiology/Oncology/Pathology reports in the last x days*
- *The number of tests applied in the last x days*
- *The number of diseases detected in the last x days*
- *Family history and social health determinants, etc.*
- *Date extraction and normalization*

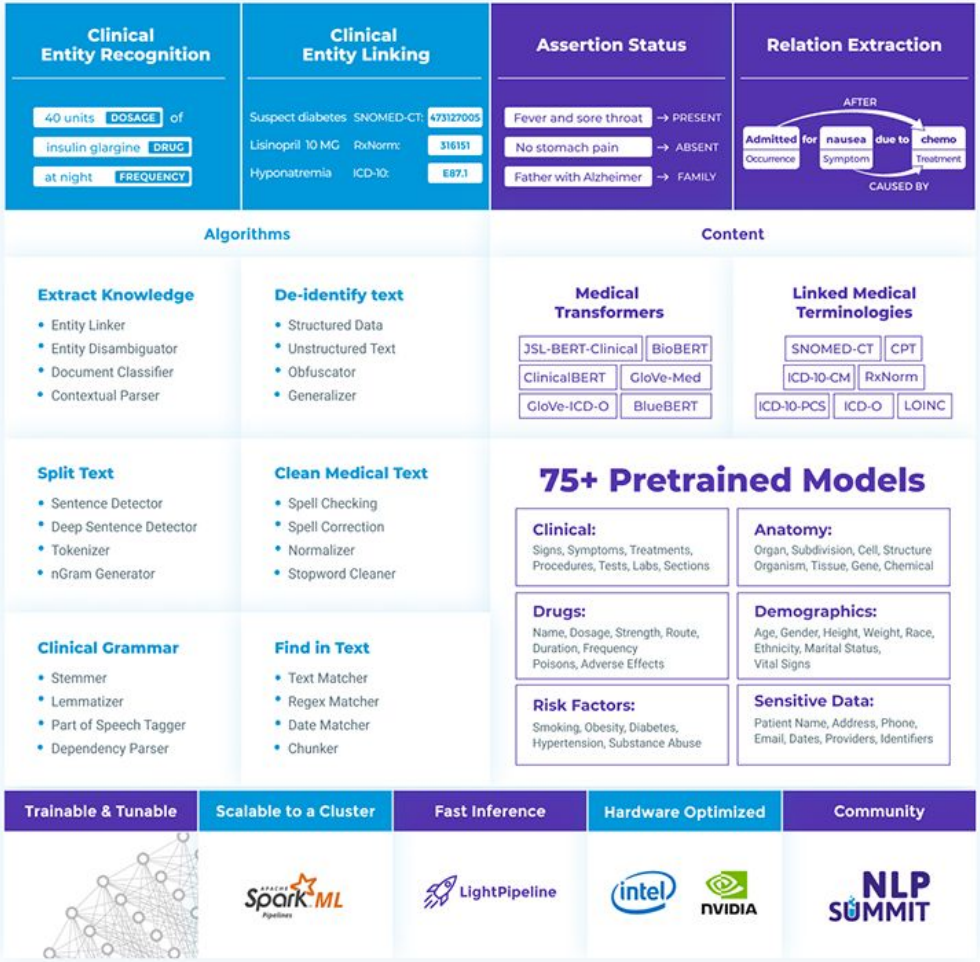
*Text embeddings thru clinical word embeddings*

*Train a DL & ML Model*

**Prediction:** Bone metastasis on June 2018

# Clinical Named Entity Recognition (NER)

- Extract structured data from free text
- Automate record keeping & abstraction process
- Feeding downstream tasks
- Features for ML models



# Pretrained NER Models

- **Clinical NER Models**

| index | model_name | index | model_name | index | model_name | index | model_name |
|---|---|---|---|---|---|---|---|
| 1 | jsl_ner_wip_clinical | 17 | ner_chexpert | 33 | ner_deid_subentity (German) | 49 | ner_jsl_greedy |
| 2 | jsl_ner_wip_greedy_clinical | 18 | ner_clinical | 34 | ner_diseases_large | 50 | ner_jsl_slim |
| 3 | jsl_ner_wip_modifier_clinical | 19 | ner_clinical_icdem | 35 | ner_drugs | 51 | ner_measurements_clinical |
| 4 | jsl_rd_ner_wip_greedy_clinical | 20 | ner_clinical_large | 36 | ner_drugs_greedy | 52 | ner_medmentions_coarse |
| 5 | ner_ade_clinical | 21 | ner_clinical_large_en | 37 | ner_drugs_large | 53 | ner_posology |
| 6 | ner_ade_clinicalbert | 22 | ner_deid_augmented | 38 | ner_events_admission_clinical | 54 | ner_posology_experimental |
| 7 | ner_ade_healthcare | 23 | ner_deid_enriched | 39 | ner_events_clinical | 55 | ner_posology_greedy |
| 8 | ner_anatomy | 24 | ner_deid_generic_augmented | 40 | ner_events_healthcare | 56 | ner_posology_healthcare |
| 9 | ner_anatomy_coarse | 25 | ner_deid_generic (German) | 41 | ner_genetic_variants | 57 | ner_posology_large |
| 10 | ner_bacterial_species | 26 | ner_deid_large | 42 | ner_healthcare | 58 | ner_posology_small |
| 11 | ner_bionlp | 27 | ner_deid_sd | 43 | ner_human_phenotype_gene_clinical | 59 | ner_profiling_clinical |
| 12 | ner_cancer_genetics | 28 | ner_deid_sd_large | 44 | ner_human_phenotype_go_clinical | 60 | ner_radiology |
| 13 | ner_cellular | 29 | ner_deid_subentity_augmented | 45 | ner_jsl | 61 | ner_radiology_wip_clinical |
| 14 | ner_chemicals | 30 | ner_deid_synthetic | 46 | ner_jsl_enriched | 62 | ner_risk_factors |
| 15 | ner_chemprot_clinical | 31 | ner_deidentify_dl | 47 | ner_nihss | 63 | ner_biomarker |
| 16 | ner_abbreviation_clinical | 32 | ner_deid_subentity_augmented_i2b2 | 48 | ner_diseases | 64 | ner_drugprot_clinical |

- **BioBert NER Models**

| index | model_name | index | model_name | index | model_name | index | model_name |
|---|---|---|---|---|---|---|---|
| 1 | jsl_ner_wip_greedy_biobert | 7 | ner_cellular_biobert | 13 | ner_events_biobert | 18 | ner_jsl_greedy_biobert |
| 2 | jsl_rd_ner_wip_greedy_biobert | 8 | ner_chemprot_biobert | 14 | ner_human_phenotype_gene_biobert | 19 | ner_posology_biobert |
| 3 | ner_ade_biobert | 9 | ner_clinical_biobert | 15 | ner_human_phenotype_go_biobert | 20 | ner_posology_large_biobert |
| 4 | ner_anatomy_biobert | 10 | ner_deid_biobert | 16 | ner_jsl_biobert | 21 | ner_profiling_biobert |
| 5 | ner_anatomy_coarse_biobert | 11 | ner_deid_enriched_biobert | 17 | ner_jsl_enriched_biobert | 22 | ner_risk_factors_biobert |
| 6 | ner_bionlp_biobert | 12 | ner_diseases_biobert | | | | |

- **BertForTokenClassification Clinical NER models**

| | model_name |
|---|---|
| 1 | bert_token_classifier_ner_ade |
| 2 | bert_token_classifier_ner_clinical |
| 3 | bert_token_classifier_ner_deid |
| 4 | bert_token_classifier_ner_drugs |
| 5 | bert_token_classifier_ner_jsl |
| 6 | bert_token_classifier_ner_jsl_slim |
| 7 | bert_token_classifier_ner_bionlp |
| 8 | bert_token_classifier_ner_bacteria |
| 9 | bert_token_classifier_ner_anatomy |
| 10 | bert_token_classifier_ner_cellular |
| 11 | bert_token_classifier_ner_chemprot |
| 12 | bert_token_classifier_ner_chemicals |
| 13 | bert_token_classifier_drug_development_trials |

| Approach | embeddings | # of models |
|---|---|---|
| BiLSTM-CNN-Char | Clinical (glove) | 70+ |
| BiLSTM-CNN-Char | Biobert | 20+ |
| Bert for Token Cls. | Biobert | 10+ |
| **Total** | | **100+** |

# NER JSL

Let's show an example of `ner_jsl` model that has about 80 clinical entity labels by changing just only the model name.

**Entities**

| | | | | |
|---|---|---|---|---|
| Injury_or_Poisoning | Direction | Test | Admission_Discharge | Death_Entity |
| Relationship_Status | Duration | Respiration | Hyperlipidemia | Birth_Entity |
| Age | Labour_Delivery | Family_History_Header | BMI | Temperature |
| Alcohol | Kidney_Disease | Oncological | Medical_History_Header | Cerebrovascular_Disease |
| Oxygen_Therapy | O2_Saturation | Psychological_Condition | Heart_Disease | Employment |
| Obesity | Disease_Syndrome_Disorder | Pregnancy | ImagingFindings | Procedure |
| Medical_Device | Race_Ethnicity | Section_Header | Symptom | Treatment |
| Substance | Route | Drug_Ingredient | Blood_Pressure | Diet |
| External_body_part_or_region | LDL | VS_Finding | Allergen | EKG_Findings |
| Imaging_Technique | Triglycerides | RelativeTime | Gender | Pulse |
| Social_History_Header | Substance_Quantity | Diabetes | Modifier | Internal_organ_or_component |
| Clinical_Dept | Form | Drug_BrandName | Strength | Fetus_NewBorn |
| RelativeDate | Height | Test_Result | Sexually_Active_or_Sexual_Orientation | Frequency |
| Time | Weight | Vaccine | Vital_Signs_Header | Communicable_Disease |
| Dosage | Overweight | Hypertension | HDL | Total_Cholesterol |
| Smoking | Date | | | |

# Attention (aka Bert) is all you need ?

| ner model | embeddings_clinical (BLSTM-CNN-Char) | | biobert (BLSTM-CNN-Char) | | BertForTokenClassification (SOTA) | |
|---|---|---|---|---|---|---|
| | micro | macro | micro | macro | micro | macro |
| ner_jsl | 0.878 | **0.814** | 0.862 | 0.711 | **0.88** | 0.71 |
| ner_jsl_slim | 0.87 | 0.766 | 0.86 | **0.778** | **0.89** | 0.75 |
| ner_deid | **0.94** | **0.77** | 0.93 | 0.77 | 0.75 | 0.63 |
| ner_drug | 0.964 | 0.964 | 0.912 | 0.911 | **1** | **0.98** |
| ner_ade | 0.84 | 0.807 | 0.839 | 0.819 | **0.89** | **0.84** |

* On average, the GLoVe embeddings are 30% faster during training compared to BERT embeddings, and more than 5x faster during inference, while being on-par in terms of F1 score.

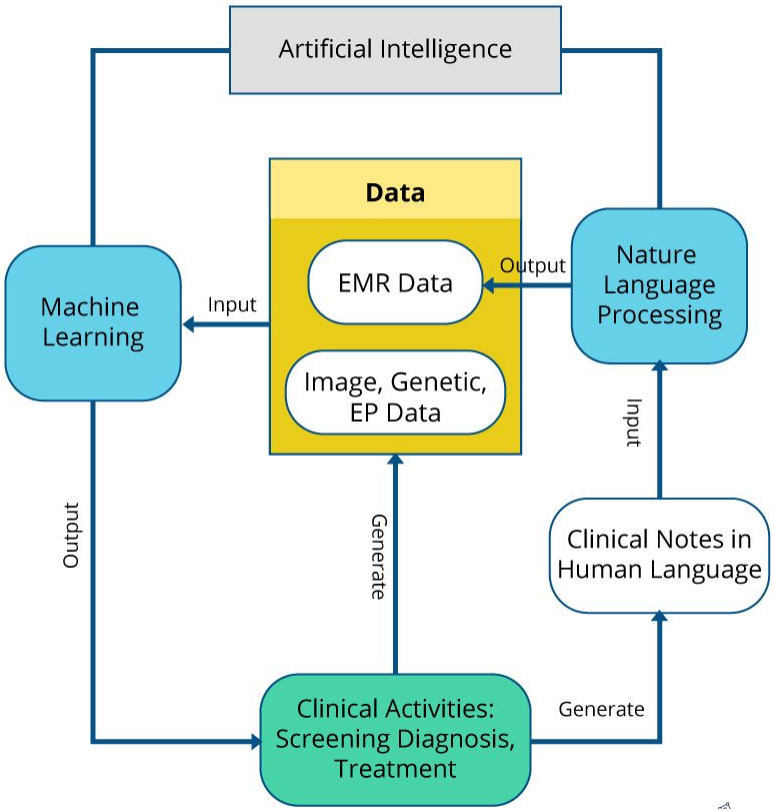
# NLP in Healthcare

"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 3 times per day."

## Named Entities

Mother with a lung cancer **ONCOLOGICAL** , a pregnant **PREGNANCY** patient is diagnosed as breast cancer **ONCOLOGICAL** in 1991 **DATE** and then admitted **ADMISSION_DISCHARGE** to Mayo Clinic **CLINICAL_DEPT** in Oct 2000 **DATE** , went under chemo **TREATMENT** for 6 months **DURATION** , discharged **ADMISSION_DISCHARGE** in April 2001 **DATE** with a prescription of 2 mg **STRENGTH** metformin **DRUG_INGREDIENT** 3 times per day **FREQUENCY** .

# Clinical Named Entity Recognition (NER)




The patient was prescribed 1 capsule of Advil for 5 days . He was seen by the endocrinology service and she was discharged on 40 units of insulin glargine at night , 12 units of insulin lispro with meals , and metformin 1000 mg two times a day . It was determined that all SGLT2 inhibitors should be discontinued indefinitely fro 3 months .

Color codes:FREQUENCY, DOSAGE, DURATION, DRUG, FORM, STRENGTH,

**Posology NER**

---

No findings in urinary system , skin color is normal , brain CT and cranial checks are clear . Swollen fingers and eyes . Extensive stage small cell lung cancer . Chemotherapy with carboplatin and etoposide . Left scapular pain status post CT scan of the thorax .

Color codes:Organ, Organism_subdivision, Organism_substance, Pathological_formation, Anatomical_system,

**Anatomy NER**

---

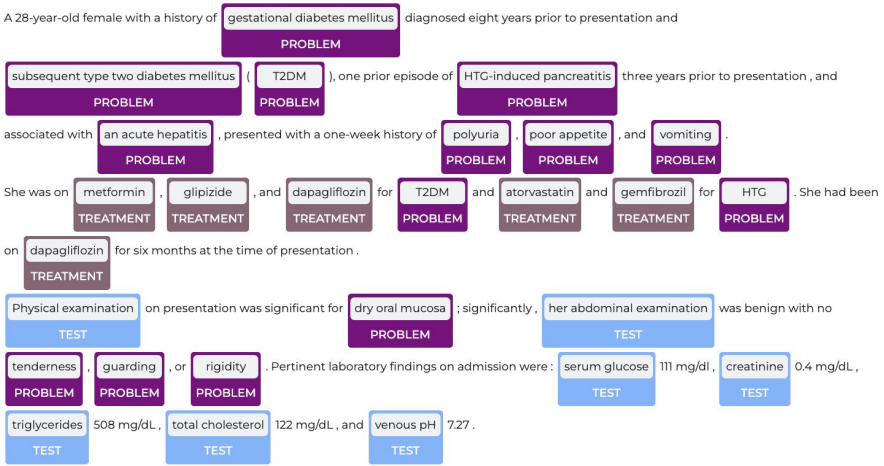
A . Record date : 2093-01-13 , David Hale , M.D . , Name : Hendrickson , Ora MR . # 7194334 Date : 01/13/93 PCP : Oliveira , 25 years-old , Record date : 2079-11-09 . Cocke County Baptist Hospital . 0295 Keats Street

Color codes:STREET, DOCTOR, AGE, HOSPITAL, PATIENT, DATE, MEDICALRECORD,

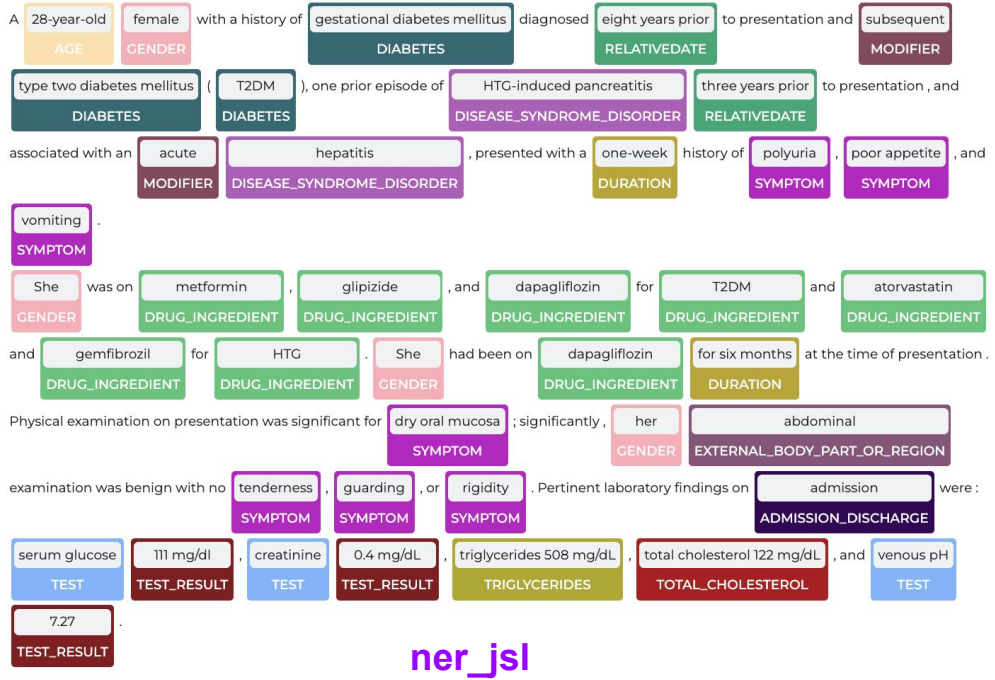
**PHI NER**

# Clinical Named Entity Recognition (NER)

A 28-year-old female with a history of gestational diabetes mellitus diagnosed eight years prior to presentation and subsequent type two diabetes mellitus (T2DM), one prior episode of HTG-induced pancreatitis three years prior to presentation, and associated with an acute hepatitis, presented with a one-week history of polyuria, poor appetite, and vomiting. She was on metformin, glipizide, and dapagliflozin for T2DM and atorvastatin and gemfibrozil for HTG. She had been on dapagliflozin for six months at the time of presentation. Physical examination on presentation was significant for dry oral mucosa ; significantly , her abdominal examination was benign with no tenderness, guarding, or rigidity. Pertinent laboratory findings on admission were: serum glucose 111 mg/dl, creatinine 0.4 mg/dL, triglycerides 508 mg/dL, total cholesterol 122 mg/dL, and venous pH 7.27.




ner_clinical




ner_jsl

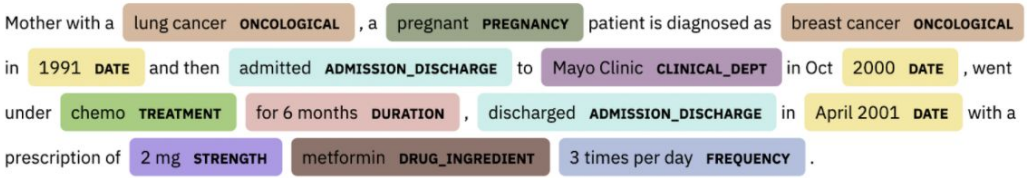
# Clinical Named Entities – Spark NLP vs Others

| Google | Azure | AWS |
|---|---|---|
| PROBLEM | DIAGNOSIS<br>SYMPTOM_OR_SIGN<br>ALLERGEN | MEDICAL_CONDITION_DX_NA<br>MEDICAL_CONDITION_SIGN<br>MEDICAL_CONDITION_SYMPTOM |
| PROCEDURE | TREATMENT_NAME | PROCEDURE_NAME<br>TREATMENT_NAME |
| MEDICINE | MEDICATION_CLASS<br>MEDICATION_NAME | MEDICATION_BRAND_NAME<br>MEDICATION_GENERIC_NAME |
| ANATOMICAL_STRUCTURE | BODY_STRUCTURE | SYSTEM_ORGAN_SITE |
| LABORATORY_DATA<br>BODY_MEASUREMENT | EXAMINATION_NAME | TEST_NAME |
| SEVERITY | CONDITION_QUALIFIER<br>CONDITION_SCALE | MEDICAL_CONDITION_ACUITY |
| MED_DOSE<br>MED_TOTALDOSE<br>MED_STRENGTH<br>MED_UNIT | DOSAGE | MEDICATION_DOSAGE<br>MEDICATION_STRENGTH<br>MEDICATION_RATE |
| MED_FREQUENCY | FREQUENCY | MEDICATION_FREQUENCY |
| MED_FORM | MEDICATION_FORM | MEDICATION_FORM |
| MED_ROUTE | MEDICATION_ROUTE | MEDICATION_ROUTE_OR_MODE |
| MED_DURATION | TIME | MEDICATION_DURATION |
| LAB_VALUE<br>MED_VALUE | MEASUREMENT_VALUE | TEST_VALUE |
| LAB_UNIT<br>BM_UNIT | MEASUREMENT_UNIT | TEST_UNIT |

## Spark NLP

Symptom, Disease_Syndrome_Disorder, Heart_Disease, VS_Finding, Communicable_Disease, Hypertension, Diabetes, Kidney_Disease, Cerebrovascular_Disease, Injury_or_Poisoning, Psychological_Condition, Total_Cholesterol, Hyperlipidemia, Obesity, Oncological, Pregnancy, EKG_Findings, Death_Entity, ImagingFindings, Female_Reproductive_Status, Fetus_NewBorn, Pregnancy_Delivery_Puerperium, Overweight, Puerperium

Test, Test_Result, Treatment, Pulse,Imaging_Technique, Labour_Delivery, Temperature, Blood_Pressure, Oxygen_Therapy, Weight, LDL, O2_Saturation, BMI, Vaccine, Respiration, Triglycerides

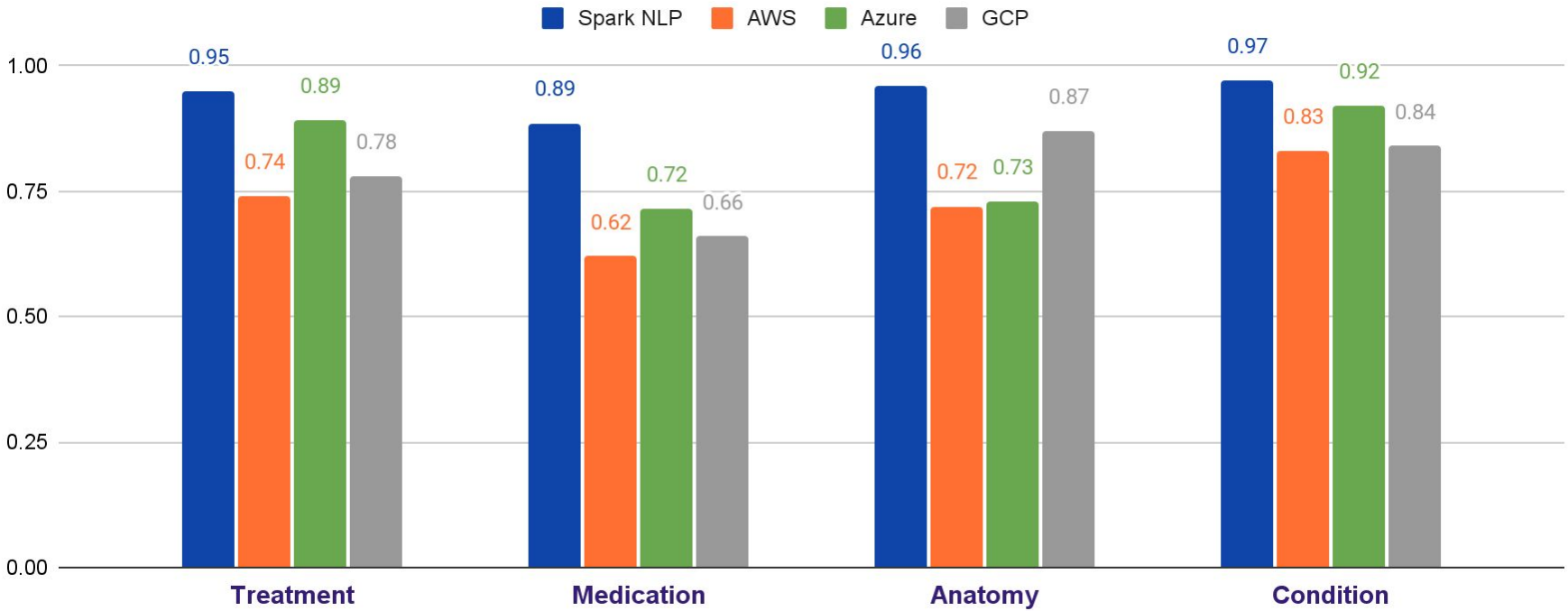


# Clinical Named Entities
# Spark NLP vs Others

| Google | Azure | AWS |
|---|---|---|
| PROBLEM | DIAGNOSIS<br>SYMPTOM_OR_SIGN<br>ALLERGEN | MEDICAL_CONDITION_DX_NA<br>MEDICAL_CONDITION_SIGN<br>MEDICAL_CONDITION_SYMPTOM |
| PROCEDURE | TREATMENT_NAME | PROCEDURE_NAME<br>TREATMENT_NAME |
| MEDICINE | MEDICATION_CLASS<br>MEDICATION_NAME | MEDICATION_BRAND_NAME<br>MEDICATION_GENERIC_NAME |
| ANATOMICAL_STRUCTURE | BODY_STRUCTURE | SYSTEM_ORGAN_SITE |
| LABORATORY_DATA<br>BODY_MEASUREMENT | EXAMINATION_NAME | TEST_NAME |
| SEVERITY | CONDITION_QUALIFIER<br>CONDITION_SCALE | MEDICAL_CONDITION_ACUITY |
| MED_DOSE<br>MED_TOTALDOSE<br>MED_STRENGTH<br>MED_UNIT | DOSAGE | MEDICATION_DOSAGE<br>MEDICATION_STRENGTH<br>MEDICATION_RATE |
| MED_FREQUENCY | FREQUENCY | MEDICATION_FREQUENCY |
| MED_FORM | MEDICATION_FORM | MEDICATION_FORM |
| MED_ROUTE | MEDICATION_ROUTE | MEDICATION_ROUTE_OR_MODE |
| MED_DURATION | TIME | MEDICATION_DURATION |
| LAB_VALUE<br>MED_VALUE | MEASUREMENT_VALUE | TEST_VALUE |
| LAB_UNIT<br>BM_UNIT | MEASUREMENT_UNIT | TEST_UNIT |

## 400+ entities from 100+ models

# NER Benchmarks




NLP SUMMIT

# Spark NLP vs AWS vs GCP vs Academic

| | | Spark NLP | Competition Best | Last Best |
|---|---|---|---|---|
| Clinical Concept Extraction | 2010 i2b2/VA | **0.876** | 0.852 | 0.862 |
| De-Identification | 2014 n2c2 | **0.961** | 0.936 | 0.955 |
| Medication Extraction | 2018 n2c2 | **0.899** | 0.896 | 0.896 |

| | | 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 | **0.648** | 0.539 | 0.478 | 0.507 | 0.850 | 0.516 | 0.642 |
| Test | 5903 | 0.782 | 0.662 | **0.717** | 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 | **0.922** |
| Avg. F1 | | | | **0.759** | | | 0.670 | | | 0.692 |

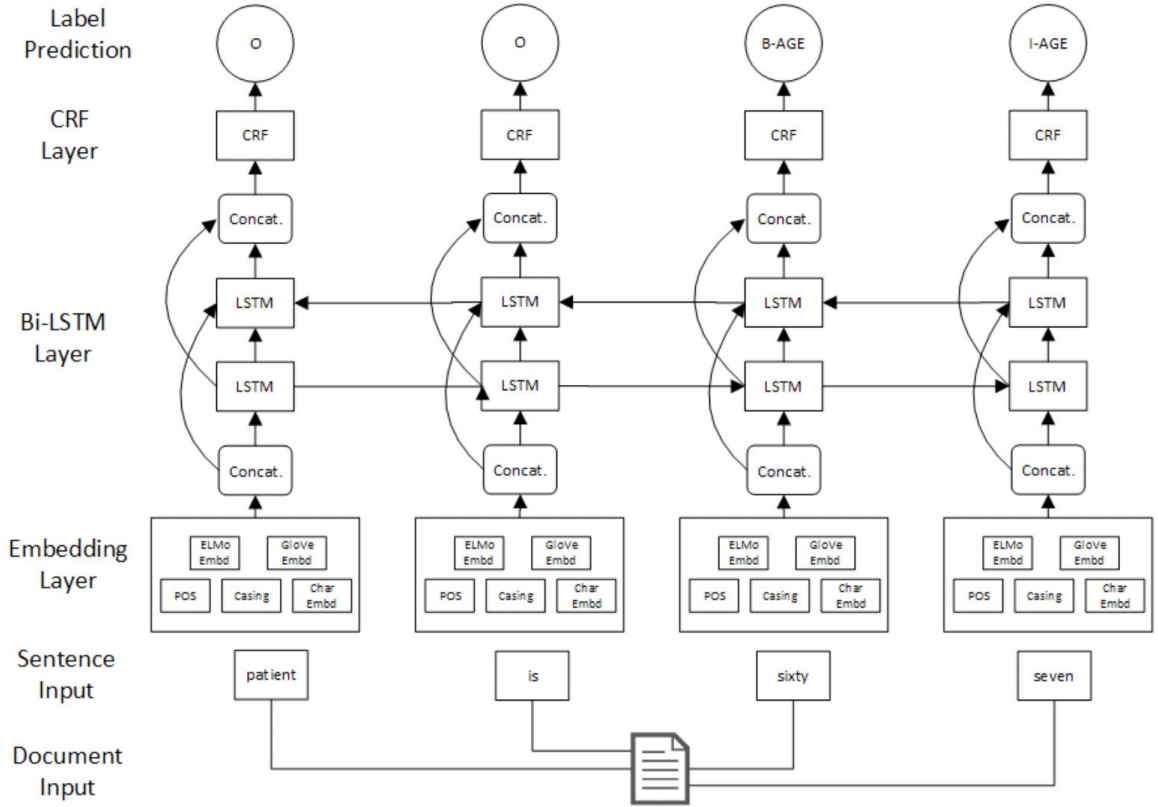
# Biomedical Named Entity Recognition

## Spark NLP vs Spacy vs Stanza

| Dataset | Entities | Spark - Biomedical | Spark - GloVe 6B | Stanza | SciSpacy |
|---|---|---|---|---|---|
| NBCI-Disease | Disease | **89.13** | 87.19 | 87.49 | 81.65 |
| BC5CDR | Chemical, Disease | **89.73** | 88.32 | 88.08 | 83.92 |
| BC4CHEMD | Chemical | **93.72** | 92.32 | 89.65 | 84.55 |
| Linnaeus | Species | 86.26 | 85.51 | **88.27** | 81.74 |
| Species800 | Species | **80.91** | 79.22 | 76.35 | 74.06 |
| JNLPBA | 5 types in cellular | **81.29** | 79.78 | 76.09 | 73.21 |
| AnatEM | Anatomy | **89.13** | 87.74 | 88.18 | 84.14 |
| BioNLP13-CG | 16 types in Cancer Genetics | **85.58** | 84.3 | 84.34 | 77.6 |

Benchmarks on BioMedical NER Datasets

# NER Architecture




**Char-CNN-BiLSTM**

**BIO schema**

| | |
|---|---|
| John | B-PER |
| Smith | I-PER |
| lives | O |
| in | O |
| New | B-LOC |
| York | I-LOC |

John Smith ⇒ PERSON
New York ⇒ LOCATION

| word | POS_tag | chunk_tag | NER_tag |
|---|---|---|---|
| She | PRP | O | B-person |
| presented | VBD | B-VP | O |
| with | IN | B-VP | O |
| left | JJ | B-NP | B-problem |
| upper | JJ | I-NP | I-problem |
| quadrant | NN | I-NP | I-problem |
| pain | NN | I-NP | I-problem |
| as | RB | O | O |
| well | RB | O | O |
| as | IN | B-VP | O |
| nausea | NN | B-NP | B-problem |

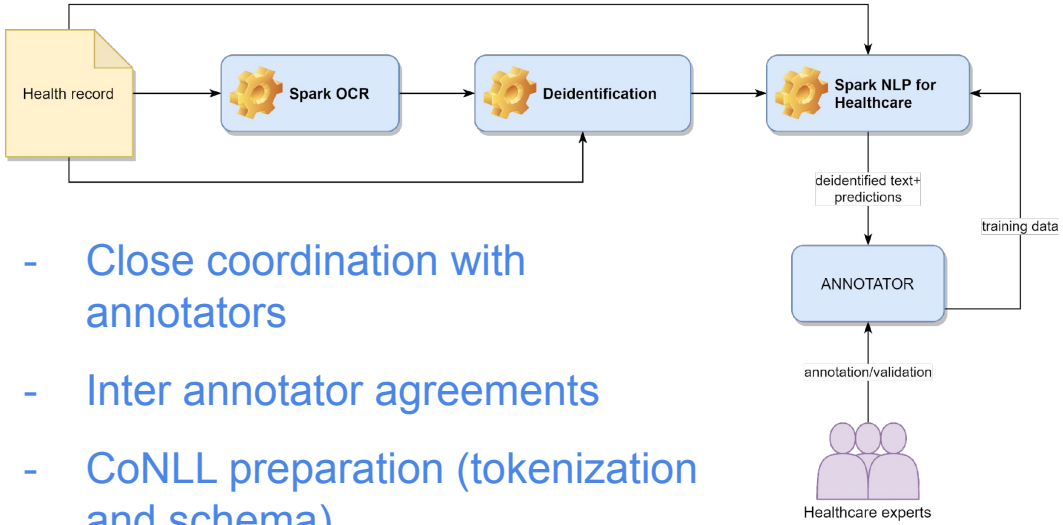
# NER in Healthcare

**BIO schema**

| | |
|---|---|
| John | B-PER |
| Smith | I-PER |
| lives | O |
| in | O |
| New | B-LOC |
| York | I-LOC |

John Smith ⇒ PERSON
New York ⇒ LOCATION

| word | POS_tag | chunk_tag | NER_tag |
|---|---|---|---|
| She | PRP | O | B-person |
| presented | VBD | B-VP | O |
| with | IN | B-VP | O |
| left | JJ | B-NP | B-problem |
| upper | JJ | I-NP | I-problem |
| quadrant | NN | I-NP | I-problem |
| pain | NN | I-NP | I-problem |
| as | RB | O | O |
| well | RB | O | O |
| as | IN | B-VP | O |
| nausea | NN | B-NP | B-problem |




- Close coordination with annotators
- Inter annotator agreements
- CoNLL preparation (tokenization and schema)

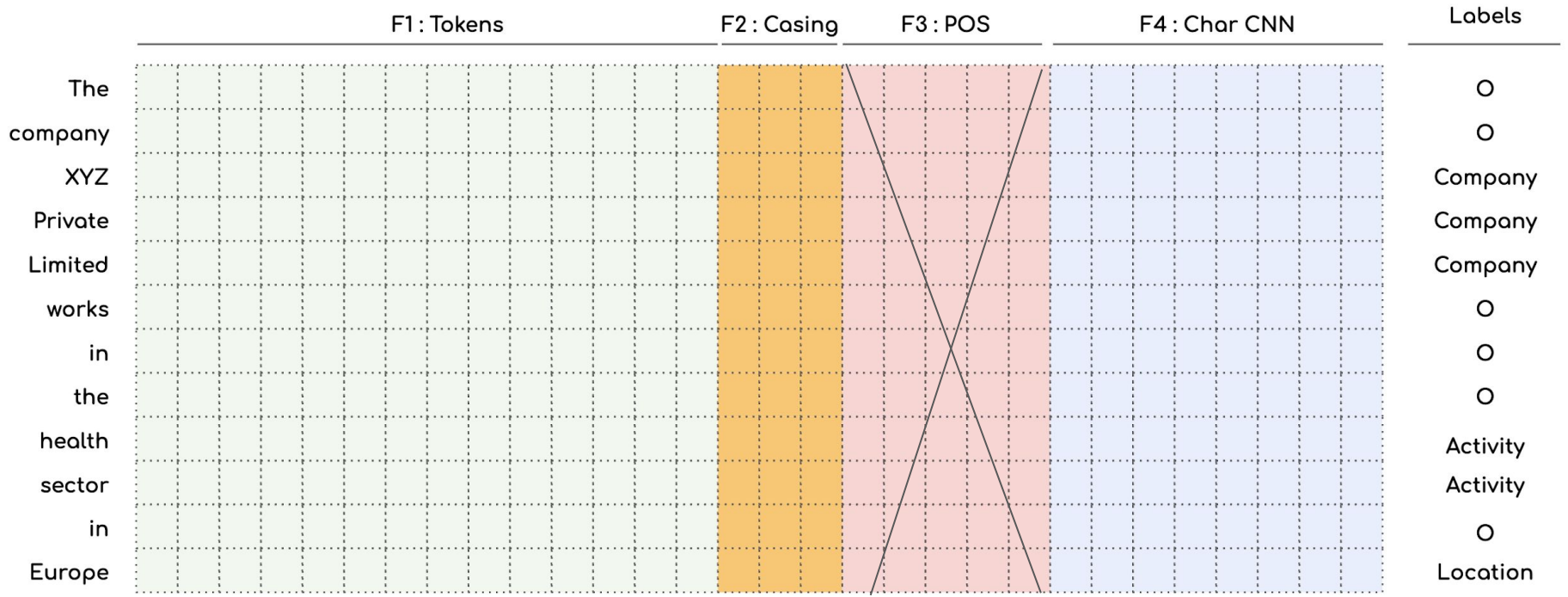
She returns today for ongoing evaluation of herEGFR mutated, stage 4 lung cancer with metastasis to her L2 vertebrae and her lungs bilaterally.

Bone negative for metastatic disease.

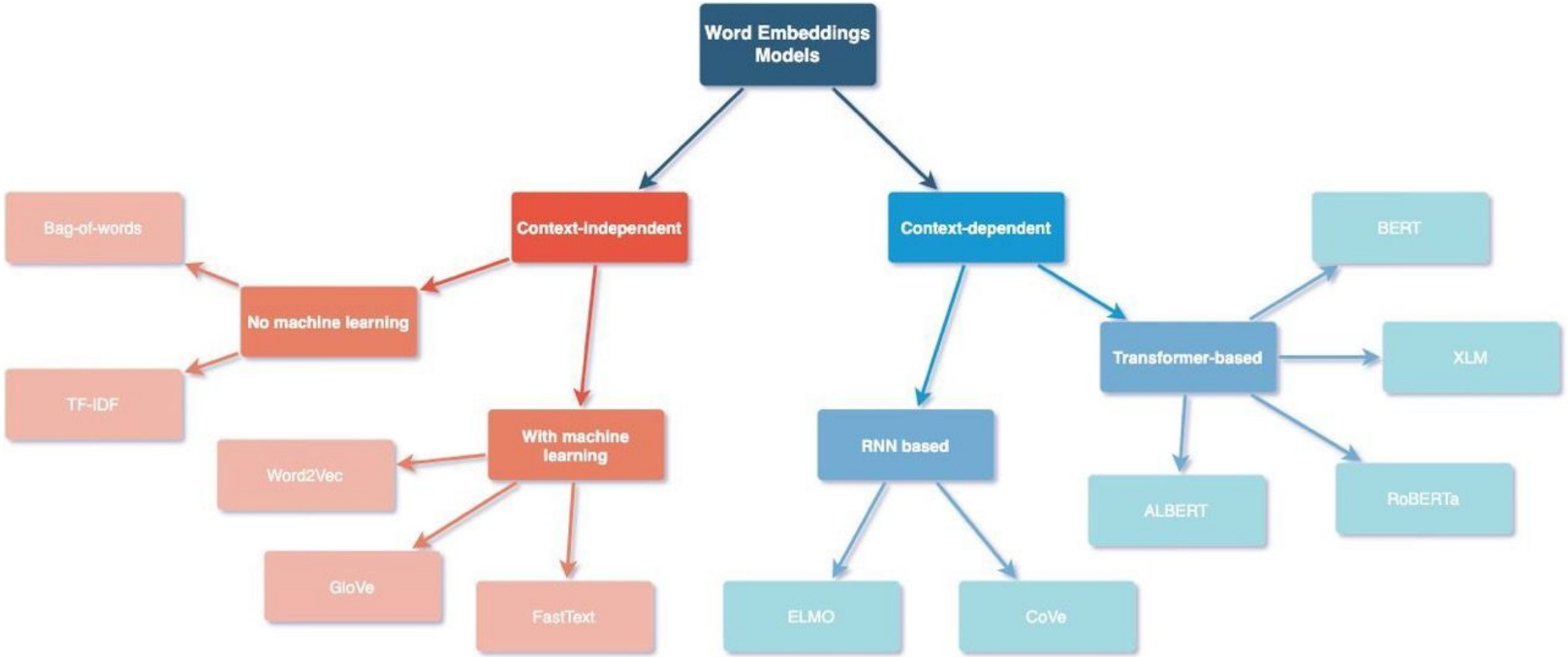
Patient denies any family history of cancer.

# NER-DL in Spark NLP

**Char-CNN-BiLSTM**



# Clinical Word/Sentence Embeddings



# AN NLP TIMELINE AND THE TRANSFORMER FAMILY

## BAG OF WORDS (BOW)
Count the occurrences of each word in the documents and use them as features.
1954

## TF-IDF
The BOW scores are modified so that rare words have high scores and common words have low scores.
1972

## WORD2VEC
Each word is mapped to a high-dimensional vector called word embedding, which captures its semantic. Word embeddings are learned by a neural network looking for word correlations on a large corpus.
2013

## RNN
RNNs compute document embeddings leveraging word context in sentences, which was not possible with word embeddings alone.

### LSTM
Capture long term dependencies.
1997

### Bidirectional RNN
Capture left-to-right and right-to-left dependencies.
1997

### Encoder-decoder RNN
An RNN creates a document embedding (i.e. the encoder) and another RNN decodes it into text (i.e. the decoder).
2014

1986

## TRANSFORMER
An encoder-decoder model that leverages attention mechanisms to compute better embeddings and to better align output to input.
2017

## BERT
Bidirectional Transformer pretrained using a combination of Masked Language Modeling and Next Sentence Prediction objectives. It uses global attention.
2018

## GPT
The first autoregressive model based on the Transformer architecture.

### GPT-2
A bigger and optimized version of GPT, pre-trained on WebText.
2019

### GPT-3
A bigger and optimized version of GPT-2, pre-trained on Common Crawl.
2020

2018

## CTRL
Similar to GPT but with control codes for conditional text generation.
2019

## TRANSFORMER-XL
It's an autoregressive Transformer which can reuse previously computed hidden-states to attend to longer context.
2019

## ALBERT
A lighter version of BERT, where (1) Next Sentence Prediction is replaced by Sentence Order Prediction, and (2) parameter-reduction techniques are used for lower memory consumption and faster training.
2019

## ROBERTA
Better version of BERT, where (1) the Masked Language Modeling objective is dynamic, (2) the Next Sentence Prediction objective is dropped, (3) the BPE tokenizer is employed, and (4) better hyperparameters are used.
2019

## XLM
Transformer pre-trained on a corpus of several languages using objectives like Causal Language Modeling, Masked Language Modeling, and Translation Language Modeling.
2019

## XLNET
Transformer-XL with a generalized autoregressive pre-training method that enables learning bidirectional dependences.
2019

## PEGASUS
A bidirectional encoder and a left-to-right decoder pre-trained with Masked Language Modeling and Gap Sentence Generation objectives.
2019

## DISTILBERT
Same as BERT but smaller and faster, while preserving over 95% of BERT's performances. Trained by distillation of the pre-trained BERT model.
2019

## XLM-ROBERTA
RoBERTa trained on a multilanguage corpus with the Masked Language Modeling objective.
2019

## BART
A bidirectional encoder and a left-to-right decoder trained by corrupting text with an arbitrary noising function and learning a model to reconstruct the original text.
2019

## CONVBERT
Better version of BERT, where self-attention blocks are replaced with new ones that leverage convolutions to better model global and local context.
2019

## FUNNEL TRANSFORMER
A type of Transformer that gradually compresses the sequence of hidden states to a shorter one and hence reduces the computation cost.
2020

## REFORMER
A more efficient Transformer thanks to local-sensitive hashing attention, axial position encoding and other optimizations.
2020

## T5
A bidirectional encoder and a left-to-right decoder pre-trained on a mix of unsupervised and supervised tasks.
2020

## LONGFORMER
A Transformer model replacing the attention matrices with sparse matrices for higher training efficiency.
2020

## PROPHETNET
A Transformer model trained with the Future N-gram Prediction objective and with a novel self-attention mechanism.
2020

## ELECTRA
Same as BERT but lighter and better. The model is trained with the Replaced Token Detection objective.
2020

## SWITCH TRANSFORMER
A sparsely-activated expert Transformer model that aims to simplify and improve over Mixture of Experts.
2021

NLPLANET The community of NLP enthusiasts!
https://www.linkedin.com/company/nlplanet
https://twitter.com/nlplanet_
https://medium.com/nlplanet

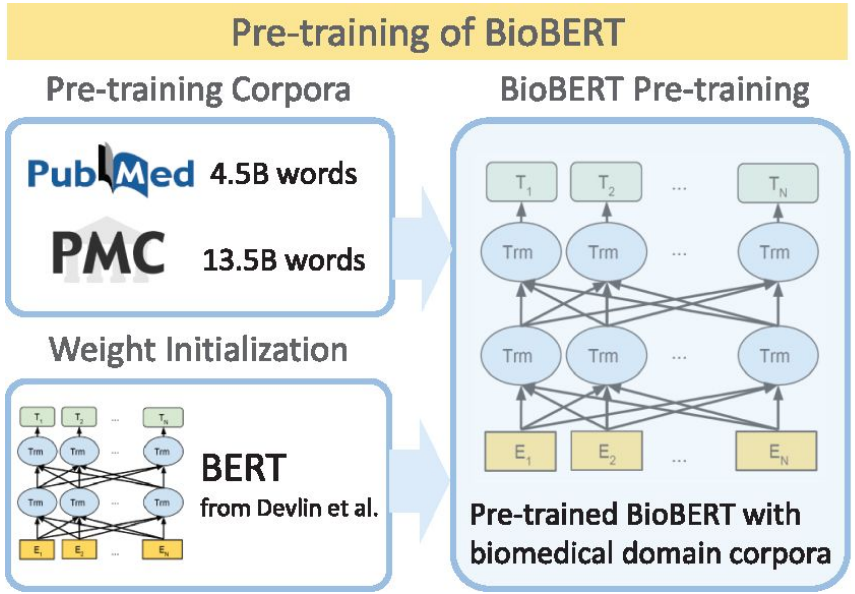
By Fabio Chiusano

# Clinical Word/Sentence Embeddings

| Clinical Glove (200d) | ICDO Glove (200d) | Sent BERT | Bio/Clinical BERT |
|---|---|---|---|
| PubMed + PMC | PubMed + ICD10 UMLS + MIMIC III | BioBert finetuned on NLI and MedNLI | Fine tuned Pubmed + PMC + Discharge summaries |

PubMed abstracts and PMC full-text articles

https://www.nlm.nih.gov/bsd/difference.html



# Part - II

- Assertion Status detection

# 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 |

```
clinical_assertion = AssertionDLModel\
    .pretrained("assertion_dl", "en", "clinical/models")\
    .setInputCols(["sentence", "ner_chunk", "embeddings"]) \
    .setOutputCol("assertion")
```

**Classify the assertions made on given medical concepts as being**

- **present,**
- **absent,**
- **possible,**
- **conditionally present under certain circumstances,**
- **hypothetically present at some future point,**
- **mentioned in the patient report but associated with someone else.**

# Assertion Status Detection

- The deep neural network architecture for assertion status detection in Spark NLP is based on a Bi-LSTM framework, and is a modified version of the architecture proposed by Federico Fancellu, Adam Lopez and Bonnie Webber (Neural Networks For Negation Scope Detection).
- In the proposed implementation, input units depend on the target tokens (a named entity) and the neighboring words that are explicitly encoded as a sequence using word embeddings.
- Similar to paper mentioned above, it is observed that that 95% of the scope tokens (neighboring words) fall in a window of 9 tokens to the left and 15 to the right of the target tokens in the same dataset. Therefore, the same window size was implemented,
- following parameters were used: learning rate 0.0012, dropout 0.05, batch size 64 and a maximum sentence length 250.
- The model has been implemented within Spark NLP as an annotator called AssertionDLModel. After training 20 epoch and measuring accuracy on the official test set, this implementation exceeds the latest state-of-the-art accuracy benchmarks

| Assertion Label | Spark NLP | Latest Best |
|---|---|---|
| Absent | 0.944 | 0.937 |
| Someone-else | 0.904 | 0.869 |
| Conditional | 0.441 | 0.422 |
| Hypothetical | 0.862 | 0.890 |
| Possible | 0.680 | 0.630 |
| Present | 0.953 | 0.957 |
| micro F1 | 0.939 | 0.934 |

*Mother with a lung cancer,*

# AssertionDLModel

| | model_name | Predicted Entities |
|---|---|---|
| 1 | assertion_dl | Present, Absent, Possible, Planned, Someoneelse, Past, Family, None, Hypotetical |
| 2 | assertion_dl_biobert | absent, present, conditional, associated_with_someone_else, hypothetical, possible |
| 3 | assertion_dl_healthcare | absent, present, conditional, associated_with_someone_else, hypothetical, possible |
| 4 | assertion_dl_large | hypothetical, present, absent, possible, conditional, associated_with_someone_else |
| 5 | assertion_dl_radiology | Confirmed, Suspected, Negative |
| 6 | assertion_jsl | Present, Absent, Possible, Planned, Someoneelse, Past, Family, None, Hypotetical |
| 7 | assertion_jsl_large | present, absent, possible, planned, someoneelse, past |
| 8 | assertion_ml | Hypothetical, Present, Absent, Possible, Conditional, Associated_with_someone_else |

John Snow LABS

# Spark NLP for Healthcare Data Scientists

**July 20-21, 2022**

**Veysel Kocaman**
**Head of Data Science**
**veysel@johnsnowlabs.com**

# Part - III

- Entity Resolution (ICD1-, RxNorm, Snomed, etc.)

# Entity Resolution in Spark NLP for Healthcare

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

| 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 |

## weighted Sentence Chunk Embeddings (after 3.2.0)

| Term | Vocab | Code | Explanation (ground truth) |
|---|---|---|---|
| **CT** | CPT-4 | 74150 | Computed tomography, abdomen; without contrast material |

NLP SUMMIT

# Clinical Entity Resolution

## ICD10CM

- sbiobertresolve_icd10cm_augmented
- sbiobertresolve_icd10pcs
- sbiobertresolve_icd10cm_augmented_billable_hcc
- sbiobertresolve_icd10cm
- sbiobertresolve_icd10cm_slim_normalized
- sbiobertresolve_icd10cm_slim_billable_hcc
- sbertresolve_icd10cm_slim_billable_hcc_med
- sbiobertresolve_icd10cm_generalised

## RxNorm

- sbiobertresolve_rxnorm
- demo_sbiobertresolve_rxnorm
- sbiobertresolve_rxnorm_dispo
- sbiobertresolve_rxnorm_disposition
- sbertresolve_rxnorm_disposition
- sbiobertresolve_rxnorm_ndc

## LOINC

- sbluebertresolve_loinc
- sbiobertresolve_loinc

**and more ...**

## UMLS

- sbiobertresolve_umls_findings
- sbiobertresolve_umls_major_concepts
- sbiobertresolve_umls_disease_syndrome
- sbiobertresolve_umls_clinical_drugs

## CPT

- sbiobertresolve_cpt
- sbiobertresolve_cpt_procedures_augmented
- sbiobertresolve_cpt_augmented
- sbiobertresolve_cpt_procedures_measurements_augmented

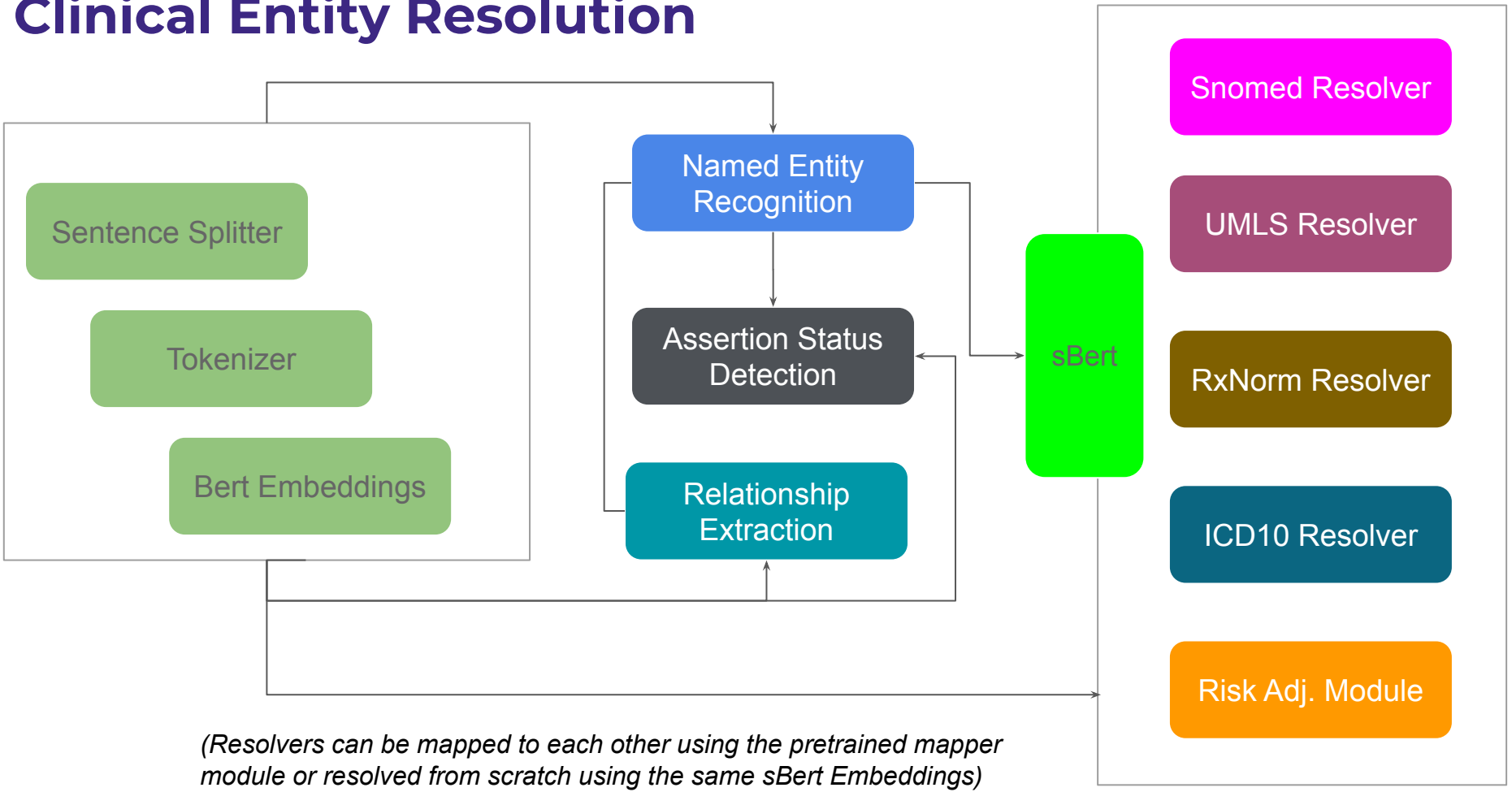
## Snomed

- sbiobertresolve_snomed_auxConcepts_int
- sbiobertresolve_snomed_findings
- sbiobertresolve_snomed_findings_int
- sbiobertresolve_snomed_auxConcepts
- sbertresolve_snomed_bodyStructure_med
- sbiobertresolve_snomed_bodyStructure
- sbiobertresolve_snomed_findings_aux_concepts
- sbertresolve_snomed_conditions

## mapping

- `icd10cm_snomed_mapping` : ICD10 Codes to Snomed Codes
- `snomed_icd10cm_mapping` : Snomed Codes to ICD Codes
- `icd10cm_umls_mapping` : ICD Codes to UMLS Codes
- `snomed_umls_mapping` : Snomed Codes to UMLS Codes
- `rxnorm_umls_mapping` : RxNorm Codes to UMLS Codes
- `mesh_umls_mapping` : MeSH Codes to UMLS Codes
- `rxnorm_mesh_mapping` : RxNorm Codes to MeSH Codes

# Clinical Entity Resolution




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

# Entity Resolution with SentenceEntityResolver

```
[ ] documentAssembler = DocumentAssembler()\
        .setInputCol("text")\
        .setOutputCol("ner_chunk")

    sbert_embedder = BertSentenceEmbeddings.pretrained('sbiobert_base_cased_mli', 'en','clinical/models')\
        .setInputCols(["ner_chunk"])\
        .setOutputCol("sentence_embeddings")\
        .setCaseSensitive(False)

    rxnorm_resolver = SentenceEntityResolverModel.pretrained("sbiobertresolve_rxnorm_augmented","en", "clinical/models") \
        .setInputCols(["ner_chunk", "sentence_embeddings"]) \
        .setOutputCol("rxnorm_code")\
        .setDistanceFunction("EUCLIDEAN")

    rxnorm_pipelineModel = PipelineModel(
        stages = [
            documentAssembler,
            sbert_embedder,
            rxnorm_resolver])

    rxnorm_lp = LightPipeline(rxnorm_pipelineModel)
```

```
sbiobert_base_cased_mli download started this may take some time.
Approximate size to download 384.3 MB
[OK!]
sbiobertresolve_rxnorm_augmented download started this may take some time.
[OK!]
```

```
text = 'aspirin 10 meq/ 5 ml oral sol'

%time p.predict(text)[cols]
```

```
CPU times: user 92.7 ms, sys: 14.4 ms, total: 107 ms
Wall time: 1.53 s
```

| resolution_rxnorm_code_target_text | resolution_rxnorm_code | resolution_rxnorm_code_k_codes | resolution_rxnorm_code_k_resolution | resolution_rxnorm_code_k_cos_dis |
|---|---|---|---|---|
| | | | [memantine hydrochloride 2 MG/ML Oral Solution, dicyclomine hydrochloride 2 MG/ML Oral Solution, codeine phosphate 2 MG/ML Oral Solution, guaifenesin 10 MG/ML Oral Solution, prednisolone 2 MG/ML Oral Solution, hydroxyzine hydrochloride 2 MG/ML Oral | |

```
[ ] # Annotator that transforms a text column from dataframe into an Annotation ready for NLP
    document_assembler = DocumentAssembler()\
        .setInputCol("text")\
        .setOutputCol("document")

    # Sentence Detector DL annotator, processes various sentences per line
    sentenceDetectorDL = SentenceDetectorDLModel.pretrained("sentence_detector_dl_healthcare", "en", 'clinical/models') \
        .setInputCols(["document"]) \
        .setOutputCol("sentence")

    # Tokenizer splits words in a relevant format for NLP
    tokenizer = Tokenizer()\
        .setInputCols(["sentence"])\
        .setOutputCol("token")

    # WordEmbeddingsModel pretrained "embeddings_clinical" includes a model of 1.7Gb that needs to be downloaded
    word_embeddings = WordEmbeddingsModel.pretrained("embeddings_clinical", "en", "clinical/models")\
        .setInputCols(["sentence", "token"])\
        .setOutputCol("word_embeddings")

    # Named Entity Recognition for clinical concepts.
    clinical_ner = MedicalNerModel.pretrained("ner_clinical", "en", "clinical/models") \
        .setInputCols(["sentence", "token", "word_embeddings"]) \
        .setOutputCol("ner")

    ner_converter_icd = NerConverterInternal() \
        .setInputCols(["sentence", "token", "ner"]) \
        .setOutputCol("ner_chunk")\
        .setWhiteList(['PROBLEM'])\
        .setPreservePosition(False)

    c2doc = Chunk2Doc()\
        .setInputCols("ner_chunk")\
        .setOutputCol("doc_ner_chunk")

    sbert_embedder = BertSentenceEmbeddings.pretrained('sbiobert_base_cased_mli', 'en','clinical/models')\
        .setInputCols(["doc_ner_chunk"])\
        .setOutputCol("sentence_embeddings")\
        .setCaseSensitive(False)

    icd_resolver = SentenceEntityResolverModel.pretrained("sbiobertresolve_icd10cm_augmented_billable_hcc","en", "clinical/models") \
        .setInputCols(["ner_chunk", "sentence_embeddings"]) \
        .setOutputCol("icd10cm_code")\
        .setDistanceFunction("EUCLIDEAN")


    # Build up the pipeline
    resolver_pipeline = Pipeline(
        stages = [
            document_assembler,
            sentenceDetectorDL,
            tokenizer,
```

# Entity Resolution with ChunkMapper

```
[ ] document_assembler = DocumentAssembler()\
    .setInputCol("text")\
    .setOutputCol("chunk")

    chunkerMapper = ChunkMapperModel.pretrained("rxnorm_mapper", "en", "clinical/models")\
    .setInputCols(["chunk"])\
    .setOutputCol("rxnorm")\
    .setRels(["rxnorm_code"])

    pipeline = Pipeline().setStages([document_assembler,
    chunkerMapper])

    model = pipeline.fit(spark.createDataFrame([['']]).toDF('text'))

    lp = LightPipeline(model)
```

```
rxnorm_mapper download started this may take some time.
[OK!]
CPU times: user 4 µs, sys: 1 µs, total: 5 µs
Wall time: 18.1 µs
[{'chunk': [Annotation(document, 0, 8, metformin, {})],
  'rxnorm': [Annotation(labeled_dependency, 0, 8, 6809, {'entity': 'metformin', 'relation': 'rxnorm_code', 'all_relations': ''})]}]
```

```
[ ] %%time

    lp.fullAnnotate("metformin")
```

```
CPU times: user 6.9 ms, sys: 803 µs, total: 7.71 ms
Wall time: 19.3 ms
[{'chunk': [Annotation(document, 0, 8, metformin, {})],
  'rxnorm': [Annotation(labeled_dependency, 0, 8, 6809, {'entity': 'metformin', 'relation': 'rxnorm_code', 'all_relations': ''})]}]
```

```
document_assembler = DocumentAssembler()\
      .setInputCol('text')\
      .setOutputCol('document')

sentence_detector = SentenceDetector()\
      .setInputCols(["document"])\
      .setOutputCol("sentence")

tokenizer = Tokenizer()\
      .setInputCols("sentence")\
      .setOutputCol("token")

ner =  MedicalBertForTokenClassifier.pretrained("bert_token_classifier_drug_development_trials", "en", "clinical/models")\
      .setInputCols("token","sentence")\
      .setOutputCol("ner")

nerconverter = NerConverter()\
      .setInputCols("sentence", "token", "ner")\
      .setOutputCol("ner_chunk")

#drug_action_treatment_mapper with "action" mappings
chunkerMapper= ChunkMapperModel().pretrained("drug_action_treatment_mapper", "en", "clinical/models")\
    .setInputCols(["ner_chunk"])\
    .setOutputCol("action_mappings")\
    .setRels(["action"])


pipeline = Pipeline().setStages([document_assembler,
                                 sentence_detector,
                                 tokenizer,
                                 ner,
                                 nerconverter,
                                 chunkerMapper])

text = [
    ["""The patient was female and patient of Dr. X. and she was given Dermovate, Aspagin"""]
]


test_data = spark.createDataFrame(text).toDF("text")

res = pipeline.fit(test_data).transform(test_data)
```

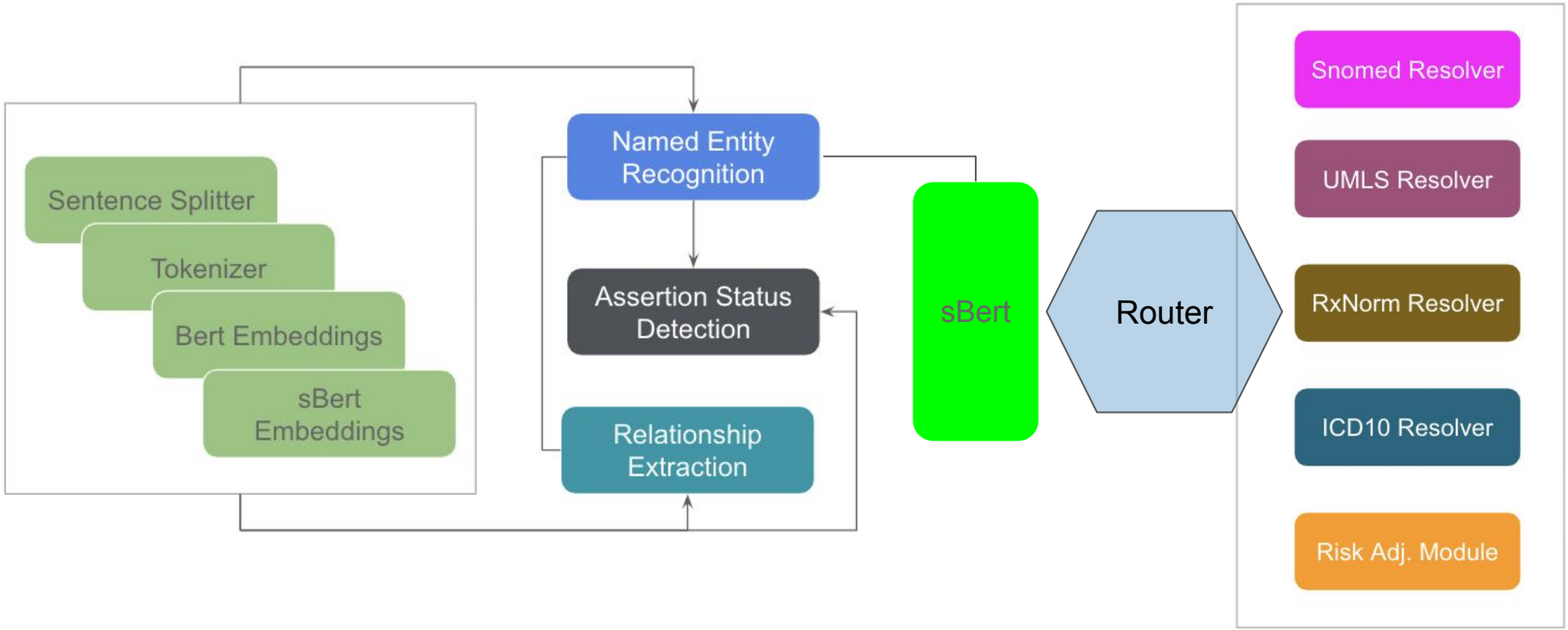
```
bert_token_classifier_drug_development_trials download started this may take some time.
[OK!]
drug_action_treatment_mapper download started this may take some time.
[OK!]
```

Chunks detected by ner model

]:
```
res.select(F.explode('ner_chunk.result').alias("chunks")).show(truncate=False)
```

```
+---------+
|chunks   |
+---------+
|Dermovate|
|Aspagin  |
+---------+
```

# Clinical Entity Resolution



```
ner = MedicalNerModel().pretrained("ner_clinical", "en", "clinical/models") \
    .setInputCols(["sentence", "token", "word_embeddings"]) \
    .setOutputCol("ner")

ner_chunk = NerConverter()\
    .setInputCols("sentence","token","ner")\
    .setOutputCol("ner_chunk")\
    .setWhiteList(["PROBLEM","TREATMENT"])

chunk2doc = Chunk2Doc().setInputCols("ner_chunk").setOutputCol("doc_jsl_chunk")

sbiobert_embeddings = BertSentenceEmbeddings.pretrained("sbiobert_base_cased_mli","en","clinical/models")\
    .setInputCols(["doc_jsl_chunk"])\
    .setOutputCol("sbert_embeddings")\
    .setCaseSensitive(False)

router_sentence_icd10 = Router() \
    .setInputCols("sbert_embeddings") \
    .setFilterFieldsElements(["PROBLEM"]) \
    .setOutputCol("problem_embeddings")

router_sentence_rxnorm = Router() \
    .setInputCols("sbert_embeddings") \
    .setFilterFieldsElements(["TREATMENT"]) \
    .setOutputCol("drug_embeddings")

icd_resolver = SentenceEntityResolverModel.pretrained("sbiobertresolve_icd10cm_slim_billable_hcc","en", "clinical/models") \
    .setInputCols(["problem_embeddings"]) \
    .setOutputCol("icd10cm_code")\
    .setDistanceFunction("EUCLIDEAN")

rxnorm_resolver = SentenceEntityResolverModel.pretrained("sbiobertresolve_rxnorm_augmented","en", "clinical/models") \
    .setInputCols(["drug_embeddings"]) \
    .setOutputCol("rxnorm_code")\
    .setDistanceFunction("EUCLIDEAN")

resolver_pipeline = Pipeline(stages=[
    documentAssembler,
    sentenceDetector,
    tokenizer,
    word_embeddings,
    ner,
    ner_chunk,
    chunk2doc,
    sbiobert_embeddings,
    router_sentence_icd10,
    router_sentence_rxnorm,
    icd_resolver,
    rxnorm_resolver
])
```

0s completed at 5:42 PM

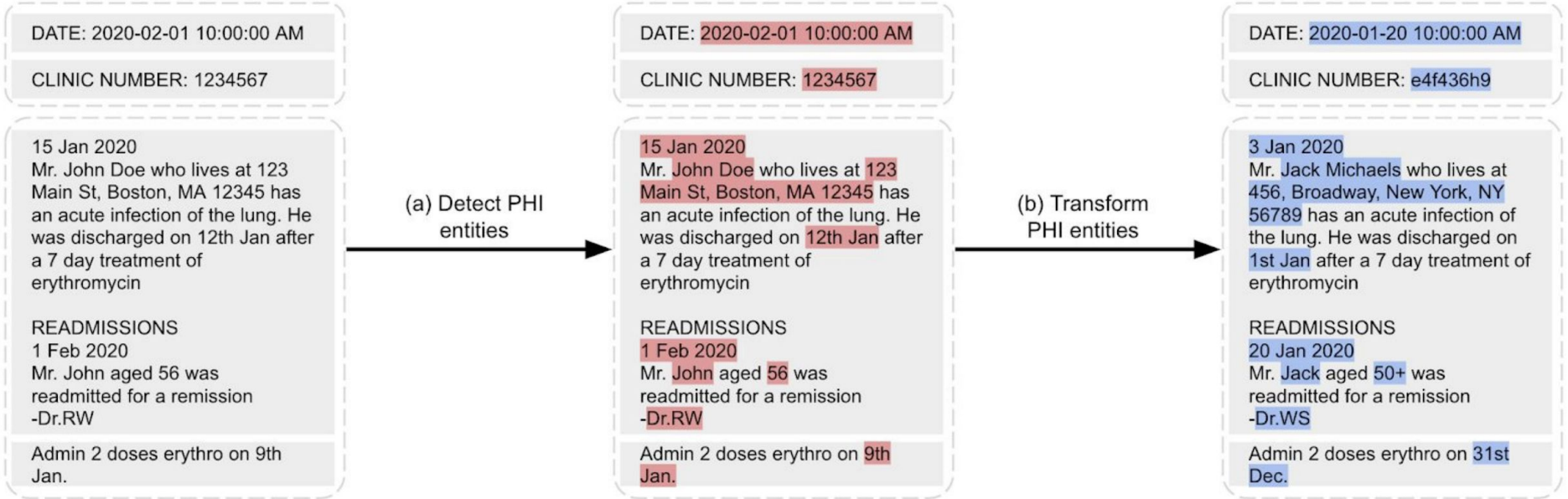
# Top - 5 Results

# Part - IV

- De-Identification and Obfuscation of PHI data

# De-Identification

* Identifies potential pieces of content with personal information about patients and remove them by replacing with semantic tags.



# De-Identification

* Identifies potential pieces of content with personal information about patients and remove them by replacing with semantic tags.

| Group Name | Included Entities |
|---|---|
| A (defined by the HIPAA Safe Harbor Implementation) | Age over 89, Phone/Fax numbers, Email addresses, Websites and URLs, IP Addresses, Dates, Social security numbers, Medical record numbers, Vehicle/Device numbers, Account/Certificate/License numbers, Health plan numbers, Biometric identifiers, Street addresses, City, Zip code, Employer names, Personal names of patients and family members |
| B | Group A, Doctor names, User IDs (of care providers), State |
| C | Group B, Hospital names, Country |
| D | Group C, Holidays, Days of the week, Occupations |

# De-Identification

* Identifies potential pieces of content with personal information about patients and remove them by replacing with semantic tags.

A . Record date : 2093-01-13 , David Hale , M.D . , Name : Hendrickson , Ora MR . # 7194334 Date : 01/13/93 PCP : Oliveira , 25 month years-old , Record date : 2079-11-09 . Cocke County Baptist Hospital . 0295 Keats Street

Color codes:DOCTOR, HOSPITAL, DATE, STREET, MEDICALRECORD, PATIENT,

Deidentified Text

```
['A .',
 'Record date : <DATE>  , <DOCTOR> , M.D .',
 ', Name : <PATIENT> , <PATIENT> MR .',
 '# <MEDICALRECORD> Date : <DATE> PCP : <DOCTOR> , 25
month years-old , Record date : <DATE> .',
 '<HOSPITAL> .',
 '<STREET>']
```

```
def get_deidentify_model():

    custom_ner_converter = NerConverter()\
      .setInputCols(["sentence", "token", "ner"])\
      .setOutputCol("ner_chunk")
      #.setWhiteList(entity_types)

    deidentify_pipeline = Pipeline(
            stages = [
            documentAssembler,
            sentenceDetector,
            tokenizer,
            word_embeddings,
            clinical_ner,
            custom_ner_converter,
            deidentification_rules
            ])

    empty_data = spark.createDataFrame([[""]]).toDF("text")

    model_deidentify = deidentify_pipeline.fit(empty_data)

    return model_deidentify
```

# Spark NLP for Healthcare - Deidentification

| | English | German | French | Spanish | Italian |
|---|---|---|---|---|---|
| PATIENT | 0.90 | 0.97 | 0.94 | 0.92 | 0.91 |
| DOCTOR | 0.94 | 0.98 | 0.99 | 0.92 | 0.92 |
| HOSPITAL | 0.91 | 1.00 | 0.94 | 0.86 | 0.90 |
| DATE | 0.98 | 1.00 | 0.98 | 0.99 | 0.98 |
| AGE | 0.94 | 0.99 | 0.86 | 0.98 | 0.98 |
| PROFESSION | 0.84 | 1.00 | 0.81 | 0.91 | 0.89 |
| ORGANIZATION | 0.77 | 0.94 | 0.77 | 0.83 | 0.74 |
| STREET | 0.9794 | 0.9802 | 0.8986 | 0.9448 | 0.9754 |
| CITY | 0.8331 | 0.9874 | 0.8643 | 0.8377 | 0.9678 |
| COUNTRY | 0.8083 | 0.9823 | 0.8983 | 0.8662 | 0.9262 |
| PHONE | 0.9412 | 0.882 | 0.9785 | 0.9027 | 0.9815 |
| USERNAME | 0.9215 | 1 | 0.9239 | 0.7407 | 0.9091 |
| ZIP | 0.9928 | - | 1 | 0.9895 | 0.9867 |

DATE: 2020-01-20 10:00:00 AM

CLINIC NUMBER: e4f436h9

3 Jan 2020
Mr. Jack Michaels who lives at 456, Broadway, New York, NY 56789 has an acute infection of the lung. He was discharged on 1st Jan after a 7 day treatment of erythromycin

READMISSIONS
20 Jan 2020
Mr. Jack aged 50+ was readmitted for a remission
-Dr.WS

Admin 2 doses erythro on 31st Dec.

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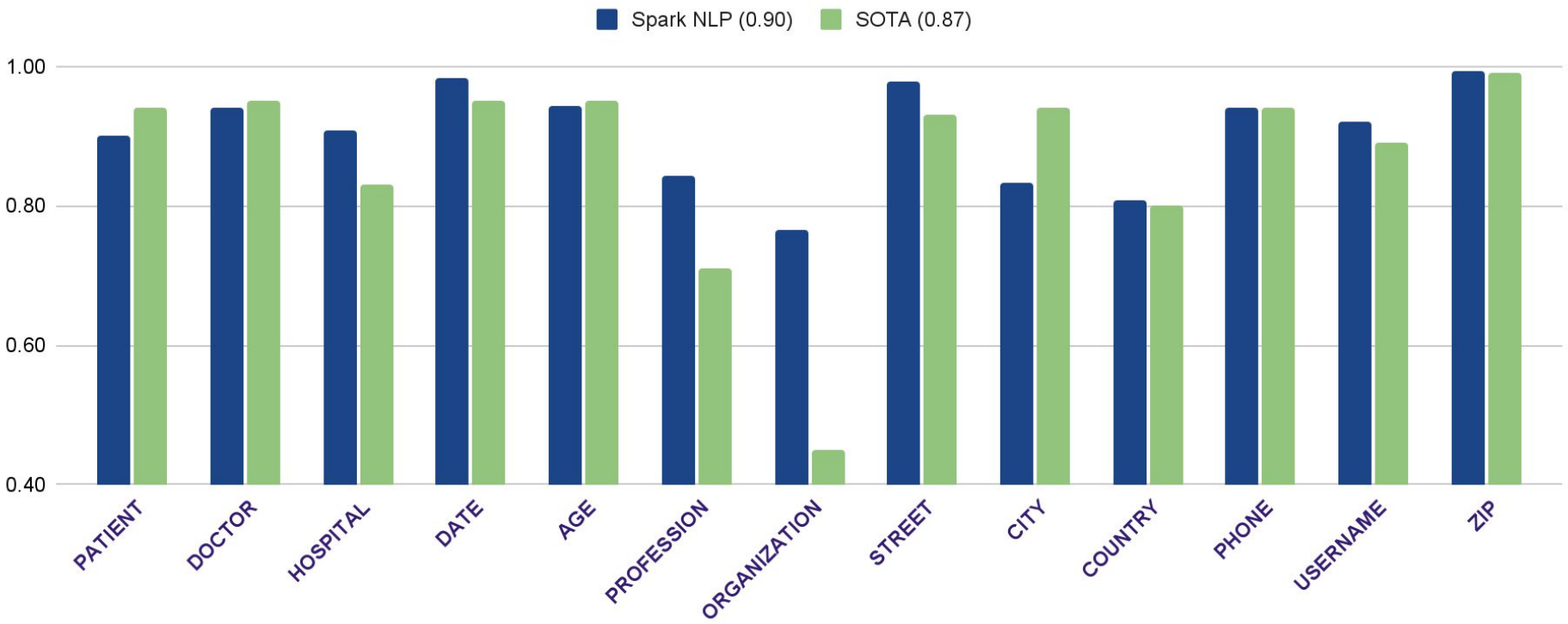
**Sub-entity (13-entity)**

# Deidentification Benchmarks



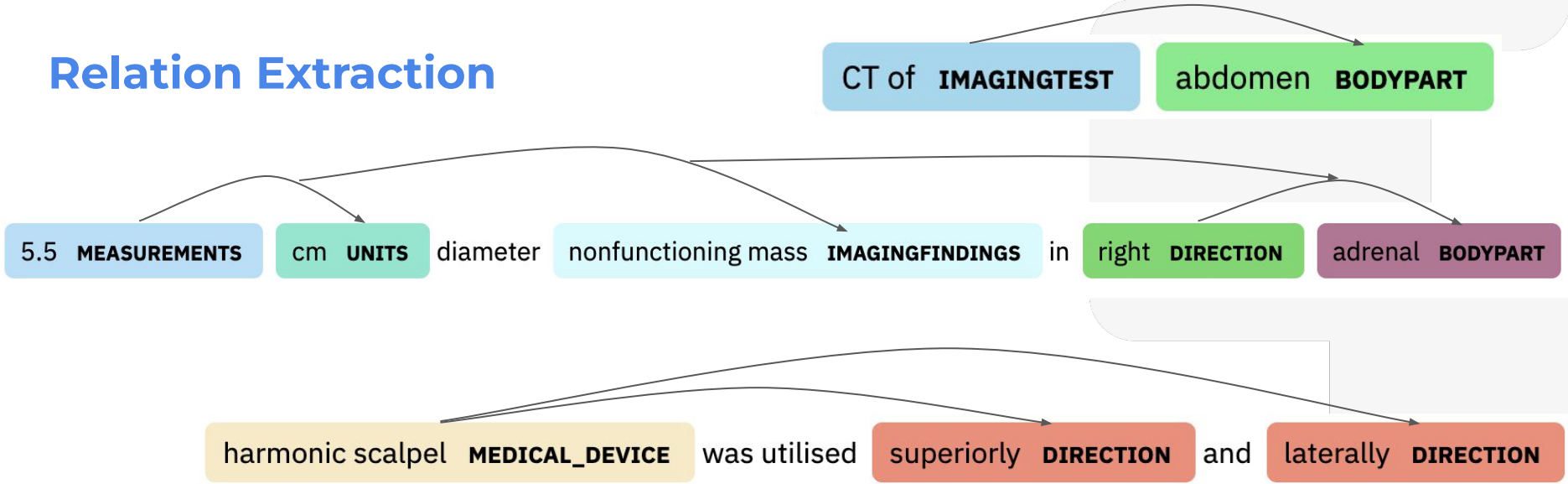
# Part - V

- Relation Extraction

# Clinical 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."

## Relation Extraction



# Clinical Relation Extraction

| | model_name |
|---|---|
| 0 | re_ade_biobert |
| 1 | re_ade_clinical |
| 2 | re_bodypart_directions |
| 3 | re_bodypart_problem |
| 4 | re_bodypart_proceduretest |
| 5 | re_chemprot_clinical |
| 6 | re_clinical |
| 7 | re_date_clinical |
| 8 | re_drug_drug_interaction_clinical |
| 9 | re_human_phenotype_gene_clinical |
| 10 | re_temporal_events_clinical |
| 11 | re_temporal_events_enriched_clinical |
| 12 | re_test_problem_finding |
| 13 | re_test_result_date |
| 14 | redl_ade_biobert |
| 15 | redl_bodypart_direction_biobert |
| 16 | redl_bodypart_problem_biobert |
| 17 | redl_bodypart_procedure_test_biobert |
| 18 | redl_chemprot_biobert |
| 19 | redl_clinical_biobert |
| 20 | redl_date_clinical_biobert |
| 21 | redl_drug_drug_interaction_biobert |
| 22 | redl_human_phenotype_gene_biobert |
| 23 | redl_temporal_events_biobert |

| Relation | Recall | Precision | F1 | SOTA |
|---|---|---|---|---|
| DRUG-ADE | 0.66 | 1.00 | **0.80** | 0.76 |
| DRUG-DOSAGE | 0.89 | 1.00 | **0.94** | 0.91 |
| DRUG-DURATION | 0.75 | 1.00 | **0.85** | 0.92 |
| DRUG-FORM | 0.88 | 1.00 | **0.94** | 0.95* |
| DRUG-FREQUENCY | 0.79 | 1.00 | **0.88** | 0.90 |
| DRUG-REASON | 0.60 | 1.00 | **0.75** | 0.70 |
| DRUG-ROUTE | 0.79 | 1.00 | **0.88** | 0.95* |
| DRUG-STRENGTH | 0.95 | 1.00 | **0.98** | 0.97 |

| Relation | Recall | Precision | F1 |
|---|---|---|---|
| OVERLAP | 0.81 | 0.73 | **0.77** |
| BEFORE | 0.85 | 0.88 | **0.86** |
| AFTER | 0.38 | 0.46 | **0.43** |

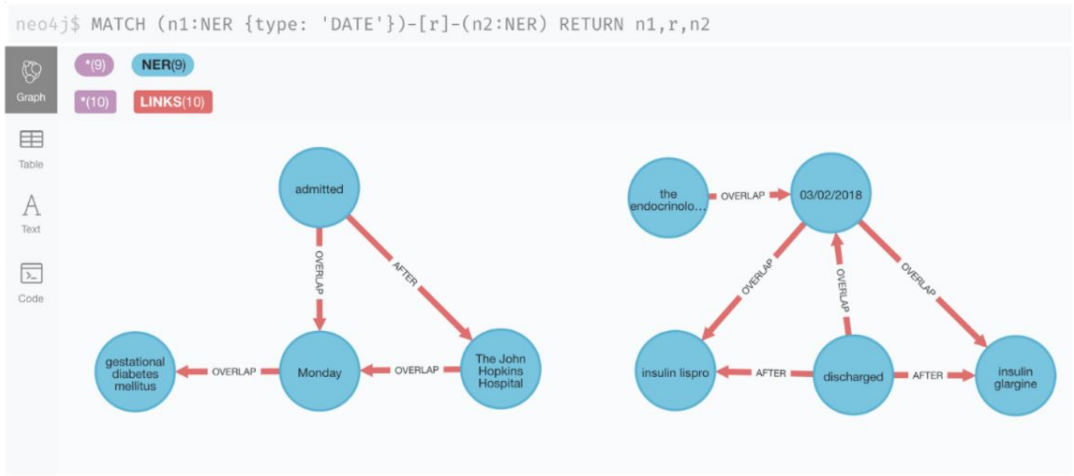
# Clinical Relation Extraction

*She is admitted to The John Hopkins Hospital on Monday with a history of gestational diabetes mellitus diagnosed. She was seen by the endocrinology service and she was discharged on 03/02/2018 on 40 units of insulin glargine and 12 units of insulin lispro.*

```
query = """
    MATCH (n1:NER {type: 'DATE'})-[r]-(n2:NER)
    RETURN n1.name AS date, r.relation AS relation, n2.name AS event
"""

df = pd.DataFrame([dict(_) for _ in conn.query(query)])
df
```

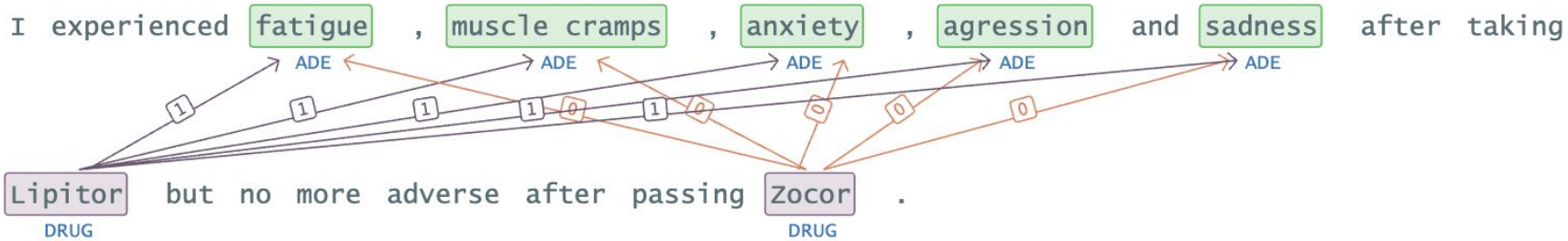
| | date | relation | event |
|---|---|---|---|
| 0 | Monday | OVERLAP | gestational diabetes mellitus |
| 1 | Monday | OVERLAP | The John Hopkins Hospital |
| 2 | Monday | OVERLAP | admitted |
| 3 | 03/02/2018 | OVERLAP | insulin lispro |
| 4 | 03/02/2018 | OVERLAP | insulin glargine |
| 5 | 03/02/2018 | OVERLAP | discharged |
| 6 | 03/02/2018 | OVERLAP | the endocrinology service |



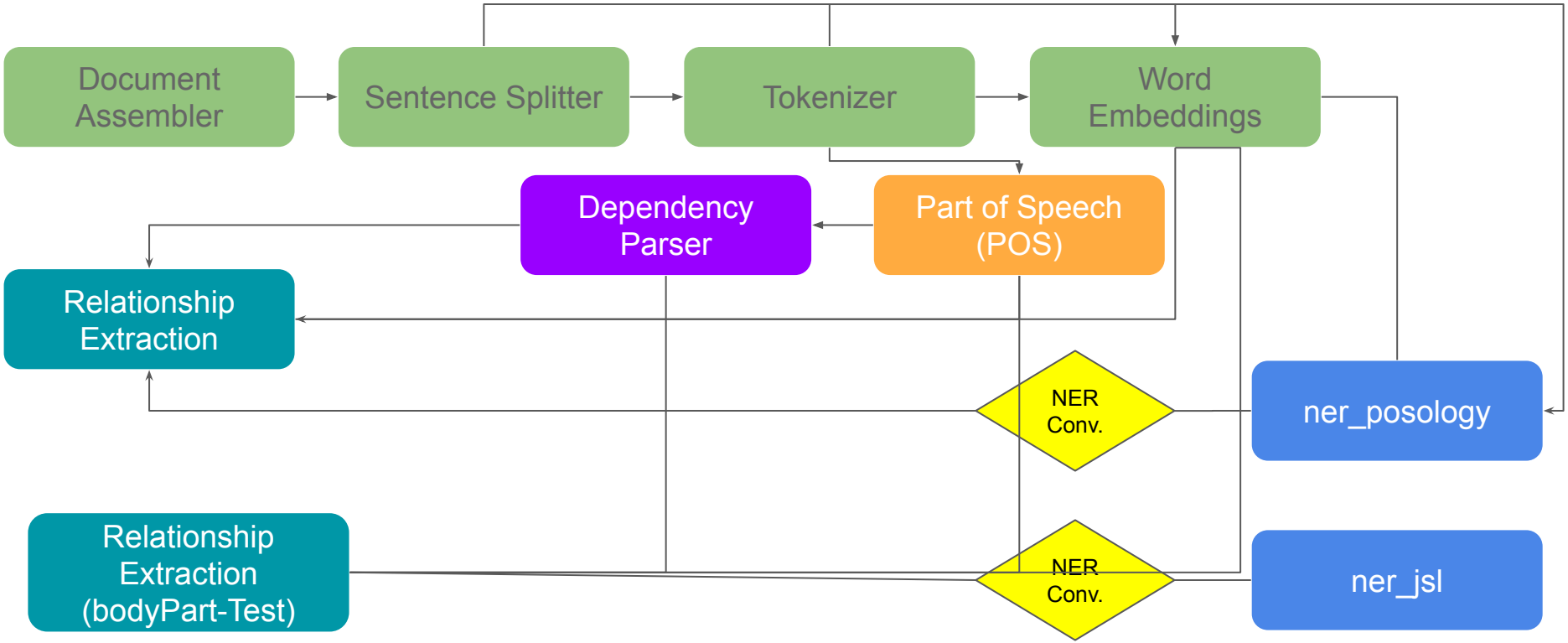
# Clinical Relation Extraction

| | relation | entity1 | entity1_begin | entity1_end | chunk1 | entity2 | entity2_begin | entity2_end | chunk2 | confidence |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | ADE | 14 | 20 | fatigue | DRUG | 82 | 88 | Lipitor | 0.9996617 |
| 1 | 0 | ADE | 14 | 20 | fatigue | DRUG | 124 | 128 | Zocor | 0.9952187 |
| 2 | 1 | ADE | 23 | 35 | muscle cramps | DRUG | 82 | 88 | Lipitor | 0.9999827 |
| 3 | 0 | ADE | 23 | 35 | muscle cramps | DRUG | 124 | 128 | Zocor | 0.91462934 |
| 4 | 1 | ADE | 38 | 44 | anxiety | DRUG | 82 | 88 | Lipitor | 0.7636133 |
| 5 | 0 | ADE | 38 | 44 | anxiety | DRUG | 124 | 128 | Zocor | 0.9999691 |
| 6 | 1 | ADE | 47 | 55 | agression | DRUG | 82 | 88 | Lipitor | 0.99999833 |
| 7 | 0 | ADE | 47 | 55 | agression | DRUG | 124 | 128 | Zocor | 0.99781835 |
| 8 | 1 | ADE | 61 | 67 | sadness | DRUG | 82 | 88 | Lipitor | 1.0 |
| 9 | 0 | ADE | 61 | 67 | sadness | DRUG | 124 | 128 | Zocor | 0.9999572 |

*I experienced fatigue, muscle cramps, anxiety, agression and sadness after taking Lipitor but no more adverse after passing Zocor.*



# Clinical Relation Extraction



# Part - VI

- **Adverse Drug Reactions (ADR)**

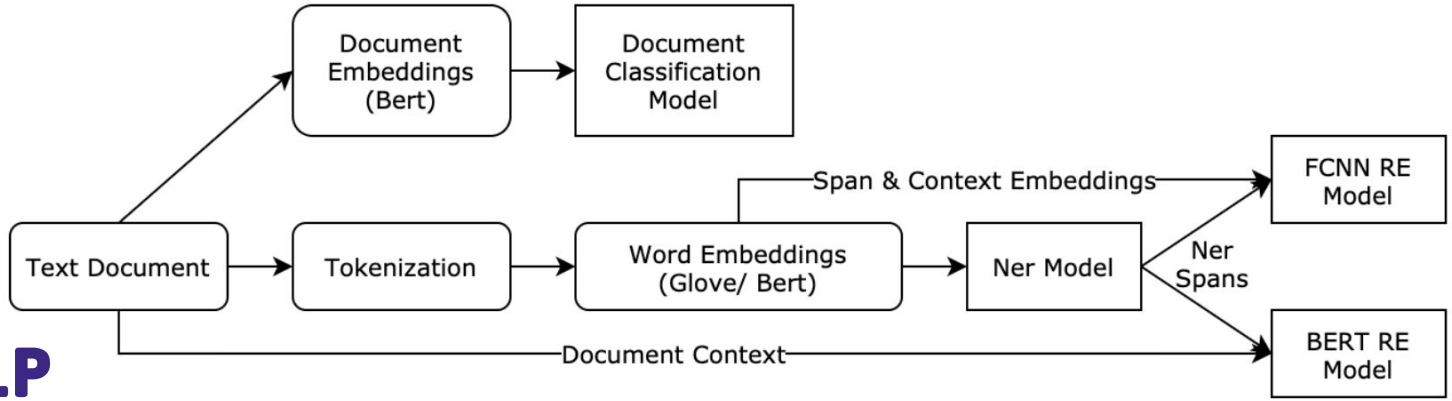
# Adverse Drug Reactions (ADR)

| Document | Class | ADE Entity | Drug Entity | relation |
|---|---|---|---|---|
| I feel a bit drowsy & have a little blurred vision after taking insulin. | ADE | drowsy<br>blurred vision | insulin<br>insulin | Positive<br>Positive |
| @yho fluvastatin gave me cramps, but lipitor suits me! | ADE | cramps<br>cramps | fluvastatin<br>lipitor | Positive<br>Negative |
| I just took advil and haven't had any gastric problems so far. | NEG | - | - | - |

Classification

Named Entity Recognition

Relation Extraction

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# Adverse Drug Reactions (ADR) Benchmark

AAAI
Association for the Advancement of Artificial Intelligence

| Dataset | GLoVe Embeddings | | | | | | BERT Embeddings | | | | | | SOTA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Precision | | Recall | | F1 | | Precision | | Recall | | F1 | | F1 |
| | strict | relax | strict | relax | strict | relax | strict | relax | strict | relax | strict | relax | |
| ADE | 88.32 | 93.77 | 89.26 | 94.80 | 88.78 | 94.27 | 90.0 | 94.47 | 93.56 | 98.22 | **91.75** | 96.31 | **91.3** |
| | 87.81 | 93.59 | 88.81 | 94.66 | 88.30 | 94.12 | 89.6 | 94.37 | 93.18 | 98.13 | 91.36 | 96.21 | |
| CADEC | 78.14 | 89.04 | 77.14 | 88.01 | 77.62 | 88.50 | 78.53 | 88.63 | 79.03 | 89.32 | **78.76** | 88.95 | **71.9** |
| | 71.87 | 86.36 | 71.67 | 86.13 | 71.75 | 86.23 | 72.38 | 86.14 | 73.64 | 87.66 | 72.99 | 86.88 | |
| SMM4H | 81.43 | 90.33 | 72.17 | 78.51 | 76.01 | 83.41 | 78.5 | 86.76 | 75.23 | 82.42 | **76.73** | 84.41 | **67.81** |
| | 83.66 | 91.34 | 71.31 | 77.86 | 76.99 | 84.06 | 79.13 | 87.09 | 74.33 | 81.81 | 76.65 | 84.36 | |

Table 2: NER metrics on benchmark datasets. For each dataset, macro and micro averaged scores are displayed on first and second row respectively. SOTA metrics for ADE, CADEC, and SMM4H are obtained from (Yan et al. 2021), (Stanovsky, Gruhl, and Mendes 2017), and (Ge et al. 2020) respectively, and are macro-averaged.

Named Entity Recognition (NER)

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# Adverse Drug Reactions (ADR) Benchmark



Classification

| Dataset | GLoVe (Avg.) Embeddings | | | BERT (Avg.) Embeddings | | | BERT Sentence Embeddings | | | SOTA |
|---|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 | F1 |
| ADE | 75.96 | 79.53 | 76.86 | 76.91 | 84.96 | 79.37 | 87.41 | 84.72 | **85.96** | **87.0** |
| | 86.84 | 81.22 | 83.43 | 88.13 | 84.38 | 85.38 | 90.97 | 91.20 | 91.03 | |
| CADEC | 85.29 | 84.24 | 84.71 | 86.50 | 86.11 | 86.30 | 87.13 | 86.32 | **86.69** | **81.5** |
| | 85.99 | 86.10 | 86.0 | 87.38 | 87.43 | 87.40 | 87.78 | 87.86 | 87.79 | |

Table 1: Classification Metrics on benchmark datasets. For each dataset, Macro and Micro averaged scores are displayed on first and second row respectively. SOTA metrics for ADE and CADEC datasets are obtained from (Huynh et al. 2016) and (Alimova and Tutubalina 2019) respectively.

Relation Extraction

| Dataset | Base (FCNN) RE | | | BERT RE | | | SOTA |
|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1 | Precision | Recall | F1 | F1 |
| ADE Corpus | 69.11 | 86.22 | **74.70** | 81.31 | 79.03 | **80.10** | **83.74** |
| ADE Enriched with n2c2 | 89.01 | 89.44 | **89.22** | 89.19 | 90.93 | **90.02** | |

Table 3: Relation Extraction performance on the ADE benchmark dataset. The test set was kept standard for a fair comparison, and all scores are macro-averaged due to high class imbalance. SOTA metrics for RE on ADE corpus as reported by (Crone 2020)

# Part - VII

- **Key Chunk Phrase Extractor**

# Chunk Key Phrase Extractor (KCPE)

| key_phrase | source | DocumentSimilarity | MMRScore | sentence |
|---|---|---|---|---|
| type two diabetes mellitus | NER | 0.7639750686118073 | 0.4583850593816694 | 0 |
| subsequent type diabetes | ngrams | 0.7503709443591438 | 0.08298243928224425 | 0 |
| HTG-induced pancreatitis years | ngrams | 0.6817062970203589 | 0.11246275270031031 | 0 |
| hepatitis obesity | ngrams | 0.6666053470245074 | 0.1177052008980295 | 0 |
| mellitus diagnosed years | ngrams | 0.6389213391545323 | 0.08129479185432026 | 0 |
| history gestational diabetes | ngrams | 0.6219876368539883 | 0.0950104202982544 | 0 |
| vomiting | ngrams | 0.5824238088130589 | 0.14864183399720493 | 0 |
| admitted starvation ketosis | ngrams | 0.5789875069392564 | 0.12008073486190007 | 0 |
| five-day amoxicillin respiratory | ngrams | 0.5330653868257814 | 0.09428153526023508 | 0 |
| 28-year-old female history | ngrams | 0.38613601247069695 | 0.12987678861407687 | 0 |

## YAKE

| keyword | score |
|---|---|
| years prior presentation | 0.006335399690627251 |
| prior presentation | 0.011644010991495998 |
| prior presentation subsequent | 0.020272229518351368 |
| weeks prior presentation | 0.020272229518351368 |
| respiratory tract infection | 0.02568455658449274 |
| anion gap | 0.025965846371439553 |
| physical examination presentation | 0.02840600503736659 |
| obtained hours presentation | 0.028532992974589392 |
| examination presentation significant | 0.028532992974589392 |
| prior | 0.029673513395379065 |
| years prior | 0.030808818777992058 |
| anion gap elevated | 0.031568192739369824 |

## CKPE

| key_phrase_candidate | DocumentSimilarity |
|---|---|
| pancreatitis years prior | 0.6491587146812722 |
| diagnosed years prior | 0.385944693969798 97 |
| respiratory tract infection | 0.34452766290310755 |
| patient treated insulin | 0.3413457416284759 |
| serum | 0.3371024001999838 |
| presentation revealed glucose | 0.31458360368143906 |
| examination presentation significant | 0.29099950377907047 |
| prior analysis due | 0.22501711661945623 |
| prior | 0.21634008371261446 |
| physical examination presentation | 0.19165189487112474 |

| key_phrase_candidate | source |
|---|---|
| 28-year-old female history | ngram |
| 28-year-old | NER |
| female history gestational | ngram |
| female | NER |
| history gestational diabetes | ngram |
| gestational diabetes mellitus | ngram |
| gestational diabetes mellitus | NER |
| diabetes mellitus diagnosed | ngram |
| mellitus diagnosed years | ngram |
| diagnosed years prior | ngram |
| eight years prior | NER |
| years prior presentation | ngram |
| prior presentation subsequent | ngram |
| presentation subsequent type | ngram |
| subsequent type diabetes | ngram |
| type diabetes mellitus | ngram |
| type two diabetes mellitus | NER |
| diabetes mellitus ( | ngram |
| mellitus ( T2DM | ngram |
| ( T2DM ), | ngram |
| T2DM ), prior | ngram |
| T2DM | NER |
| ), prior episode | ngram |
| prior episode HTG-induced | ngram |
| episode HTG-induced pancreatitis | ngram |
| HTG-induced pancreatitis years | ngram |
| HTG-induced pancreatitis | NER |
| pancreatitis years prior | ngram |
| three years prior | NER |
| years prior presentation | ngram |
| prior presentation , | ngram |
| presentation , acute | ngram |
| , acute hepatitis | ngram |

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# Thank you !

**Veysel Kocaman**

Principal Data Scientist

John Snow Labs

# Spark NLP Resources

Spark NLP Official page
Spark NLP Workshop Repo
JSL Youtube channel
JSL Blogs
Introduction to Spark NLP: Foundations and Basic Components (Part-I)
Introduction to: Spark NLP: Installation and Getting Started (Part-II)
Named Entity Recognition with Bert in Spark NLP
Text Classification in Spark NLP with Bert and Universal Sentence Encoders
Spark NLP 101 : Document Assembler
Spark NLP 101: LightPipeline
https://www.oreilly.com/radar/one-simple-chart-who-is-interested-in-spark-nlp/
https://blog.dominodatalab.com/comparing-the-functionality-of-open-source-natural-language-processing-libraries/
https://databricks.com/blog/2017/10/19/introducing-natural-language-processing-library-apache-spark.html
https://databricks.com/fr/session/apache-spark-nlp-extending-spark-ml-to-deliver-fast-scalable-unified-natural-language-processing
https://medium.com/@saif1988/spark-nlp-walkthrough-powered-by-tensorflow-9965538663fd
https://www.kdnuggets.com/2019/06/spark-nlp-getting-started-with-worlds-most-widely-used-nlp-library-enterprise.html
https://www.forbes.com/sites/forbestechcouncil/2019/09/17/winning-in-health-care-ai-with-small-data/#1b2fc2555664
https://medium.com/hackernoon/mueller-report-for-nerds-spark-meets-nlp-with-tensorflow-and-bert-part-1-32490a8f8f12
https://www.analyticsindiamag.com/5-reasons-why-spark-nlp-is-the-most-widely-used-library-in-enterprises/
https://www.oreilly.com/ideas/comparing-production-grade-nlp-libraries-training-spark-nlp-and-spacy-pipelines
https://www.oreilly.com/ideas/comparing-production-grade-nlp-libraries-accuracy-performance-and-scalability
https://www.infoworld.com/article/3031690/analytics/why-you-should-use-spark-for-machine-learning.html

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End-to-End No-Code Development of NER model for Text with Annotation Lab
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How to Build a Foundation of AI-based Healthcare Systems Through Language Models?
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3. 

Automated Patient Risk Adjustment and Medicare HCC Coding from Clinical Notes
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4. 

End-to-End No-Code Development of Visual NER Models for PDFs and Images
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A Hierarchical Approach for Automated ICD-10 Coding Using Phrase-level Attention
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6. 

End-to-End No-Code Development of AI Models for Text and Images
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Opportunities and Challenges of Applying Advances in NLP to Healthcare
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8. 

Current State-of-the-Art Accuracy for Key Medical Natural Language Processing Benchmarks
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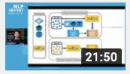
9. 

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Collaborative Healthcare NLP: Customisable NLP platforms for health and related research
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Using Spark NLP in R: a Drug Standardization Case Study
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The Quest for Proactive and Reactive Healthcare
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The Unified NLP Platform
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24. 

Industry Survey Analysis: AI in Healthcare 2022
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Using NLP at Scale to Process Patient Charts for Identifying Patient Encounters
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Transfer Learning From Existing Diseases Via Hierarchical Multi-Modal BERT Models to Predict COVID19
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Supporting Mental Healthcare Delivery Using NLP
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Using Spark NLP to De-Identify Doctor Notes in the German Language
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Accelerating Use of the Digital Medical Record with Optimized Structured & Unstructured Data
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Is it Enough to Simply Apply Language Model for Optimal Text Classification?
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