John Snow LABS

Spark NLP for Healthcare Data Scientists

Oct 13-14, 2022

Veysel Kocaman
Head of Data Science
veysel@johnsnowlabs.com

Agenda

Day	Dur.	Topic	Notebooks	Instructor
Day-1	50 min	- Intro to John Snow Labs and Spark NLP - Healthcare NLP in Spark NLP	-	Veysel
	50 min	- Clinical Named Entity Recognition - Contextual Parser (rule based NER) - Zero Shot NER - Chunk Merger	1, 1.2, 1.6, 7	Veysel
	50 min	- Clinical Assertion Status Model	2	Veysel
	50 min	- Clinical Relation Extraction Model - Clinical Relation Extraction with Knowledge Graph (Neo4j) - Zero Shot Relation Extraction	10, 10.1, 10.2, 10.3	Hasham
Day-2	50 min	- Clinical Pretrained Pipelines	11	Veysel
	50 min	- Misc *(ADE,, ChunkKeyPhraseExtractor, ChunkSentenceSplitter, Generic Clf, Gender Clf)*	8, 9, 18, 16, 21	Veysel
	50 min	- Clinical Entity Resolution - ChunkMapper	3, 3.1, 13, 13.1, 26	Muhammed
	50 min	- De-Identification and Obfuscation of PHI	4	Hasham

Colab Notebooks

spark-nlp==4.2
spark-nlp-jsl==4.2

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_JSL/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

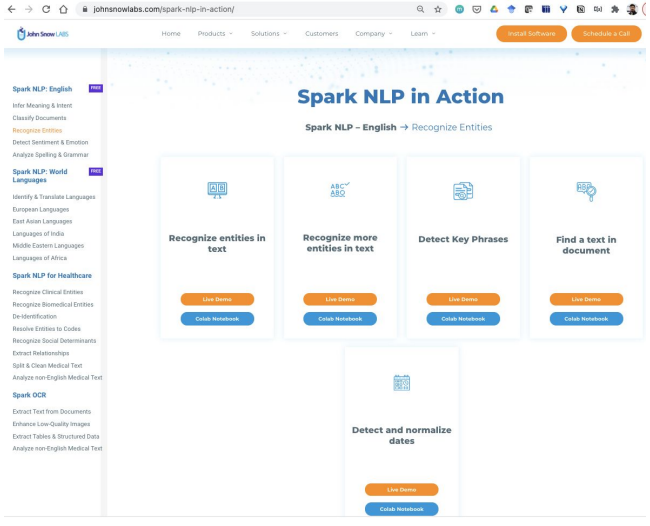
8.Generic_Classifier.ipynb
21.Gender_Classifier.ipynb

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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Spark NLP: English
Infer Meaning & Intent
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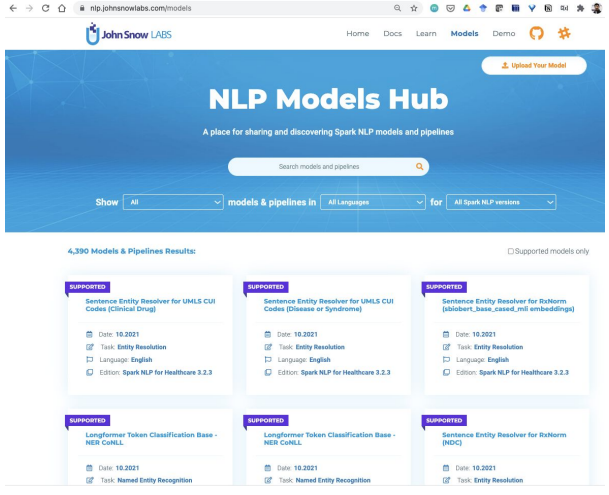
Recognize Entities
Detect Sentiment & Emotion
Analyze Spelling & Grammar
Spark NLP: World Languages
Identify & Translate Languages
European Languages
East Asian Languages
Languages of India
Middle Eastern Languages
Languages of Africa
Spark NLP for Healthcare
Recognize Clinical Entities
Recognize Biomedical Entities
De-identification
Resolve Entities to Codes
Recognize Social Determinants
Extract Relationships
Split & Clean Medical Text
Analyze non-English Medical Text
Spark OCR
Extract Text from Documents
Enhance Low-Quality Images
Extract Tables & Structured Data
Analyze non-English Medical Text
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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NLP Models Hub
A place for sharing and discovering Spark NLP models and pipelines
Search models and pipelines
Show
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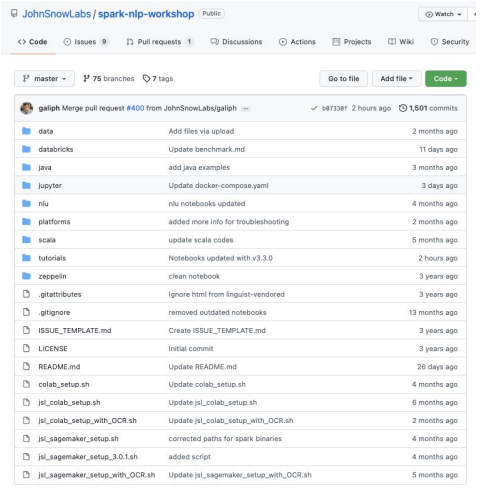
models & pipelines in
All Languages
for
All Spark NLP versions
4,390 Models & Pipelines Results:
Supported models only
SUPPORTED
Sentence Entity Resolver for UMLS CUI Codes (Clinical Drug)
Sentence Entity Resolver for UMLS CUI Codes (Disease or Syndrome)
Sentence Entity Resolver for RxNorm (sbiobert_base_cased_mli embeddings)
Date: 10.2021
Task: Entity Resolution
Language: English
Edition: Spark NLP for Healthcare 3.2.3
Longformer Token Classification Base - NER CoNLL
Sentence Entity Resolver for RxNorm (NDC)
Task: Named Entity Recognition
Task: Entity Resolution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Public
Watch
Code
Issues 9
Pull requests 1
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Actions
Projects
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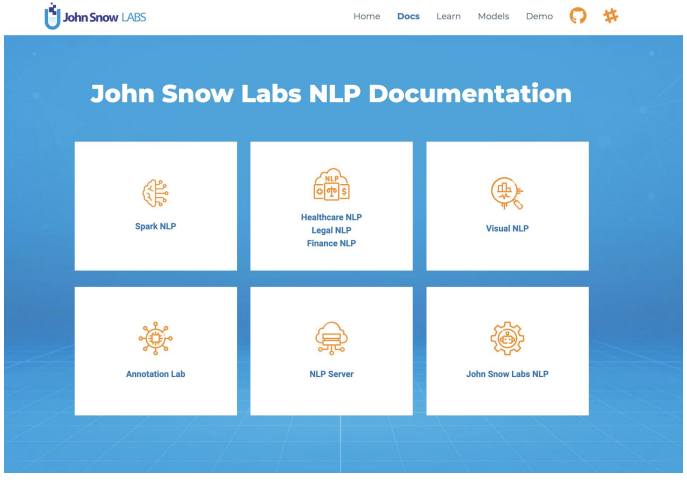
Security
master
75 branches
7 tags
Go to file
Add file
Code
galiph Merge pull request #400 from JohnSnowLabs/galiph
b07330f 2 hours ago
1,501 commits
data Add files via upload 2 months ago
databricks Update benchmark.md 11 days ago
java add java examples 3 months ago
jupyter Update docker-compose.yaml 3 days ago
nlu nlu notebooks updated 4 months ago
platforms added more info for troubleshooting 2 months ago
scala update scala codes 5 months ago
tutorials Notebooks updated with v3.3.0 2 hours ago
zeppelin clean notebook 3 years ago
.gitattributes Ignore html from linguist-vendored 3 years ago
.gitignore removed outdated notebooks 13 months ago
ISSUE_TEMPLATE.md Create ISSUE_TEMPLATE.md 3 years ago
LICENSE Initial commit 3 years ago
README.md Update README.md 26 days ago
colab_setup.sh Update colab_setup.sh 4 months ago
jsl_colab_setup.sh Update jsl_colab_setup.sh 6 months ago
jsl_colab_setup_with_OCR.sh Update jsl_colab_setup_with_OCR.sh 2 months ago
jsl_sagemaker_setup.sh corrected paths for spark binaries 4 months ago
jsl_sagemaker_setup_3.0.1.sh added script 4 months ago
jsl_sagemaker_setup_with_OCR.sh Update jsl_sagemaker_setup_with_OCR.sh 5 months ago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Visual NLP
Annotation Lab
NLP Server
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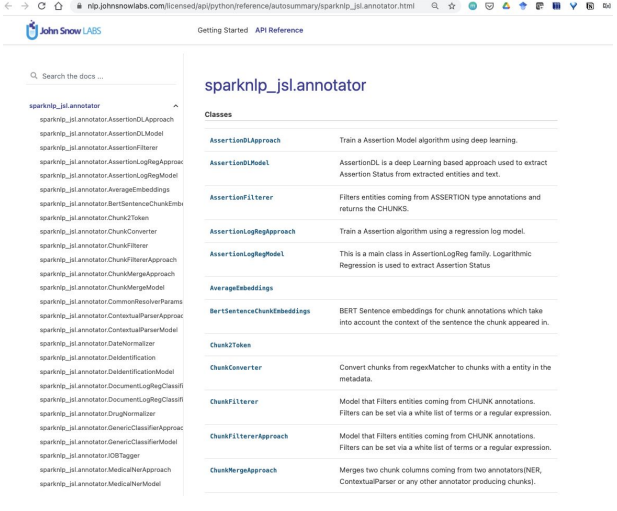
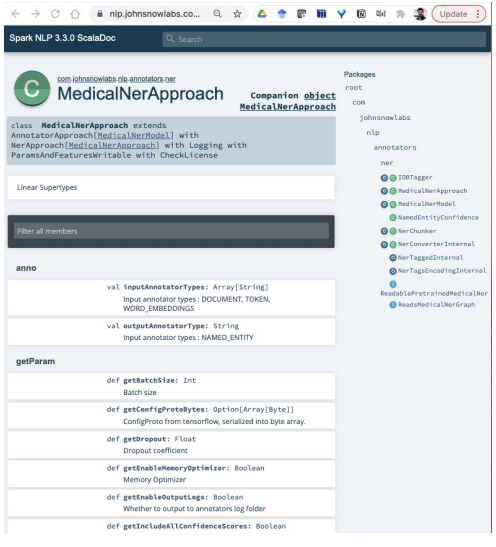

nlp.johnsnowlabs.com/licensed/api/python/reference/autosummary/sparknlp_jsl.annotator.html
Getting Started
API Reference
Search the docs ...
sparknlp_jsl.annotator
sparknlp_jsl.annotator.AssertionDLApproach
sparknlp_jsl.annotator.AssertionDLModel
sparknlp_jsl.annotator.AssertionFilterer
sparknlp_jsl.annotator.AssertionLogRegApproac
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[MedicalNerApproach] 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

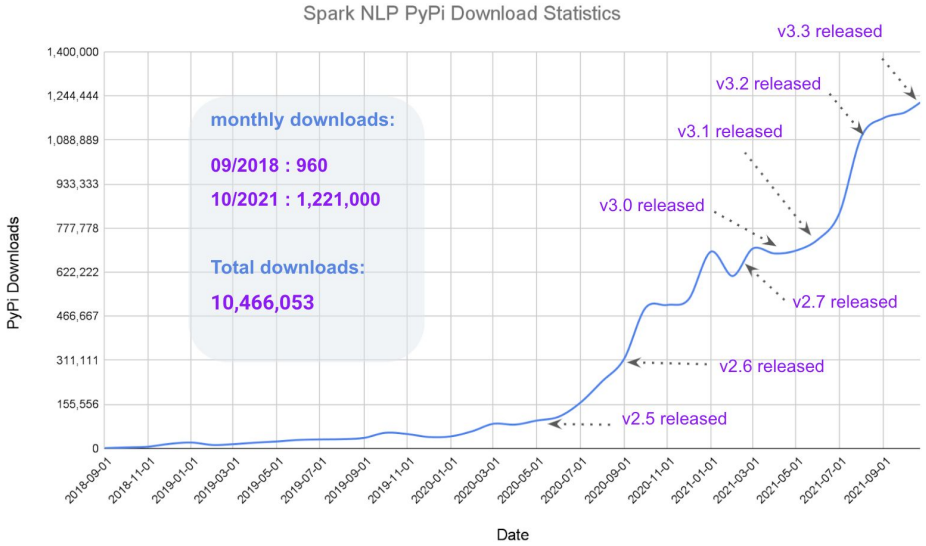
Part - I

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

Introducing Spark NLP

Daily ~ 100K
Monthly ~ 2.8M

PyPI link	https://pypi.org/project/spark-nlp
Total downloads	37,247,559
Total downloads - 30 days	2,762,599
Total downloads - 7 days	678,099



- 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) **- downloaded 38 million times !**
  - Delivering a mission-critical, enterprise grade NLP library (used by multiple Fortune 500)
  - Full-time development team (a new release every other week)

TRUSTED BY


Microsoft


Google


amazon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databricks


verizon


indeed


CapitalOne


viacom


McKESSON


MERCK


Roche


selectdata


UiPath
Reboot Work.


ASCO
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DISCOVERY


cnrs


Imperial College
London


Georgia
Tech


STANFORD
UNIVERSITY

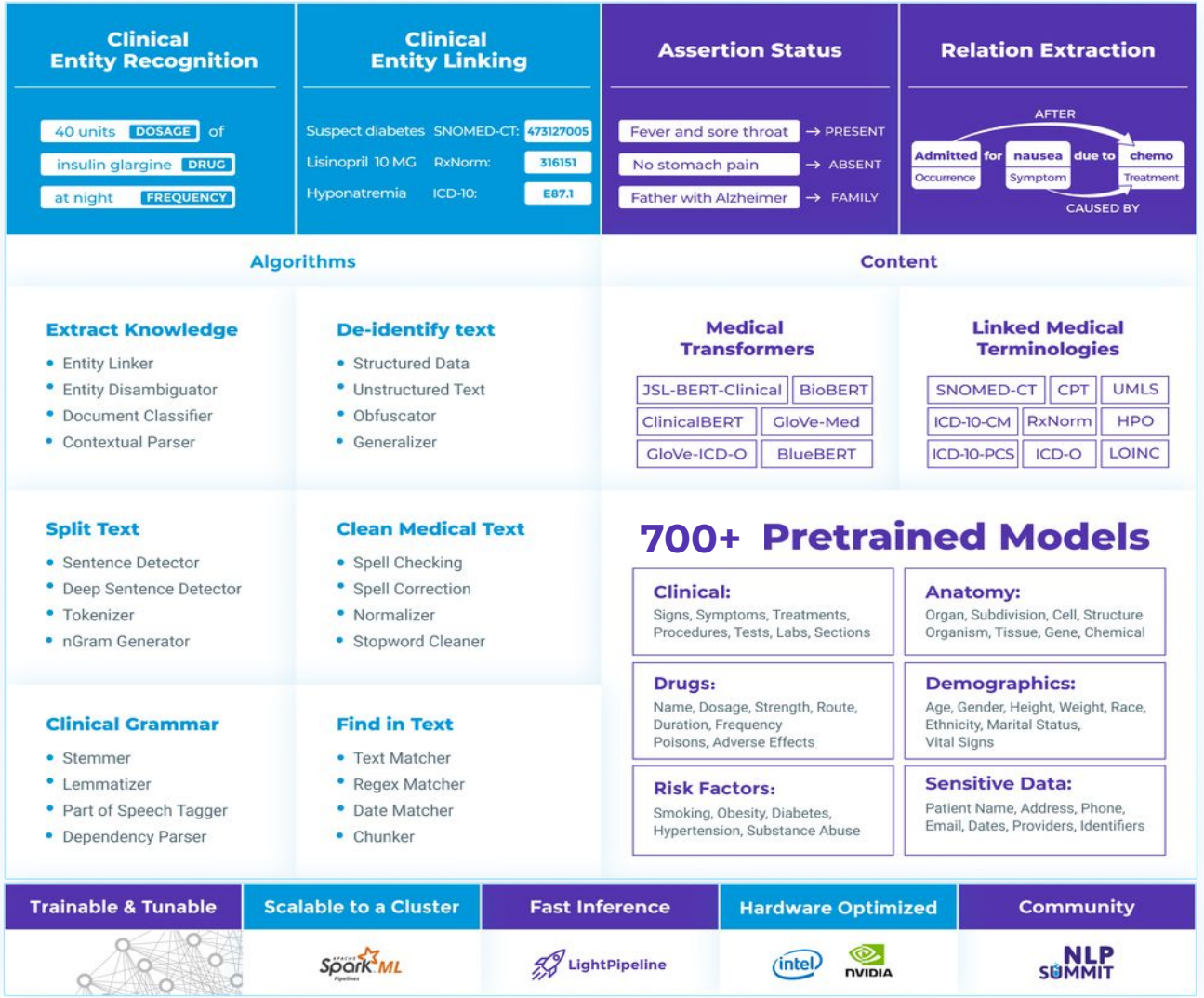
John Snow LABS

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

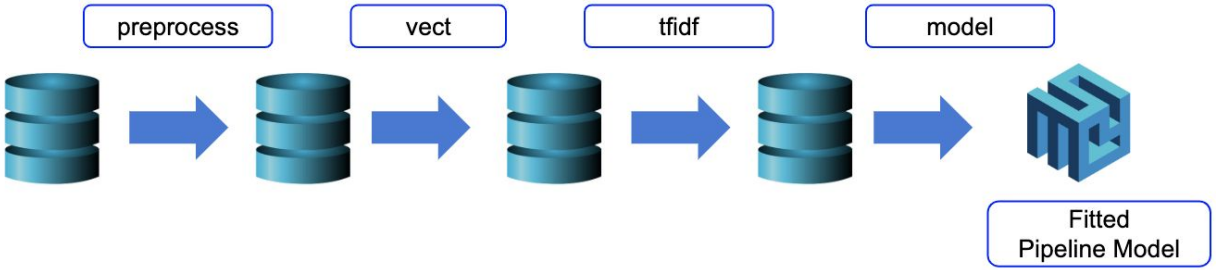
Introduction

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.

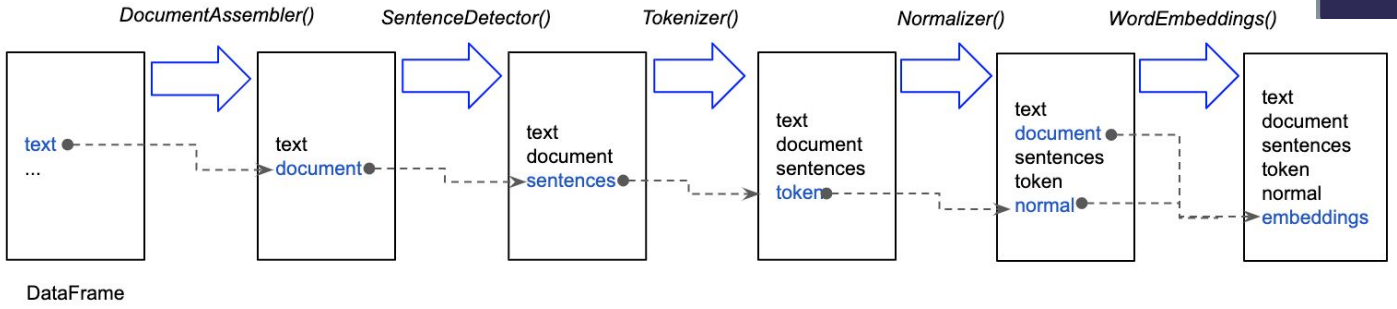
- ✓ 6 academic publications & events and 1 patent application, 20+ medium blogposts
- ✓ new SOTA benchmarks on Clinical NER challenges (i2b2 2010 Clinical, i2b2 2014 Deid, n2c2 2018 Medication)
- ✓ new SOTA benchmarks on Adverse Drug Reaction NER datasets (ADE, CADEC, SMM4H)
- ✓ new SOTA benchmarks on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

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).

Healthcare NLP

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

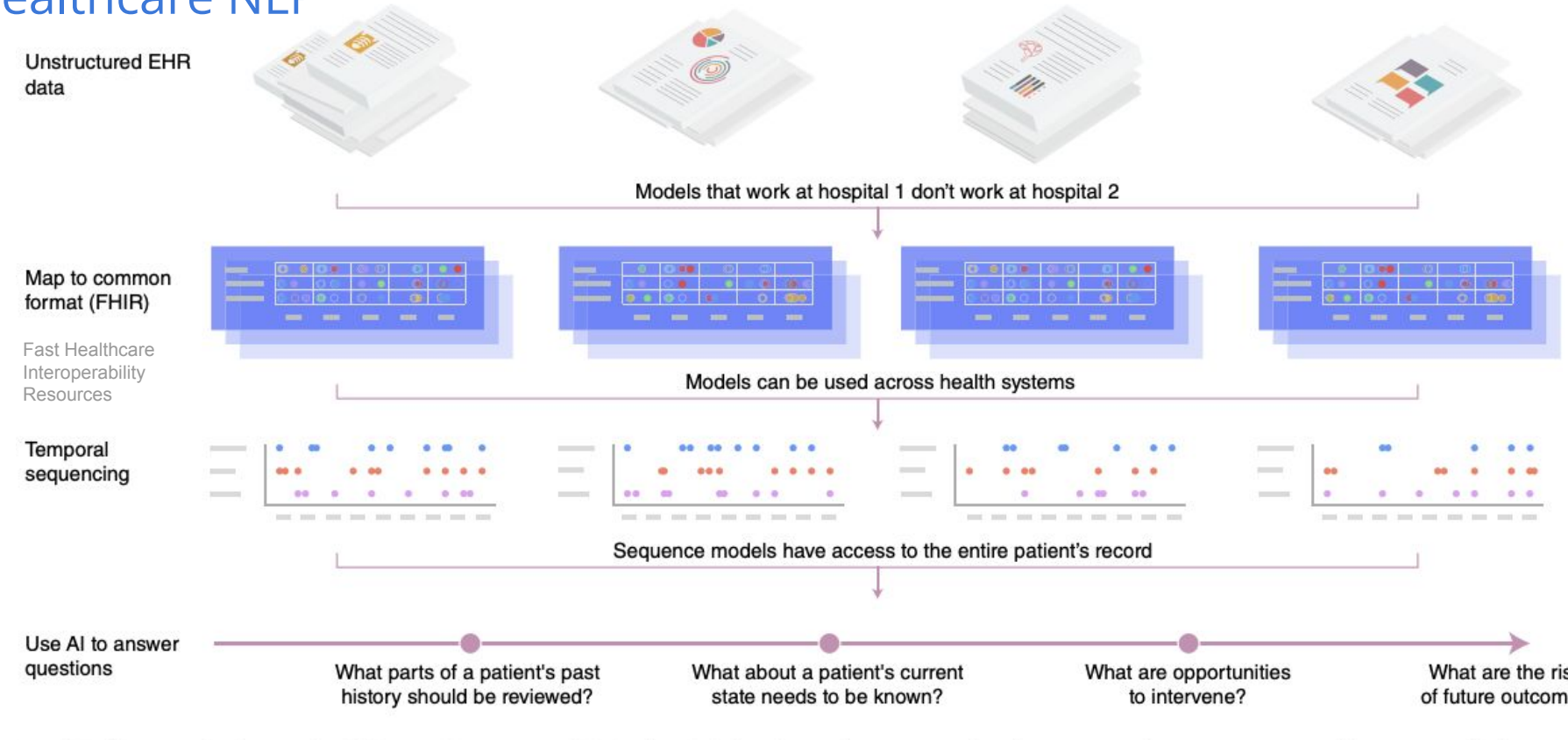
Healthcare specific needs:

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

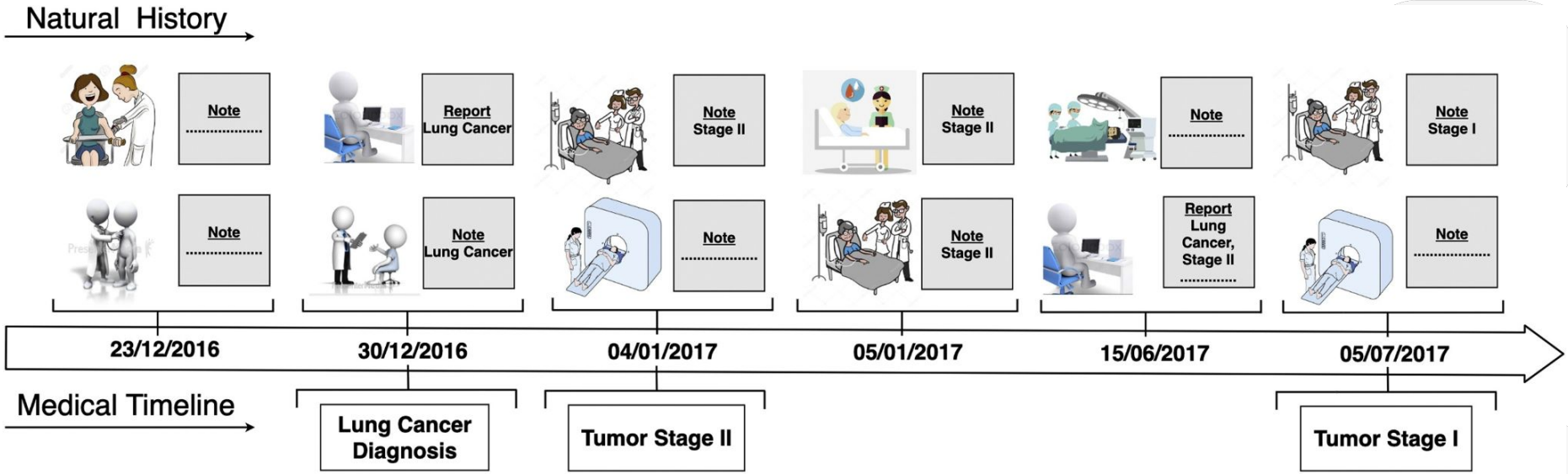
Healthcare NLP



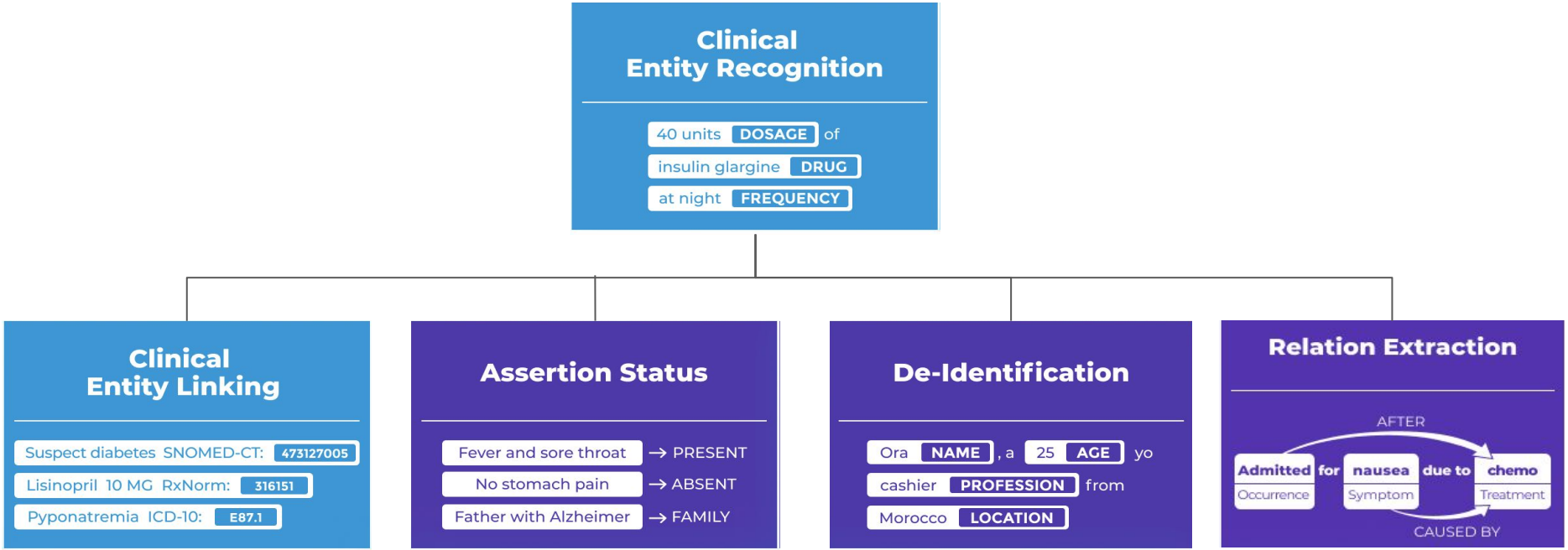
NLP SUMMIT

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

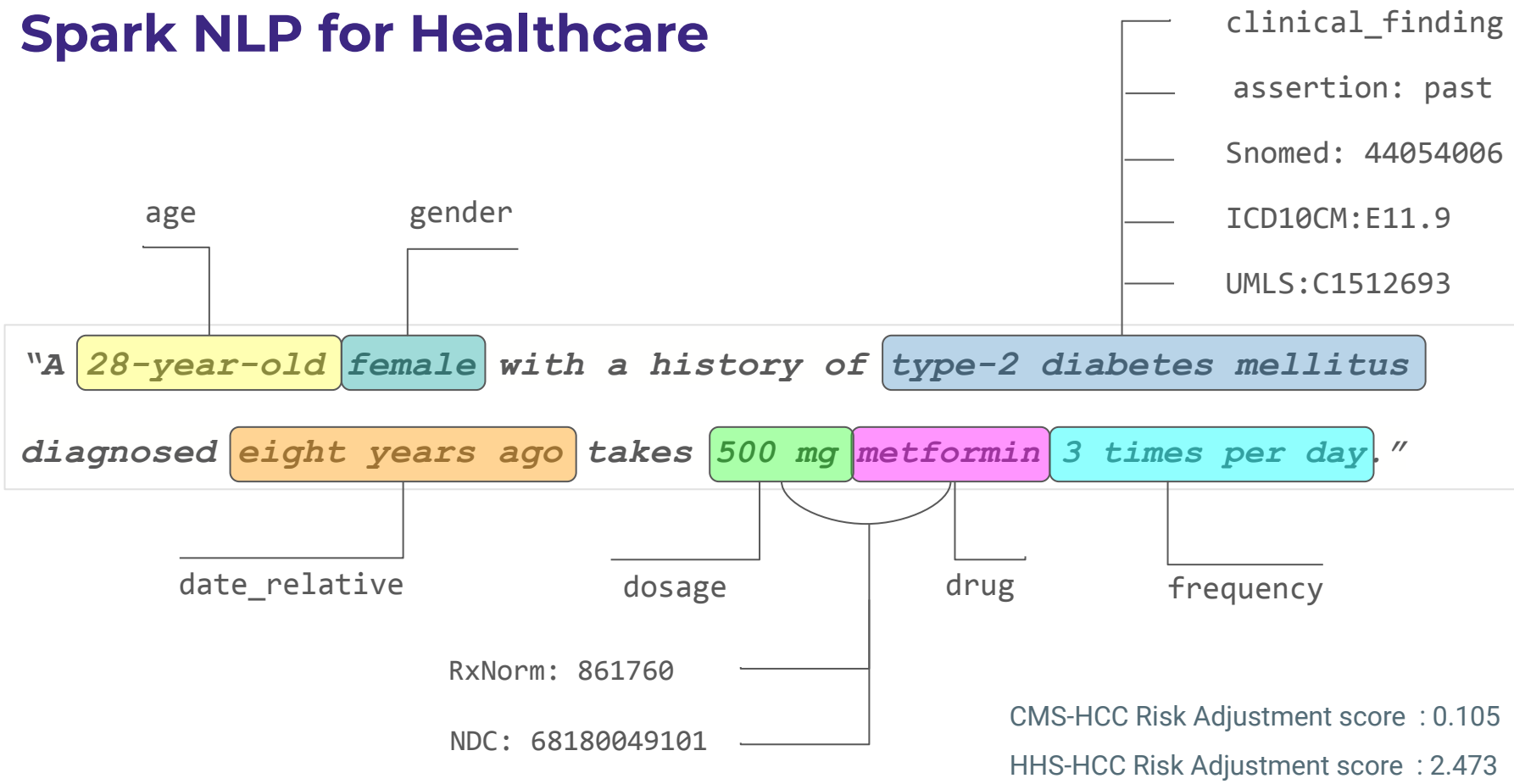
Putting the clinical facts on a timeline



NLP in Healthcare



Spark NLP for Healthcare



Spark NLP for Healthcare

Named Entity Recognition

ICD10 Resolver

Snomed Resolver

UMLS Resolver

Assertion Status Detection

Risk Adj. Module

RxNorm Resolver

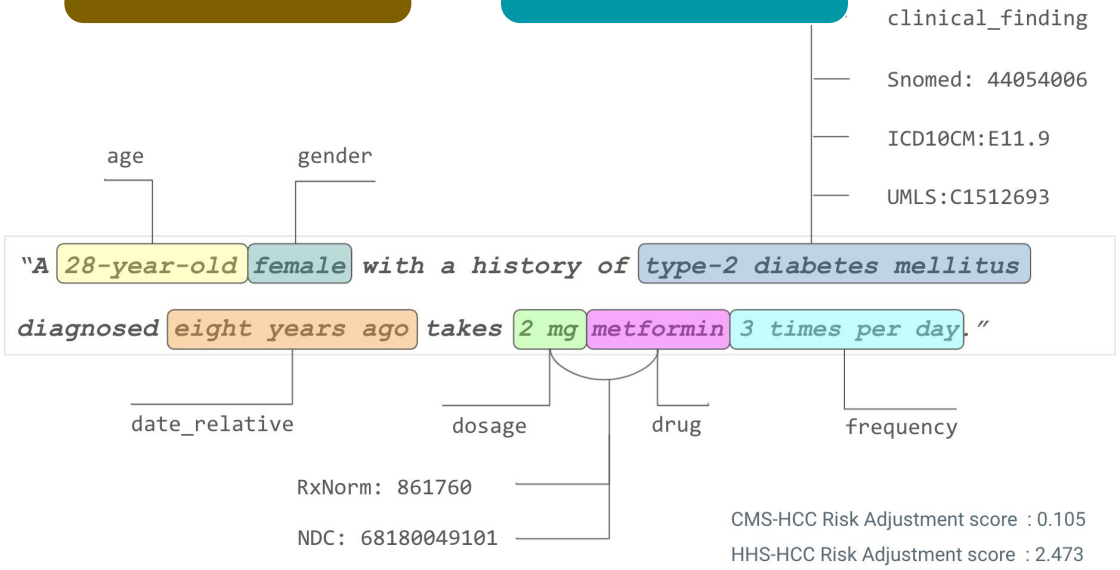
Relationship Extraction

Sentence Splitter

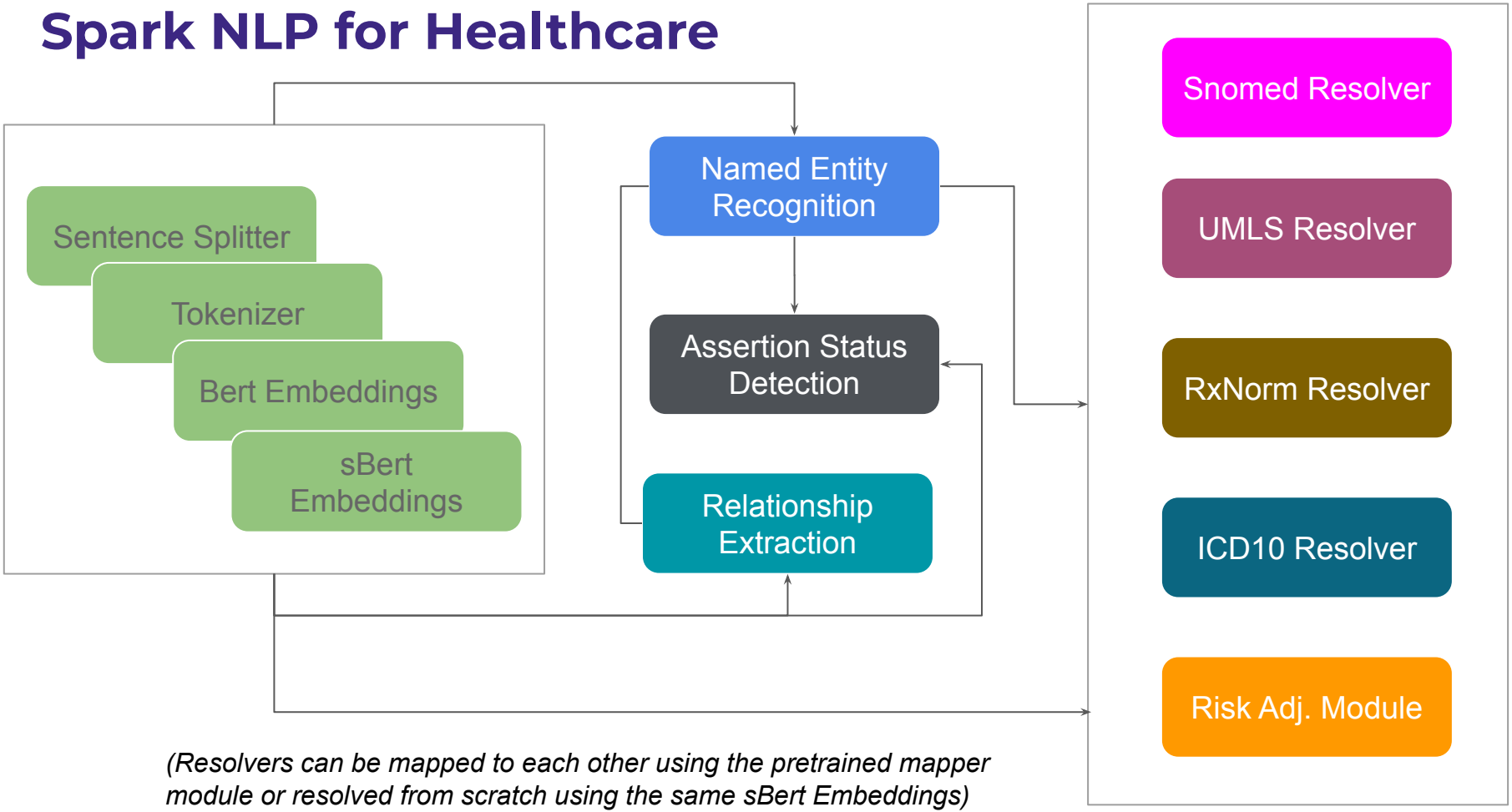
Tokenizer

Bert Embeddings

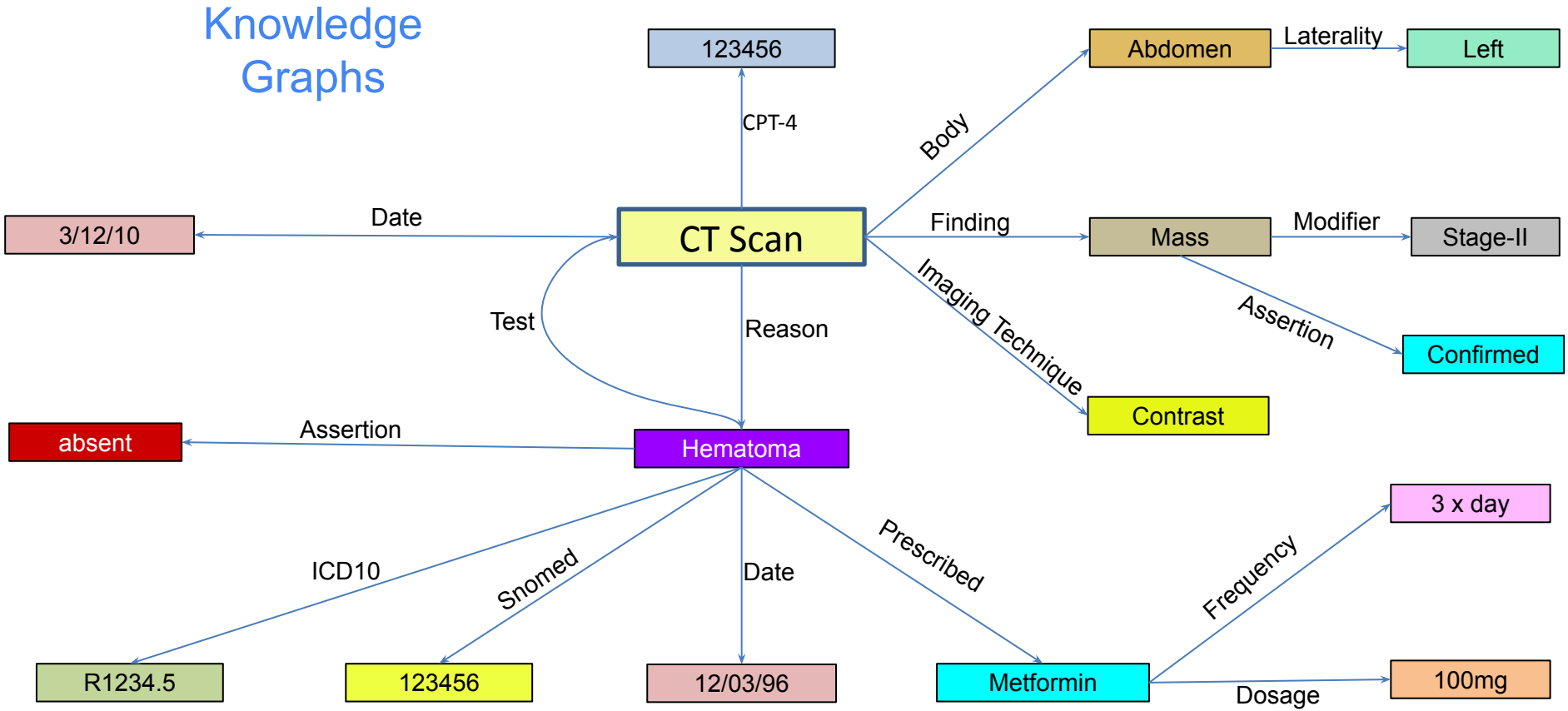
sBert Embeddings



Spark NLP for Healthcare

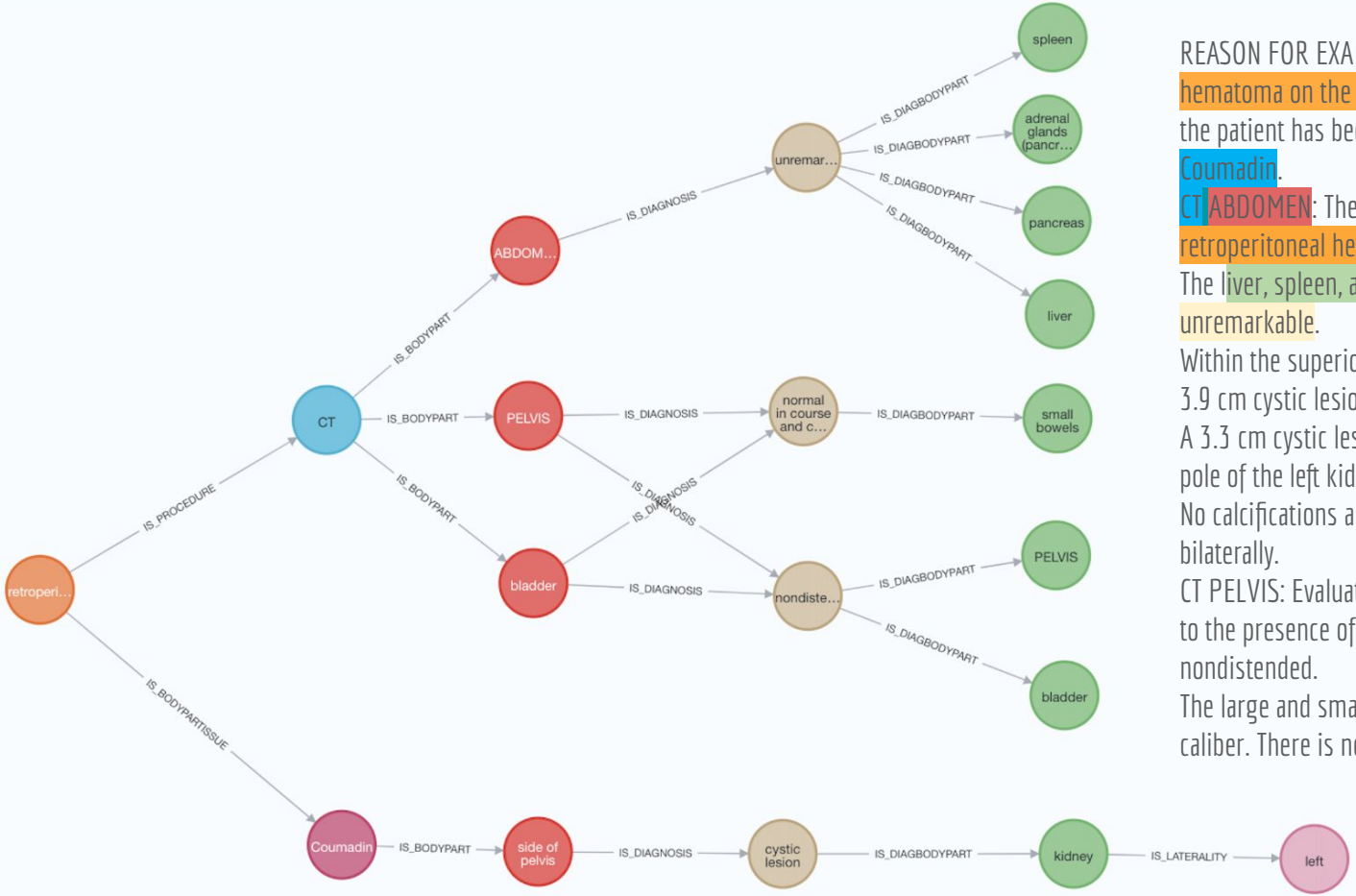


(Resolvers can be mapped to each other using the pretrained mapper module or resolved from scratch using the same sBert Embeddings)


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)

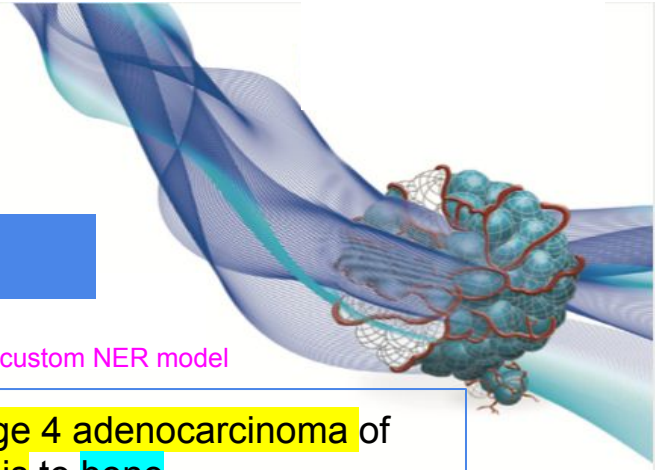
*(21) IS_BODYPARTISSUE(1) IS_PROCEDURE(1) IS_BODYPART(4) IS_DIAGNOSIS(6) IS_DIAGBODYPART(8) IS_LATERALITY(1)



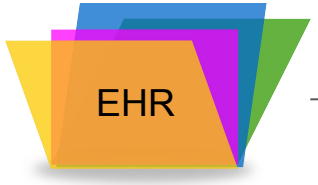
REASON FOR EXAM: Evaluate for retroperitoneal hematoma on the right side of pelvis,
the patient has been following, is currently on Coumadin.
CT ABDOMEN: There is no evidence for a retroperitoneal hematoma.
The liver, spleen, adrenal glands, and pancreas are unremarkable.
Within the superior pole of 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*

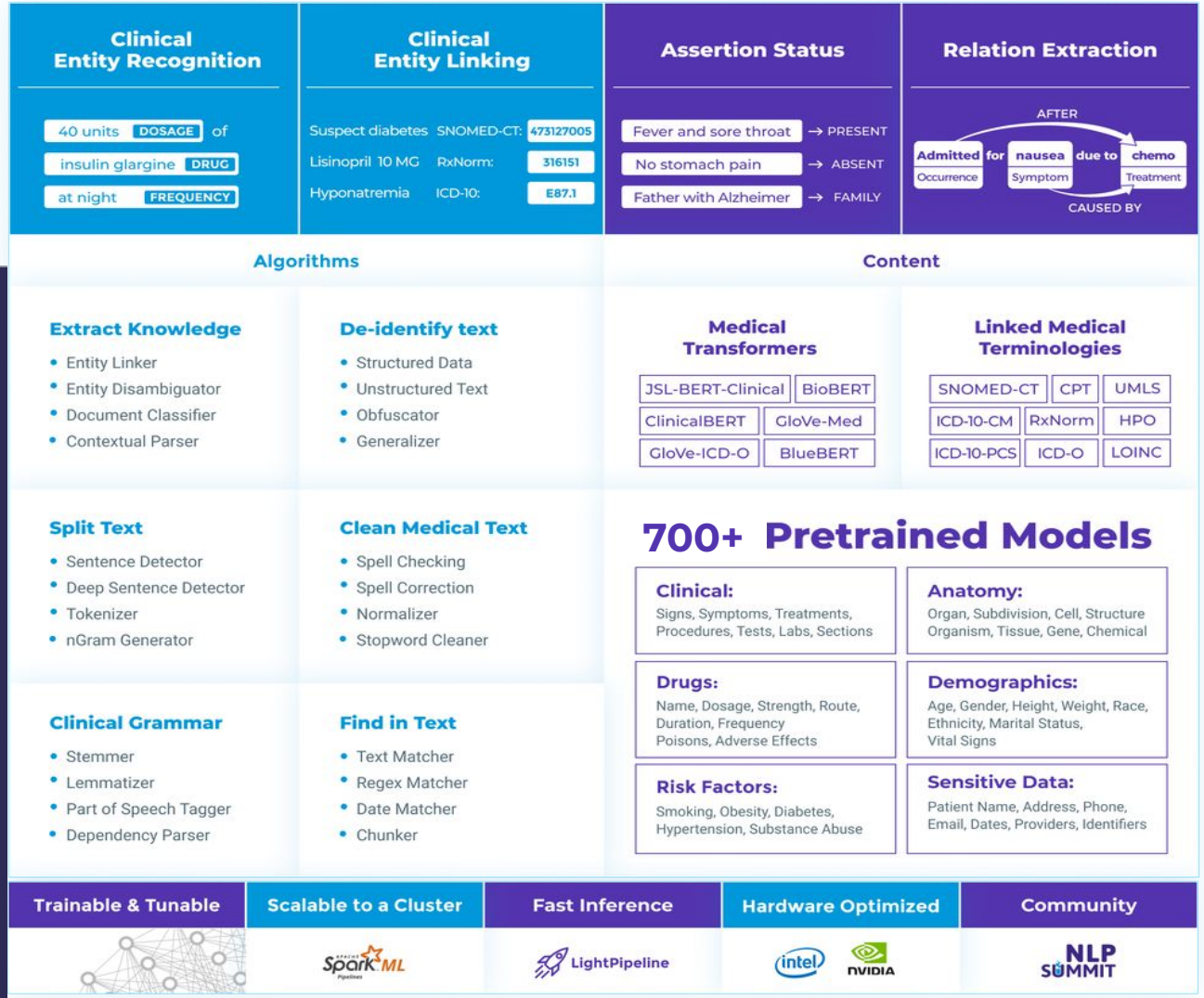
Text embeddings thru clinical word embeddings

Train a DL & ML Model

Prediction: Bone metastasis on June 2018

Spark NLP for Healthcare - Pipeline Components

```
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)
```



DocumentAssembler

✓ Prepares data into a format that is processable by Spark NLP

"A 28-year-old female with a history of gestational diabetes mellitus diagnosed eight years prior to presentation and subsequent type two diabetes mellitus"

text

DocumentAssembler

	document	begin	end
0	A 28-year-old female with a history of gestational diabetes mellitus diagnosed eight years prior to presentation and subsequent type two diabetes mellitus	0	153

document

```
documentAssembler = DocumentAssembler()\
    .setInputCol("text")\
    .setOutputCol("document")
```

SentenceDetectorDLModel

- ✓ Detects sentence boundaries using a deep learning approach.
- ✓ `sentence_detector_dl_healthcare` is quite successful for clinical documents

	document	begin	end
0	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 , associated with an acute hepatitis , and obesity with a body mass index (BMI) of 33.5 kg/m2 , presented with a one-week history of polyuria , polydipsia , poor appetite , and vomiting . Two weeks prior to presentation , she was treated with a five-day course of amoxicillin for a respiratory tract infection . 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 , bicarbonate 18 mmol/l , anion gap 20 , creatinine 0.4 mg/dL , triglycerides 508 mg/dL , total cholesterol 122 mg/dL , glycated hemoglobin (HbA1c) 10% , and venous pH 7.27 . Serum lipase was normal at 43 U/L . Serum acetone levels could not be assessed as blood samples kept hemolyzing due to significant lipemia . The patient was initially admitted for starvation ketosis , as she reported poor oral intake for three days prior to admission . However , serum chemistry obtained six hours after presentation revealed her glucose was 186 mg/dL , the anion gap was still elevated at 21 , serum bicarbonate was 16 mmol/L , triglyceride level peaked at 2050 mg/dL , and lipase was 52 U/L . The β-hydroxybutyrate level was obtained and found to be elevated at 5.29 mmol/L - the original sample was centrifuged and the chylomicron layer removed prior to analysis due to interference from turbidity caused by lipemia again . The patient was treated with an insulin drip for euDKA and HTG with a reduction in the anion gap to 13 and triglycerides to 1400 mg/dL , within 24 hours . Her euDKA was thought to be precipitated by her respiratory tract infection in the setting of SGLT2 inhibitor use . The patient 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 . She had close follow-up with endocrinology post discharge .	0	2515

document

	sentence	begin	end
0	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 , associated with an acute hepatitis , and obesity with a body mass index (BMI) of 33.5 kg/m2 , presented with a one-week history of polyuria , polydipsia , poor appetite , and vomiting .	0	433
1	Two weeks prior to presentation , she was treated with a five-day course of amoxicillin for a respiratory tract infection .	435	557
2	She was on metformin , glipizide , and dapagliflozin for T2DM and atorvastatin and gemfibrozil for HTG .	559	662
3	She had been on dapagliflozin for six months at the time of presentation .	664	737
4	Physical examination on presentation was significant for dry oral mucosa ; significantly , her abdominal examination was benign with no tenderness , guarding , or rigidity .	739	911
5	Pertinent laboratory findings on admission were : serum glucose 111 mg/dl , bicarbonate 18 mmol/l , anion gap 20 , creatinine 0.4 mg/dL , triglycerides 508 mg/dL , total cholesterol 122 mg/dL , glycated hemoglobin (HbA1c) 10% , and venous pH 7.27 .	913	1162
6	Serum lipase was normal at 43 U/L .	1164	1198
7	Serum acetone levels could not be assessed as blood samples kept hemolyzing due to significant lipemia .	1200	1303

sentence

```
sentenceDetector = SentenceDetectorDLModel\
    .pretrained("sentence_detector_dl_healthcare", "en","clinical/models")\
    .setInputCols(["document"])\
    .setOutputCol("sentence")
```

Tokenizer / RegexTokenizer

- ✓ Splits words in a relevant format for NLP
- ✓ RegexTokenizer splits text by a regex pattern.
- ✓ Input for most of the DL models

	sentence	begin	end
0	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 , associated with an acute hepatitis , and obesity with a body mass index (BMI) of 33.5 kg/m2 , presented with a one-week history of polyuria , polydipsia , poor appetite , and vomiting .	0	433
1	Two weeks prior to presentation , she was treated with a five-day course of amoxicillin for a respiratory tract infection .	435	557
2	She was on metformin , glipizide , and dapagliflozin for T2DM and atorvastatin and gemfibrozil for HTG .	559	662
3	She had been on dapagliflozin for six months at the time of presentation .	664	737
4	Physical examination on presentation was significant for dry oral mucosa ; significantly , her abdominal examination was benign with no tenderness , guarding , or rigidity .	739	911
5	Pertinent laboratory findings on admission were : serum glucose 111 mg/dl , bicarbonate 18 mmol/l , anion gap 20 , creatinine 0.4 mg/dL , triglycerides 508 mg/dL , total cholesterol 122 mg/dL , glycated hemoglobin (HbA1c) 10% , and venous pH 7.27 .	913	1162
6	Serum lipase was normal at 43 U/L .	1164	1198
7	Serum acetone levels could not be assessed as blood samples kept hemolyzing due to significant lipemia .	1200	1303

	token	begin	end	sentence
0	A	0	0	0
1	28-year-old	2	12	0
2	female	14	19	0
3	with	21	24	0
4	a	26	26	0
5	history	28	34	0
6	of	36	37	0
7	gestational	39	49	0
8	diabetes	51	58	0
9	mellitus	60	67	0

	token	begin	end	sentence
73	Two	435	437	1
74	weeks	439	443	1
75	prior	445	449	1
76	to	451	452	1
77	presentation	454	465	1
78	,	467	467	1
79	she	469	471	1
80	was	473	475	1
81	treated	477	483	1
82	with	485	488	1

sentence / document

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

token

```
regexTokenizer = RegexTokenizer() \
   .setInputCols(["document"]) \
   .setOutputCol("regexToken") \
   .setToLowercase(True) \
   .setPattern("\\s+")
```

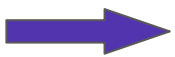
WordEmbeddingsModel

- ✓ Pretrained models can be loaded maps tokens to vectors
- ✓ `embeddings_clinical` can be preferred in clinical documents

	token	begin	end	sentence
0	A	0	0	0
1	28-year-old	2	12	0
2	female	14	19	0
3	with	21	24	0
4	a	26	26	0
5	history	28	34	0
6	of	36	37	0
7	gestational	39	49	0
8	diabetes	51	58	0
9	mellitus	60	67	0

	token	begin	end	sentence
73	Two	435	437	1
74	weeks	439	443	1
75	prior	445	449	1
76	to	451	452	1
77	presentation	454	465	1
78	,	467	467	1
79	she	469	471	1
80	was	473	475	1
81	treated	477	483	1
82	with	485	488	1

token



```
+--------------------------------------------------------------------+
|                                                          embeddings|
+--------------------------------------------------------------------+
|[-0.570580005645752,0.44183000922203064,0.7010200023651123,-0.417...|
|[-0.542639970779419,0.4147599935531616,1.0321999788284302,-0.4024...|
|[-0.2708599865436554,0.04400600120425224,-0.020260000601410866,-0...|
|[0.6191999912261963,0.14650000631809235,-0.08592499792575836,-0.2...|
|[-0.3397899866104126,0.20940999686717987,0.4634799957275390 6,-0.6...|
+--------------------------------------------------------------------+
```

embeddings

```
word_embeddings =
WordEmbeddingsModel.pretrained("embeddings_clinical","en","clinical/models")\
   .setInputCols(["sentence","token"])\
   .setOutputCol("embeddings")\
```

MedicalNerModel/NerModel

- ✓ Assigns an NER label to each token.
- ✓ The default model is `ner_clinical`, if no name is provided.

	token	begin	end
0	A	0	0
1	28-year-old	2	12
2	female	14	19
3	with	21	24
4	a	26	26
5	history	28	34
6	of	36	37
7	gestational	39	49
8	diabetes	51	58
9	mellitus	60	67

token

	token	begin	end	label	confidence
0	A	0	0	O	0.9998
1	28-year-old	2	12	O	0.9991
2	female	14	19	O	0.996
3	with	21	24	O	0.9998
4	a	26	26	O	0.9989
5	history	28	34	O	0.8485
6	of	36	37	O	0.9613
7	gestational	39	49	B-PROBLEM	0.8199
8	diabetes	51	58	I-PROBLEM	0.9809
9	mellitus	60	67	I-PROBLEM	0.9607

named_entity

```
clinical_ner = MedicalNerModel.pretrained("ner_clinical_large","en","clinical/models")\
    .setInputCols(["sentence","token","embeddings"])\
    .setOutputCol("ner")\
    .setLabelCasing("upper")
```

BertForTokenClassifier

✓ Loads Bert Models with a token classification head for Named-Entity-Recognition (NER) tasks.

"A 28-year-old female with a history of gestational diabetes mellitus diagnosed eight years prior to presentation and subsequent type two diabetes mellitus"

	begin	end	token	label	metadata
0	0	0	A	O	{'sentence': '0', 'Some(O)': '0.999487', 'Some(B-TEST)': '4.54522E-5', 'Some(I-PROBLEM...
1	2	12	28-year-old	O	{'sentence': '0', 'Some(O)': '0.99780965', 'Some(B-TEST)': '2.268446E-4', 'Some(I-PROB...
2	14	19	female	O	{'sentence': '0', 'Some(O)': '0.99946886', 'Some(B-TEST)': '2.7098458E-5', 'Some(I-PRO...
3	21	24	with	O	{'sentence': '0', 'Some(O)': '0.99975836', 'Some(B-TEST)': '8.164151E-6', 'Some(I-PROB...
4	26	26	a	O	{'sentence': '0', 'Some(O)': '0.99976975', 'Some(B-TEST)': '1.953544E-5', 'Some(I-PROB...
5	28	34	history	O	{'sentence': '0', 'Some(O)': '0.99965894', 'Some(B-TEST)': '1.4398003E-5', 'Some(I-PRO...
6	36	37	of	O	{'sentence': '0', 'Some(O)': '0.9997003', 'Some(B-TEST)': '6.0822117E-6', 'Some(I-PROB...
7	39	49	gestational	B-PROBLEM	{'sentence': '0', 'Some(O)': '1.2003799E-5', 'Some(B-TEST)': '1.2508507E-5', 'Some(I-P...
8	51	58	diabetes	I-PROBLEM	{'sentence': '0', 'Some(O)': '6.9626126E-6', 'Some(B-TEST)': '3.292549E-6', 'Some(I-PR...
9	60	67	mellitus	I-PROBLEM	{'sentence': '0', 'Some(O)': '1.0308599E-5', 'Some(B-TEST)': '2.3517548E-6', 'Some(I-P...
10	69	77	diagnosed	O	{'sentence': '0', 'Some(O)': '0.99924546', 'Some(B-TEST)': '1.260147E-5', 'Some(I-PROB...

```
tokenClassifier = MedicalBertForTokenClassifier.pretrained("bert_token_classifier_ner_clinical", "en", "clinical/models")\
   .setInputCols("token", "sentence")\
   .setOutputCol("ner")\
   .setCaseSensitive(True)
```

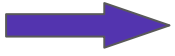
Reference notebook : Clinical Named Entity Recognition (NER)

NerConverter / NerConverterInternal

✓ Converts a IOB or IOB2 representation of NER to a user-friendly one, by associating the tokens of recognized entities and their label

	label	begin	end	words	confidence
0	O	27	27	a	0.9989
1	O	29	35	history	0.8485
2	O	37	38	of	0.9613
3	B-PROBLEM	40	50	gestational	0.8199
4	I-PROBLEM	52	59	diabetes	0.9809
5	I-PROBLEM	61	68	mellitus	0.9607

named_entity



	chunks	begin	end	entities	confidence
0	gestational diabetes mellitus	40	68	PROBLEM	0.9205
1	subsequent type two diabetes mellitus	118	154	PROBLEM	0.75560004
2	T2DM	158	161	PROBLEM	0.9928
3	HTG-induced pancreatitis	187	210	PROBLEM	0.97975004
4	an acute hepatitis	264	281	PROBLEM	0.9519333
5	obesity	289	295	PROBLEM	0.997

chunk

```
from sparknlp_jsl.annotator import NerConverterInternal
from sparknlp.annotator import NerConverter

ner_converter = NerConverterInternal()\
   .setInputCols(["sentence","token","ner"])\
   .setOutputCol("ner_chunk")\
# Optional
   .setWhiteList(["PROBLEM"]) # List of entities to process
   .setBlackList(["TREATMENT", "TEST"]) # List of entities to be excluded.
   .setThreshold(0.99) # Confidence threshold to filter the chunk entities.
   .setReplaceLabels({"Drug_BrandName": "Drug"}) # Replace label in only NerConverterInternal
```

ChunkMerger

- ✓ Merges chunk columns coming from two or more annotators.
- ✓ NER, ContextualParser, TextMatcher, or any other annotator producing chunks are supported.

"A 63 years old man presents to the hospital with a history of recurrent infections that include cellulitis, pneumonias, and upper respiratory tract infections."

deid_ner_chunk

	begin	end	chunk	entity
0	3	4	63	AGE

clinical_ner_chunk

	begin	end	chunk	entity
0	63	82	recurrent infections	PROBLEM
1	97	106	cellulitis	PROBLEM
2	109	118	pneumonias	PROBLEM
3	126	159	upper respiratory tract infections	PROBLEM

merged_ner_chunk

	begin	end	chunk	entity
0	3	4	63	AGE
1	63	82	recurrent infections	PROBLEM
2	97	106	cellulitis	PROBLEM
3	109	118	pneumonias	PROBLEM
4	126	159	upper respiratory tract infections	PROBLEM

```
chunk_merger = ChunkMergeApproach()\
    .setInputCols('clinical_ner_chunk', "deid_ner_chunk")\
    .setOutputCol('merged_ner_chunk')\
    #Optional
    .setMergeOverlapping()\ # Sets whether to merge overlapping matched chunks.
    .setFalsePositivesResource()\ # Sets file with false positive pairs
    .setReplaceDictResource()\ # Sets replace dictionary pairs
    .setChunkPrecedence()\ # Sets what is the precedence when two chunks have the same start and end indices.
    .setBlackList()\ # If defined, list of entities to ignore. The rest will be processed.
```

ChunkMapper

- ✓ Maps entities with their correspondings which are based on pre-defined dictionary
- ✓ Very useful in medical coding resolution.
- ✓ Supports multi dictionaries in a single model

"The patient was female and patient of Dr. X. and she was given Dermovate, Aspagin"

	ner_chunk	begin	end
0	Dermovate	63	71
1	Aspagin	74	80

token

	ner_chunk	begin	end	mapping_result	relation	all_relations
0	Dermovate	63	71	lupus	treatment	discoid lupus erythematosus:::empeines:::psori...
1	Aspagin	74	80	ankylosing spondylitis	treatment	arthralgia:::pain:::bursitis:::headache:::migr...

named_entity

```
chunkerMapper_treatment= ChunkMapperModel().pretrained("drug_action_treatment_mapper", "en", "clinical/models")\
   .setInputCols(["ner_chunk"])\
   .setOutputCol("mappings")\
   .setRels(["treatment"])# should be one of the relations from the model
```

Reference notebook : Chunk Mapping

DrugNormalizer

✓ Transforms text to the format used in the RxNorm and SNOMED standards

	text
0	Sodium Chloride/Potassium Chloride 13bag
1	interferon alfa-2b 10 million unit (1 ml) injec
2	aspirin 10 meq/ 5 ml oral sol

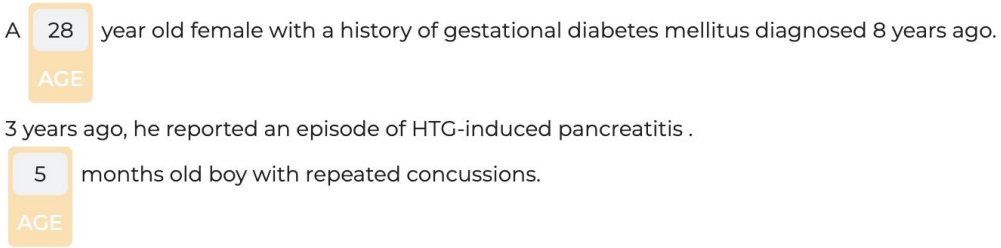
	normalized_text
0	Sodium Chloride / Potassium Chloride 13 bag
1	interferon alfa - 2b 10000000 unt (1 ml) injection
2	aspirin 2 meq/ml oral solution

```
drugNormalizer = DrugNormalizer()\
   .setInputCols(["document"])\
   .setOutputCol("document_normalized")
   #Optional
   .setPolicy()\ # all / abbreviations / dosages
```

Reference notebook : Clinical Drug Normalizer

ContextualParser

✓ Allows users to extract entities from a document based on pattern matching.




```
age = {
 "entity": "Age",
 "ruleScope": "sentence",
 "matchScope":"token",
 "regex":"\\d{1,3}",
 "prefix":["age of", "age"],
 "suffix": ["-years-old", "years-old", "-year-old", "-months-old",
            "-month-old", "-months-old","-day-old", "years old",
            "-days-old", "month old","years", "year", "months", "old"
            "days old", "year old"],
 "contextLength": 25,
 "contextException": ["ago"],
 "exceptionDistance": 12}
```

```
age_contextual_parser = ContextualParserApproach()\
    .setInputCols(["sentence", "token"]) \
    .setOutputCol("chunk_age") \
    .setJsonPath("age.json") \
    .setCaseSensitive(False) \
    .setPrefixAndSuffixMatch(False)\
    .setShortestContextMatch(True)\
    .setOptionalContextRules(False)
```

Reference notebook : ContextualParser (Rule Based NER)

Deidentification

✓ Allows users to mask or replace PHI (Protected Health Information) entities.

sentence
Patient AIQING, 25 years-old (ssid : 321-55-3699), born in Beijing, was transfered to the The Johns Hopkins Hospital.

deid_entity_label
Patient <NAME>, <AGE> years-old (ssid : <ID>), born in <LOCATION>, was transfered to the The <LOCATION>
deid_same_length
Patient [****], ** years-old (ssid : [*********]), born in [*****], was transfered to the The [**********]
deid_fixed_length
Patient *******, ******* years-old (ssid : *******), born in *******, was transfered to the The *******
obfuscated
Patient Olene Ronde, 41 years-old (ssid : G074713), born in China, was transfered to the Avenue Hospital

```
deidentification = DeIdentification()\
   .setInputCols(["sentence", "token", "ner_chunk"])\
   .setOutputCol("deidentified")\
   .setMode("mask") # "obfuscate"
   # Optional
   .setReturnEntityMappings(True)\
   .setMaskingPolicy("entity_labels") # "same_length_chars", "deid_fixed_length", "fixed_length_chars"
   .setObfuscateDate(False)
   .setObfuscateRefSource("file") # "file", "both"
```

Reference notebook : Clinical Deidentification

Spell Checker

- ✓ A flexible, configurable and "re-usable by parts" model.
  - ✓ Different correction candidates for each word - **word level**.
  - ✓ The surrounding text of each word, i.e. it's context - **sentence level**.
  - ✓ The relative cost of different correction candidates according to the edit operations at the character level it requires - **subword level**.

"Alliow me tao introdduce myhelf, I am a man of waelth und tiaste"

"Allow me to introduce myself, I am a man of wealth and taste"

```
spellModel = ContextSpellCheckerModel\
   .pretrained('spellcheck_dl')\
   .setInputCols("token")\
   .setOutputCol("checked")\
   .setErrorThreshold(4.0)\
   .setTradeoff(6.0)
```

Reference notebook : Context Spell Checker

TextMatcher

- ✓ Matches exact phrases (by token) provided in a file against a Document.
- ✓ A text file of predefined phrases must be provided with `setEntities`

```
"A 28-year-old female with a history
of gestational diabetes mellitus and
coronary artery disease"
```

	begin	end	entity	entity
0	39	67	gestational diabetes mellitus	DISEASE
1	73	95	coronary artery disease	DISEASE

```
entityExtractor = TextMatcher() \
   .setInputCols(["document", "token"]) \
   .setEntities("phrases.txt", ReadAs.TEXT) \
   .setOutputCol("entity") \
   .setEntityValue("DISEASE")\
   .setCaseSensitive(False)
```

```
Phrases.txt
-----------
gestational diabetes mellitus
coronary artery disease
Lower respiratory infections
```

Normalizer

✓ Removes all dirty characters from text following a regex pattern and transforms words based on a provided dictionary

```
"#publiHUCA #Emergency Emergency department observation of patients with acute heart failure prior to hospital admission: impact on short-term prognosis "
```

	token
0	#publiHUCA
1	#Emergency
2	Emergency
3	department
4	observation

token

	token	normalized
0	#publiHUCA	publihuca
1	#Emergency	emergency
2	Emergency	emergency
3	department	department
4	observation	observation

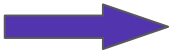
token

```
normalizer = Normalizer() \
   .setInputCols(["token"]) \
   .setOutputCol("normalized")\
   .setLowercase(True)\ # lowercase tokens
   .setCleanupPatterns(["[^\w\d\s]"]) # remove punctuations (keep alphanumeric chars)
   .setSlangDictionary(path) # txt file with delimited words to be transformed into something else
```

DocumentNormalizer

✓ Normalize documents once that they have been processed and indexed

```
"<div id="theworldsgreatest" class='my-right my-hide-small my-wide toptext'
style="font-family:'Segoe UI',Arial,sans-serif">
   THE WORLD'S LARGEST WEB DEVELOPER SITE
   <h1 style="font-size:300%;">THE WORLD'S LARGEST WEB DEVELOPER SITE</h1>
   <p style="font-size:160%;">Lorem Ipsum is simply dummy text of the printing
and typesetting industry. Lorem Ipsum has been the industry's standard dummy
text ever since the 1500s, when an unknown printer took a galley of type and
scrambled it to make a type specimen book.</p>
 </div> </div> "
```



```
“the world's largest web developer site the world's
largest web developer site lorem ipsum is simply dummy
text of the printing and typesetting industry. lorem
ipsum has been the industry's standard dummy text ever
since the 1500s, when an unknown printer took a galley of
type and scrambled it to make a type specimen book. “
```

document **document**

```
documentNormalizer = DocumentNormalizer() \
   .setInputCols("document") \
   .setOutputCol("normalizedDocument") \
   .setAction("clean") \
   .setPatterns(cleanUpPatterns) \
   .setReplacement(" ") \
   .setPolicy("pretty_all") \
   .setLowercase(True)
```

RegexMatcher

✓ Uses a reference file to match a set of regular expressions and associate them with a provided identifier.

```
'The patient (123-45-7890) was
discharged from the hospital oun 10th
January.'
```

	clinical_entities	begin	end	label
0	123-45-7890	13	23	SSN

```
regex_matcher = RegexMatcher()\
   .setInputCols('document')\
   .setStrategy("MATCH_ALL")\
   .setOutputCol("regex_matches")\
   .setExternalRules(path='./regex_rules.txt', delimiter=',')
```

```
regex_rules.txt
-----------
\d{3}.?\d{2}.?\d{4}, SSN
```

NerOverwriter

✓ Overwrites or replaces the labels of entities of specified strings.

```
"Mr.Brown was described warfarin 5 mg"
```

	token	ner_label
0	Mr.Brown	O
1	was	O
2	described	O
3	warfarin	B-TREATMENT
4	5	O
5	mg	O

	token	ner_label	ner_overwritten
0	Mr.Brown	O	B-People
1	was	O	O
2	described	O	O
3	warfarin	B-TREATMENT	B-DRUG
4	5	O	O
5	mg	O	O

```
nerOverwriter = NerOverwriter() \
   .setInputCols(["ner"]) \
   .setOutputCol("ner_overwritten")\
   .setNerWords(["Mr.Brown"])\
   .setNewNerEntity("B-People")\
   .setReplaceEntities({"B-TREATMENT" : "B-DRUG"})
```

BertSentenceEmbeddings

✓ Calculates BERT embeddings for sequence

"Patient has a headache for the last 2 weeks, needs to get a head CT, and appears anxious when she walks fast. No alopecia noted. She denies pain"

	sentence	sentence_embeddings
0	Patient has a headache for the last 2 weeks, n...	-0.08882622 -0.09253775 -0.025744002 -0.105720...

```
Classifier = BertForSequenceClassification.pretrained("bert_sequence_classifier_covid_sentiment", "en", "clinical/models")\
   .setInputCols(["document","token"])\
   .setOutputCol("class")
```

BertForSequenceClassifier

✓ Loads BERT Models with sequence classification/regression for multi-class document classification tasks.

	text	result
0	British Department of Health confirms first two cases of in UK	[neutral]
1	so my trip to visit my australian exchange student just got canceled bc of coronavirus. im heartbroken :(	[negative]
2	I wish everyone to be safe at home and stop pandemic	[positive]

```
Classifier = BertForSequenceClassification.pretrained("bert_sequence_classifier_covid_sentiment", "en", "clinical/models")\
   .setInputCols(["document","token"])\
   .setOutputCol("class")
```

Reference notebook : Medical BertForSequence

AssertionDLModel

✓ A Deep Learning based approach is used to extract Assertion Status from extracted entities and text.

"Patient has a headache for the last 2 weeks, needs to get a head CT, and appears anxious when she walks fast. No alopecia noted. She denies pain"

	entities_ner_chunk	entities_ner_chunk_class	assertion
0	a headache	PROBLEM	present
0	a head CT	TEST	present
0	anxious	PROBLEM	present
0	alopecia	PROBLEM	absent
0	pain	PROBLEM	absent

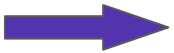
```
clinical_assertion = AssertionDLModel.pretrained("assertion_dl", "en", "clinical/models") \
   .setInputCols(["sentence", "ner_chunk", "embeddings"]) \
   .setOutputCol("assertion")
```

Reference notebook : Clinical Assertion Status Model

RelationExtractionModel

- ✓ Extracts and classifies instances of relations between named entities.
- ✓ Relation pairs need to be defined with setRelationPairs, to specify between which entities the extraction should be done.

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



chunk1	entity1	entity2_begin	entity2_end	chunk2	entity2	relation
fatigue	ADE	82	88	Lipitor	DRUG	1
fatigue	ADE	124	128	Zocor	DRUG	0
muscle cramps	ADE	82	88	Lipitor	DRUG	1
muscle cramps	ADE	124	128	Zocor	DRUG	0
anxiety	ADE	82	88	Lipitor	DRUG	1
anxiety	ADE	124	128	Zocor	DRUG	0
agression	ADE	82	88	Lipitor	DRUG	1
agression	ADE	124	128	Zocor	DRUG	0
sadness	ADE	82	88	Lipitor	DRUG	1
sadness	ADE	124	128	Zocor	DRUG	0

```
reModel = RelationExtractionModel()\
   .pretrained("re_ade_clinical", "en", 'clinical/models')\
   .setInputCols(["embeddings", "pos_tags", "ner_chunks", "dependencies"])\
   .setOutputCol("relations")\
   .setMaxSyntacticDistance(10)\
   .setRelationPairs(["drug-ade, ade-drug"])\
   .setRelationPairsCaseSensitive(False)
```

Reference notebook : Clinical Relation Extraction

RelationExtractionDLModel

✓ A Deep Learning based approach is used to extract Assertion Status from extracted entities and text.

"The patient was prescribed 1 unit of Advil for 5 days after meals. The patient was also given 1 unit of Metformin daily. He was seen by the endocrinology service and she was discharged on 40 units of insulin glargine at night."

	sentence	entity1_begin	entity1_end	chunk1	entity1	entity2_begin	entity2_end	chunk2	entity2	relation
0	0	28	33	1 unit	DOSAGE	38	42	Advil	DRUG	DOSAGE-DRUG
1	0	38	42	Advil	DRUG	44	53	for 5 days	DURATION	DRUG-DURATION
2	1	96	101	1 unit	DOSAGE	106	114	Metformin	DRUG	DOSAGE-DRUG
3	1	106	114	Metformin	DRUG	116	120	daily	FREQUENCY	DRUG-FREQUENCY
4	2	190	197	40 units	DOSAGE	202	217	insulin glargine	DRUG	DOSAGE-DRUG
5	2	202	217	insulin glargine	DRUG	219	226	at night	FREQUENCY	DRUG-FREQUENCY

```
reModel = RelationExtractionModel().pretrained("posology_re")\
   .setInputCols(["embeddings", "pos_tags", "ner_chunks", "dependencies"])\
   .setOutputCol("relations")\
   .setMaxSyntacticDistance(4)
```

Reference notebook : Clinical Named Entity Recognition (NER)

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.

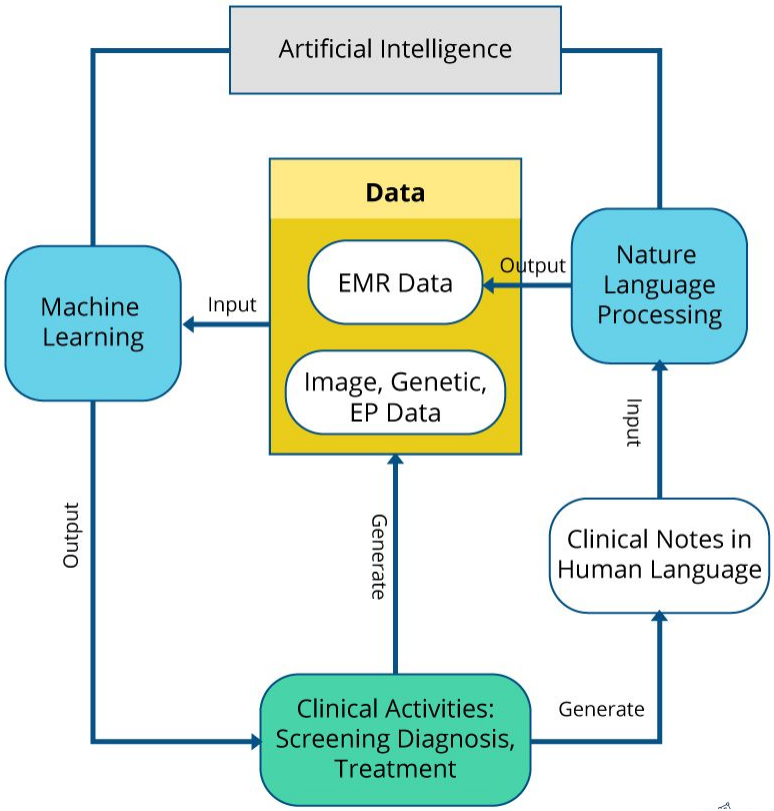
NLP in Healthcare

"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

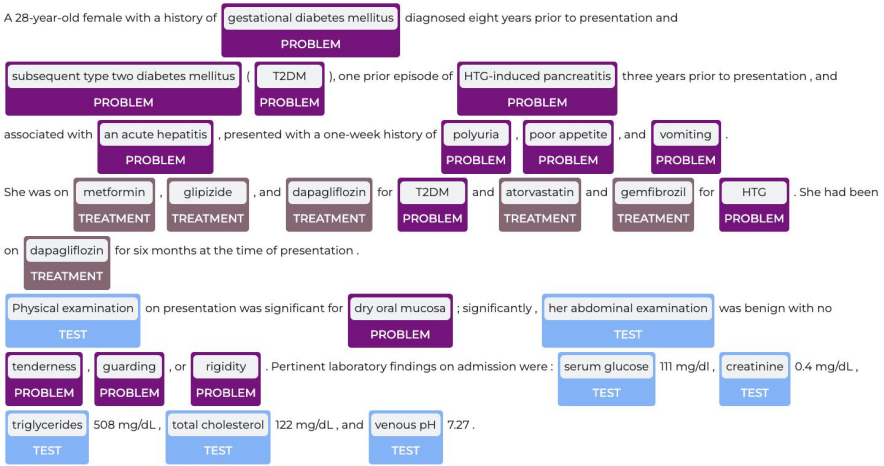
A . Record date : 2093-01-13 , David Hale , M.D . , Name : Hendrickson , Ora MR . # 7194334 Date : 01/13/93 PCP : Oliveira , 25 years-old , Record date : 2079-11-09 . Cocke County Baptist Hospital . 0295 Keats Street

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

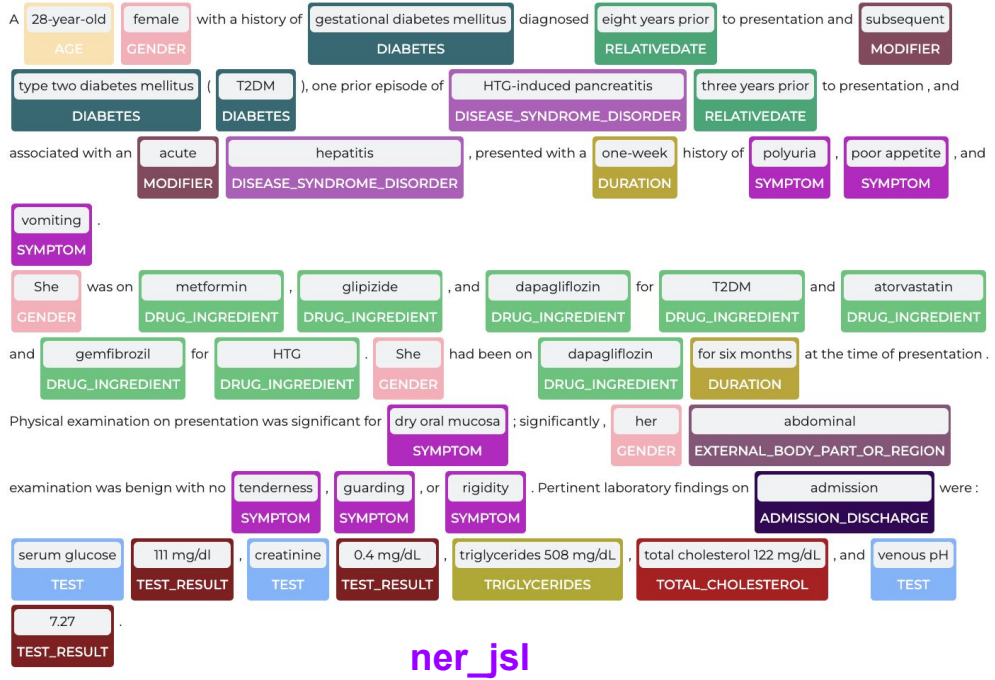
PHI NER

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

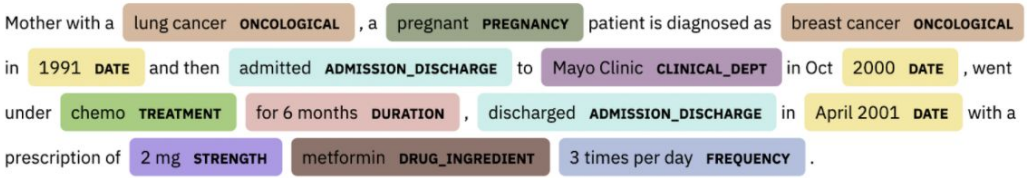
Clinical Named Entities – Spark NLP vs Others

Google	Azure	AWS
PROBLEM	DIAGNOSIS SYMPTOM_OR_SIGN ALLERGEN	MEDICAL_CONDITION_DX_NA MEDICAL_CONDITION_SIGN MEDICAL_CONDITION_SYMPTOM
PROCEDURE	TREATMENT_NAME	PROCEDURE_NAME TREATMENT_NAME
MEDICINE	MEDICATION_CLASS MEDICATION_NAME	MEDICATION_BRAND_NAME MEDICATION_GENERIC_NAME
ANATOMICAL_STRUCTURE	BODY_STRUCTURE	SYSTEM_ORGAN_SITE
LABORATORY_DATA BODY_MEASUREMENT	EXAMINATION_NAME	TEST_NAME
SEVERITY	CONDITION_QUALIFIER CONDITION_SCALE	MEDICAL_CONDITION_ACUITY
MED_DOSE MED_TOTALDOSE MED_STRENGTH MED_UNIT	DOSAGE	MEDICATION_DOSAGE MEDICATION_STRENGTH 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 MED_VALUE	MEASUREMENT_VALUE	TEST_VALUE
LAB_UNIT 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

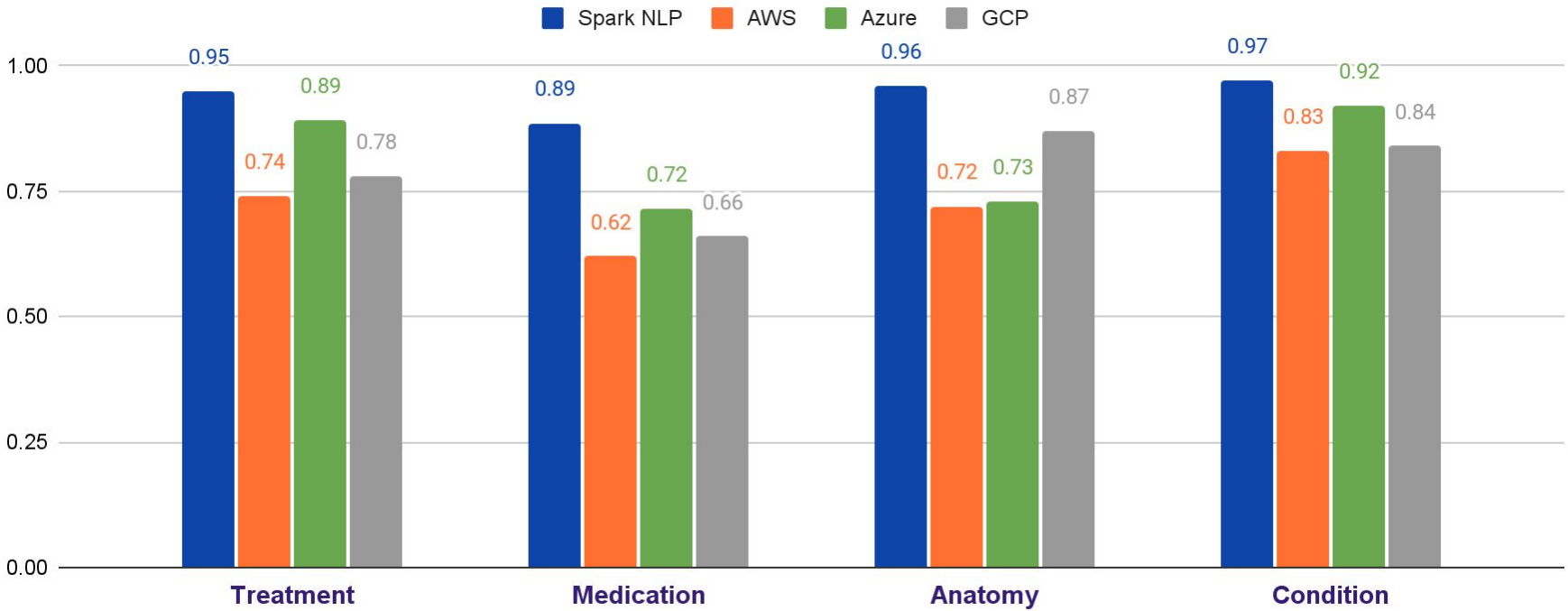


Clinical Named Entities
Spark NLP vs Others

Google	Azure	AWS
PROBLEM	DIAGNOSIS SYMPTOM_OR_SIGN ALLERGEN	MEDICAL_CONDITION_DX_NA MEDICAL_CONDITION_SIGN MEDICAL_CONDITION_SYMPTOM
PROCEDURE	TREATMENT_NAME	PROCEDURE_NAME TREATMENT_NAME
MEDICINE	MEDICATION_CLASS MEDICATION_NAME	MEDICATION_BRAND_NAME MEDICATION_GENERIC_NAME
ANATOMICAL_STRUCTURE	BODY_STRUCTURE	SYSTEM_ORGAN_SITE
LABORATORY_DATA BODY_MEASUREMENT	EXAMINATION_NAME	TEST_NAME
SEVERITY	CONDITION_QUALIFIER CONDITION_SCALE	MEDICAL_CONDITION_ACUITY
MED_DOSE MED_TOTALDOSE MED_STRENGTH MED_UNIT	DOSAGE	MEDICATION_DOSAGE MEDICATION_STRENGTH 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 MED_VALUE	MEASUREMENT_VALUE	TEST_VALUE
LAB_UNIT 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

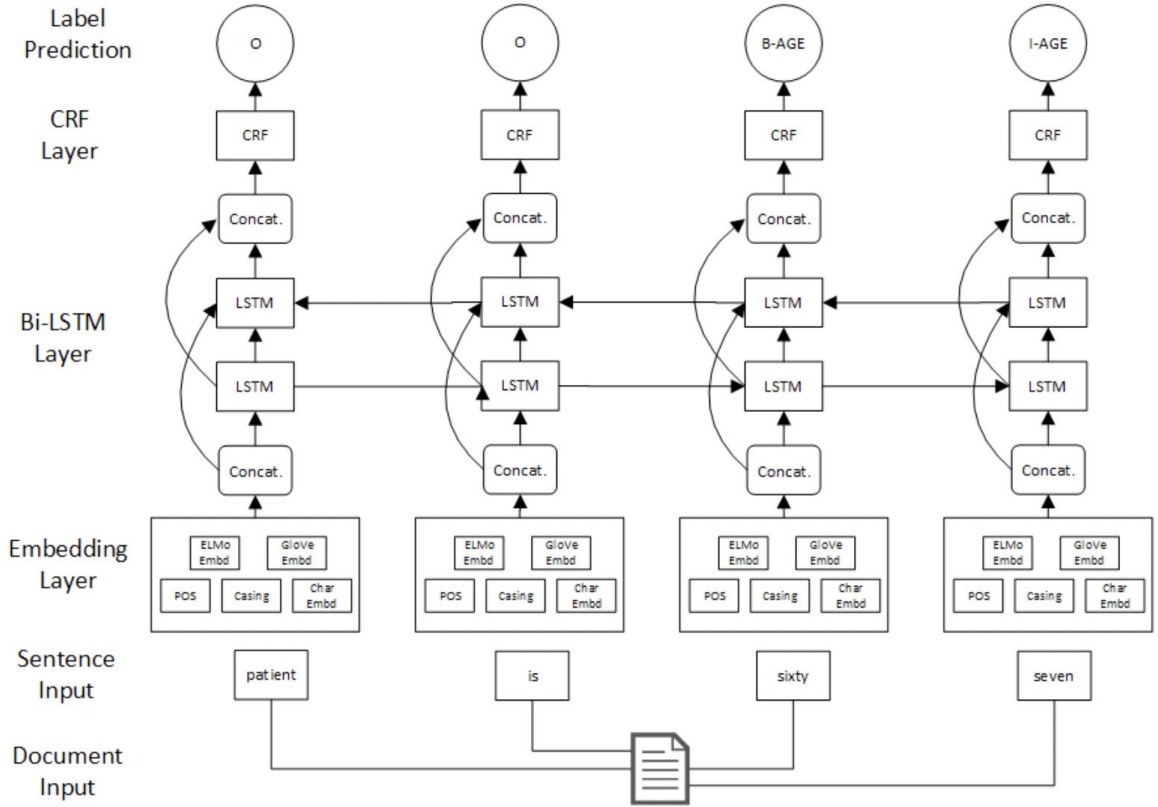
Biomedical Named Entity Recognition

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

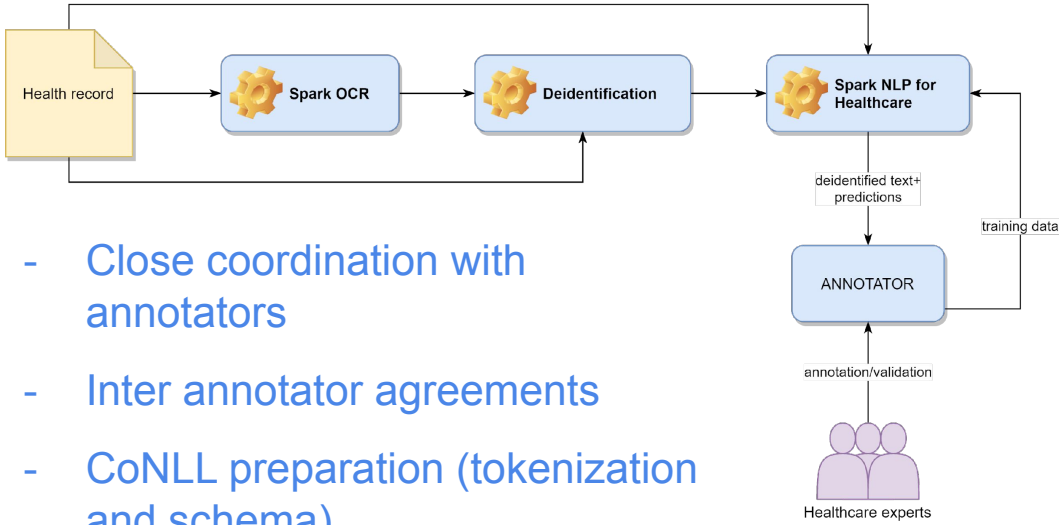
NER in Healthcare

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)

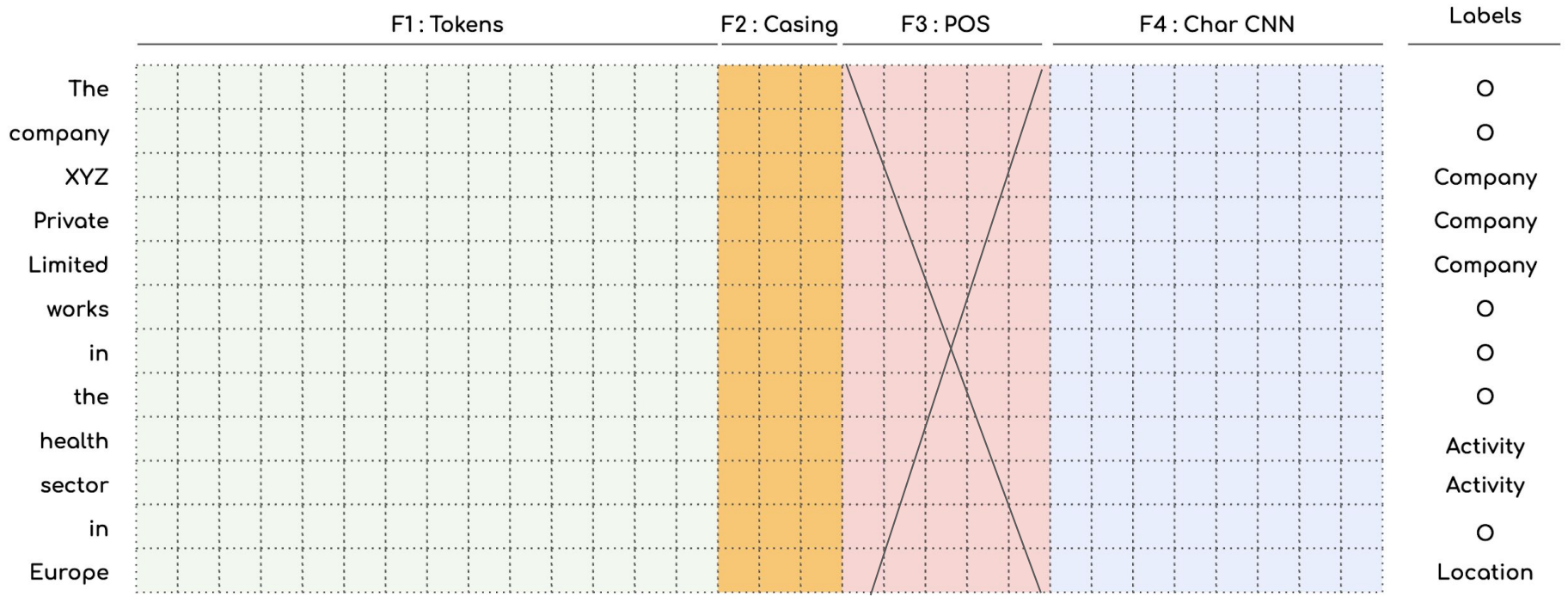
She returns today for ongoing evaluation of herEGFR mutated, stage 4 lung cancer with metastasis to her L2 vertebrae and her lungs bilaterally.

Bone negative for metastatic disease.

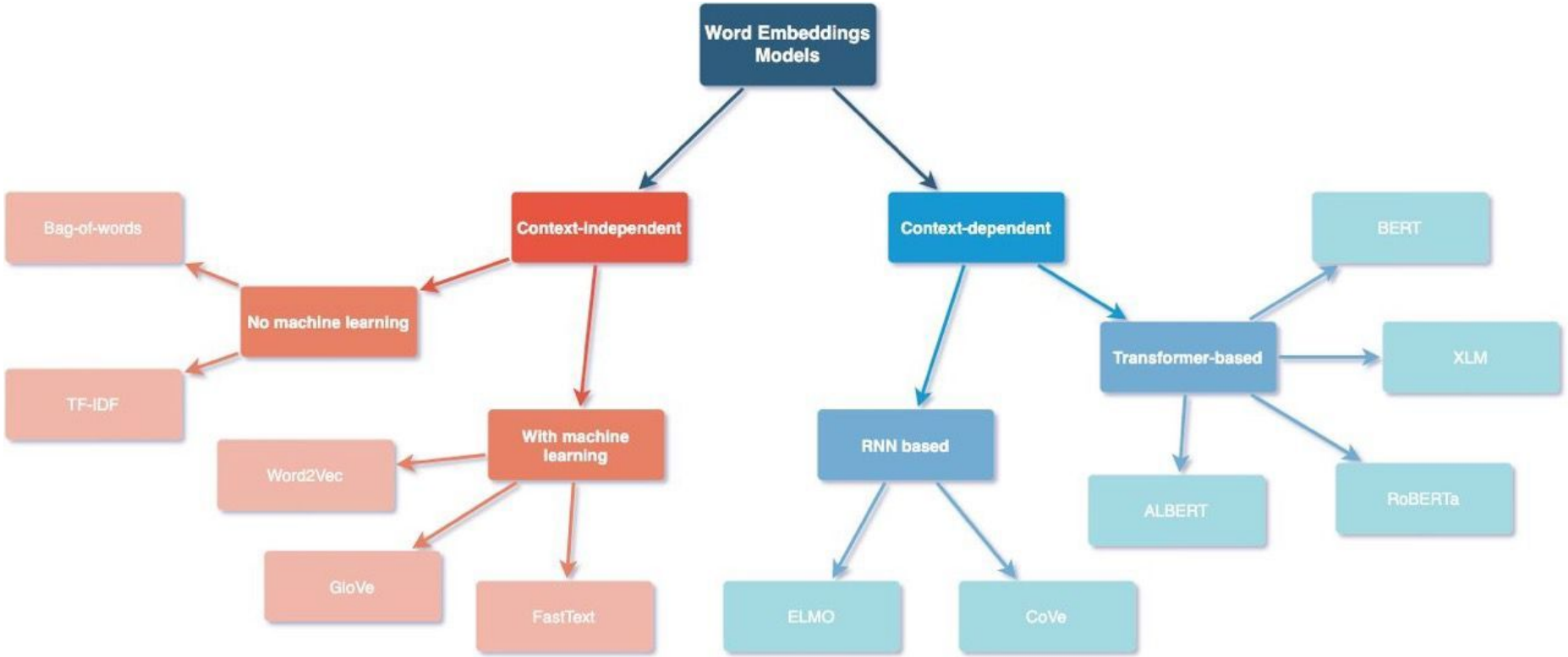
Patient denies any family history of cancer.

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

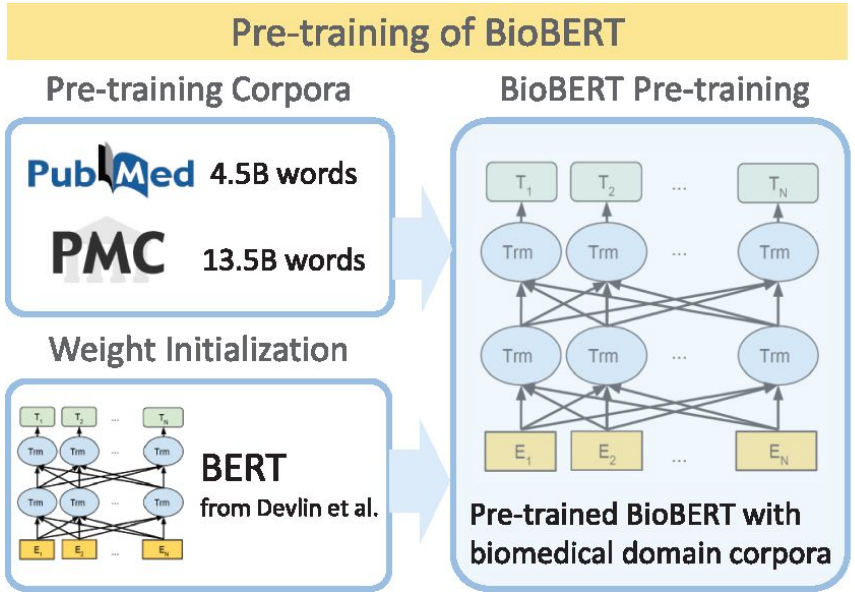
By Fabio Chiusano

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
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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

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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

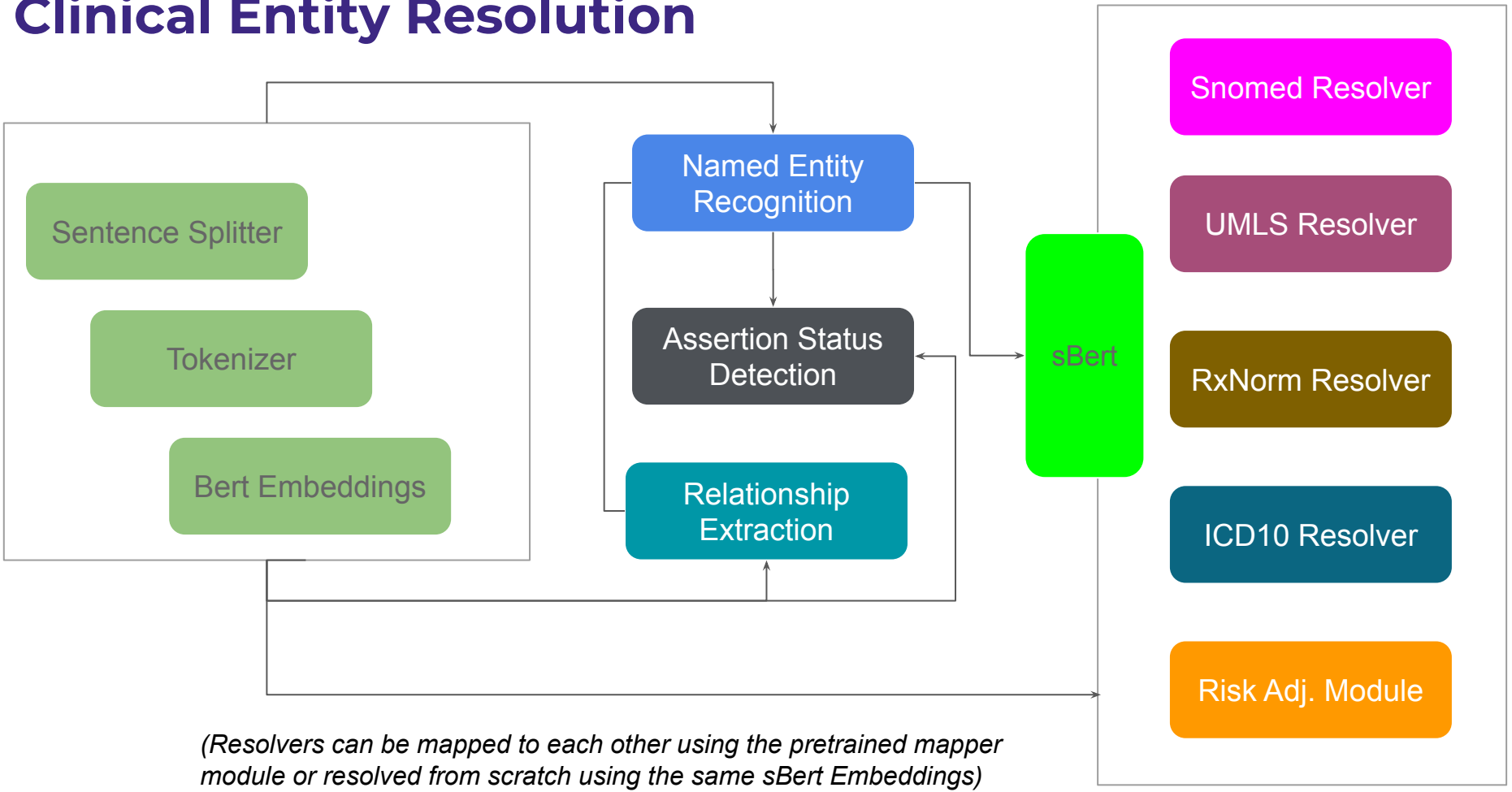
Snomed

- 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)
```

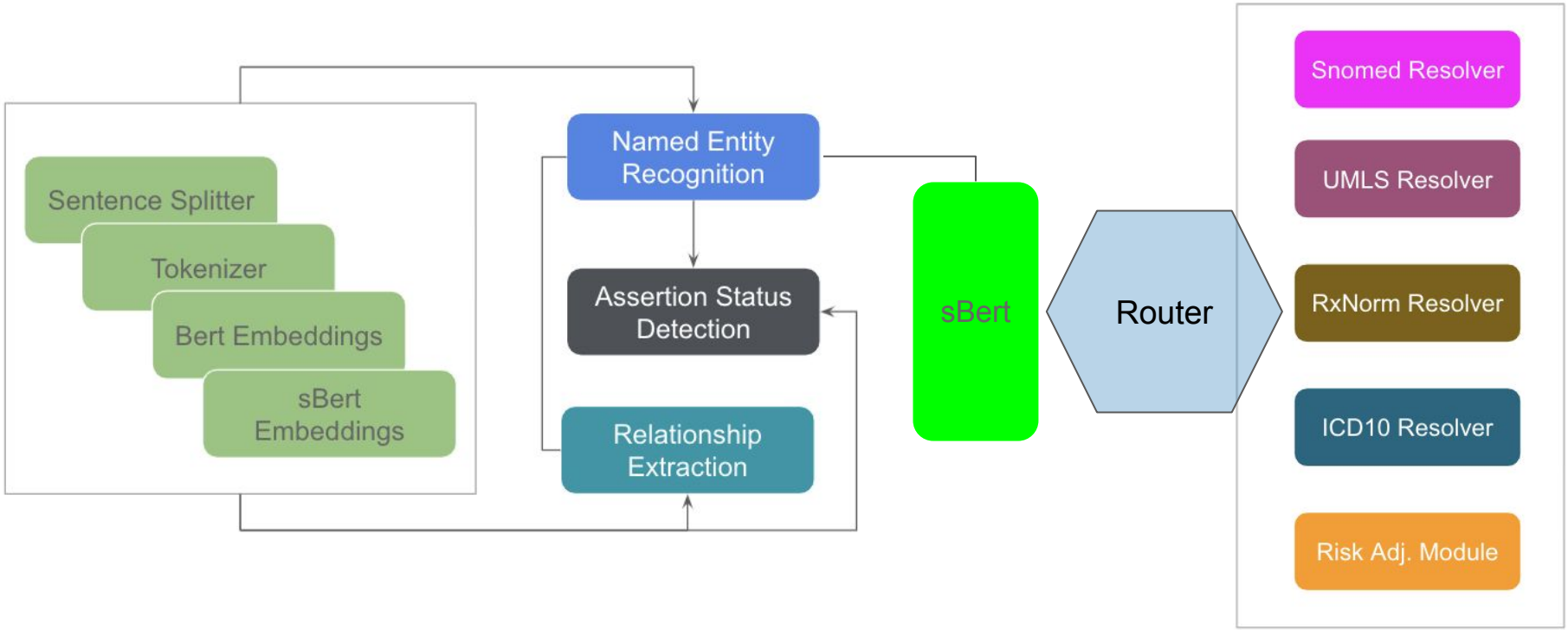
```
bert_token_classifier_drug_development_trials download started this may take some time.
[OK!]
drug_action_treatment_mapper download started this may take some time.
[OK!]
```

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

Background & Motivation

Why de-identify?

- Organizations in possession of documents containing Protected Health Information (PHI) must follow privacy rules

- De-identification enables sharing of health data for medical research studies, policy assessments, other studies/assessments without violating patient privacy or requiring individual authorizations (HIPAA / GDPR restrictions around sharing no longer apply)

Protected Health Information (PHI)

All info created or received by an entity that:

- Relates to past/present/future health or condition of an individual; the provision of health care; or the past/present/future payment for the provision of health care
- Identifies the individual; or with respect to which there is a reasonable basis to believe the information can be used to identify the individual

PHI includes many common identifiers: names, geographic locations, dates, phone numbers, email, IDs, SSN, medical record numbers, etc

Spark NLP in Action

John Snow LABS

Spark NLP for Healthcare → De-Identification

Deidentify structured data

Live Demo

Colab Netbook

Deidentify free text documents

Live Demo

Colab Netbook

Deidentify DICOM documents

Live Demo

Colab Netbook

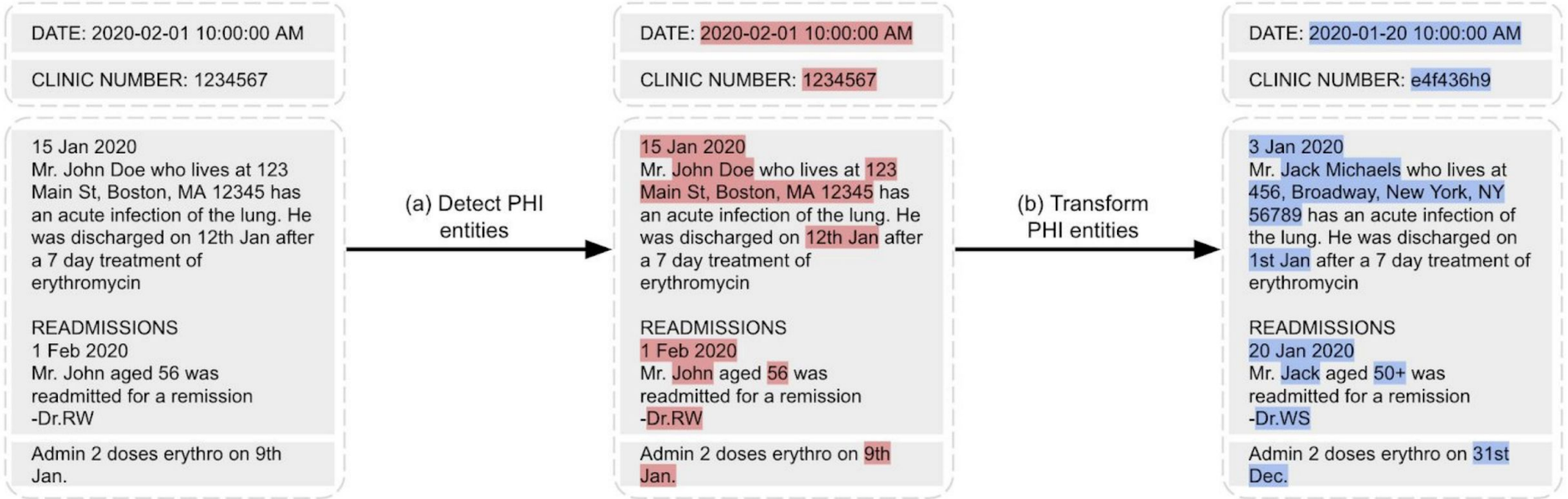
De-identify PDF documents - HIPAA Compliance

Live Demo

Colab Netbook

De-Identification

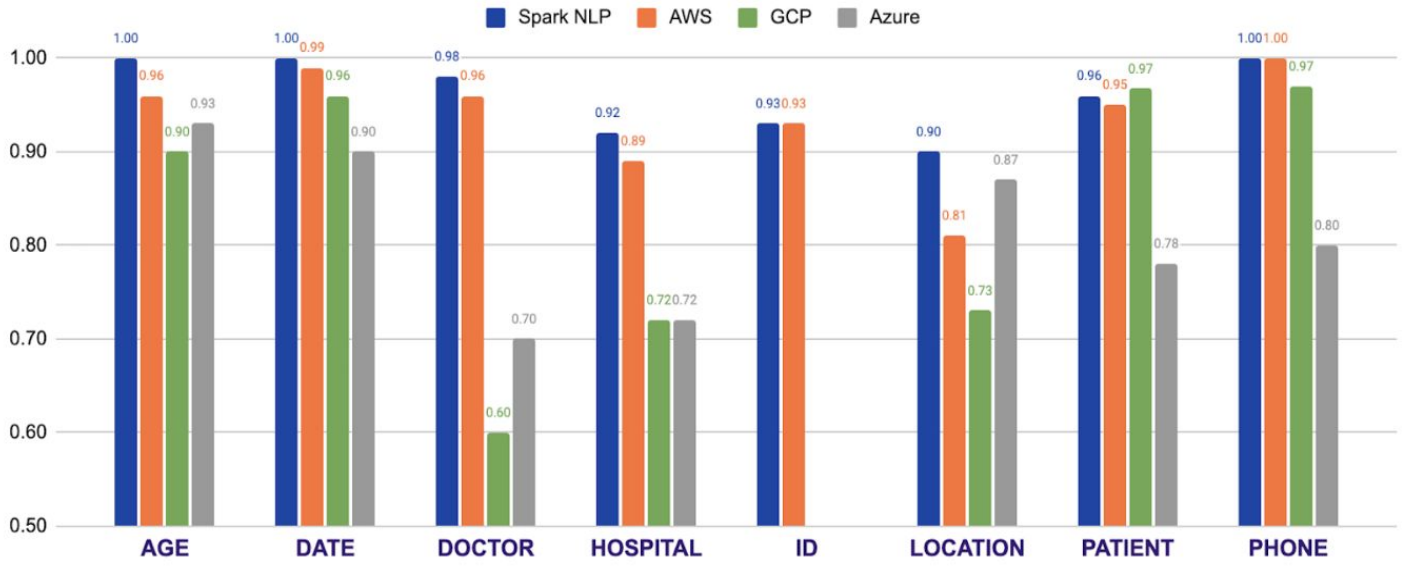
* Identifies potential pieces of content with personal information about patients and remove them by replacing with semantic tags.



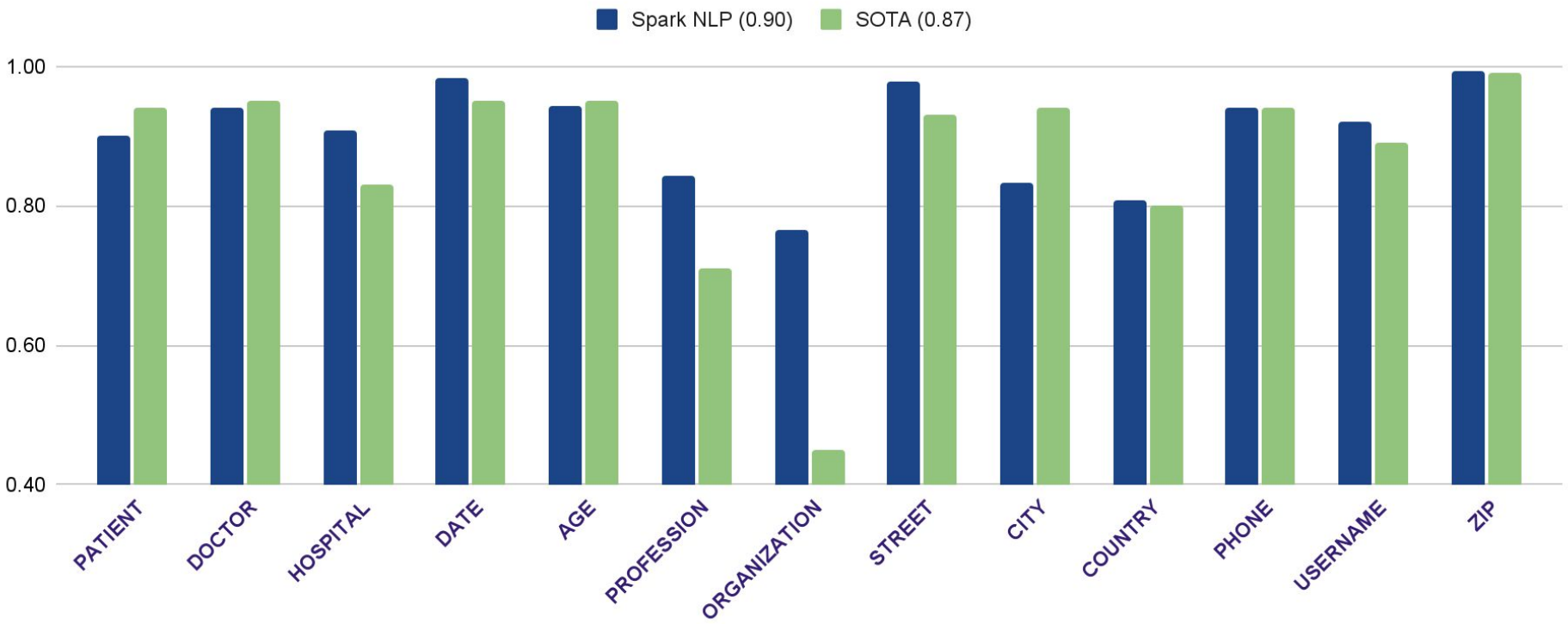
Veysel Kocaman

May 2 · 17 min read · Listen

Comparison of Key Medical NLP Benchmarks — Spark NLP vs AWS, Google Cloud and Azure



Deidentification Benchmarks



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How Providence Health De-Identified 700 Million Patient Notes with Spark NLP

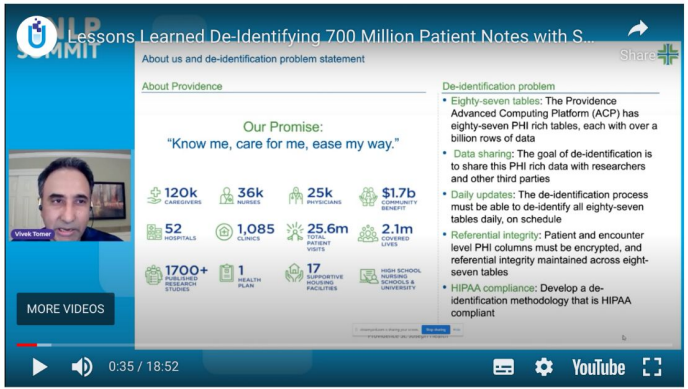
Accuracy:

99.19 | correctly de-identified sentences

Performance:

2.46 hours | to de-identify **500K** patient notes.

See how we did it



De-identify

Software

We support:

- Tabular (headers, values)
- Text (NER, text matching)
- PDF: Text or Scanned
- Images (OCR & metadata)
- DICOM (OCR & metadata)

So you can:

- Replace (or delete a field)
- Mask (hash identifiers or shift dates)
- Obfuscate (name, locations, organizations)
- Generalize (disease codes, dates, addresses)

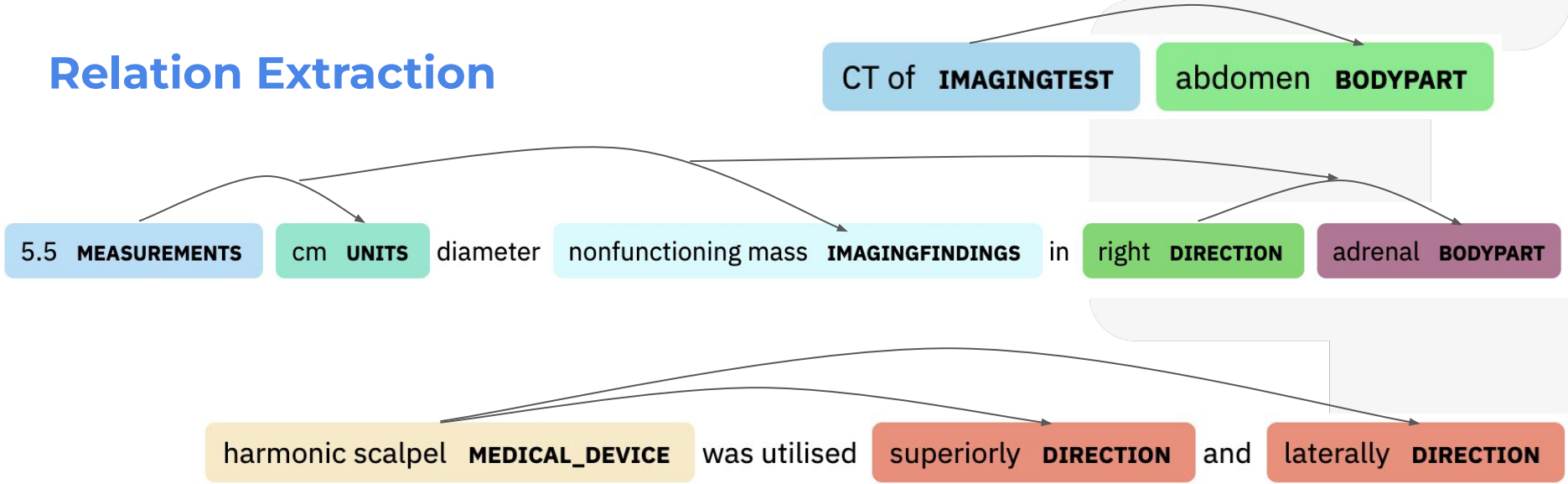
Part - V

- 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**

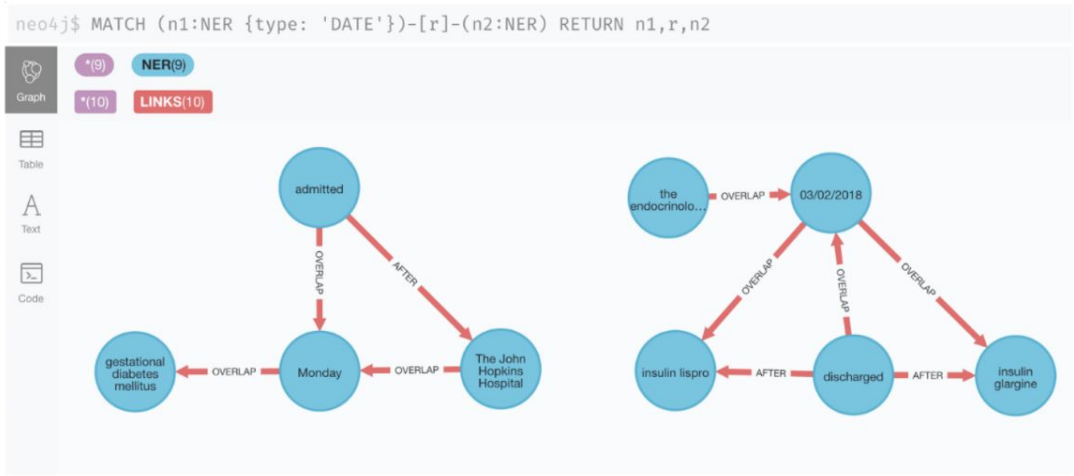
Clinical Relation Extraction

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
```

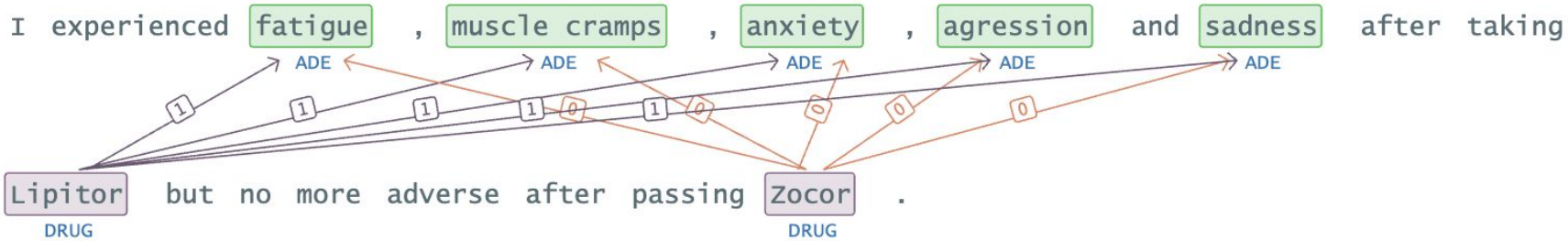
	date	relation	event
0	Monday	OVERLAP	gestational diabetes mellitus
1	Monday	OVERLAP	The John Hopkins Hospital
2	Monday	OVERLAP	admitted
3	03/02/2018	OVERLAP	insulin lispro
4	03/02/2018	OVERLAP	insulin glargine
5	03/02/2018	OVERLAP	discharged
6	03/02/2018	OVERLAP	the endocrinology service



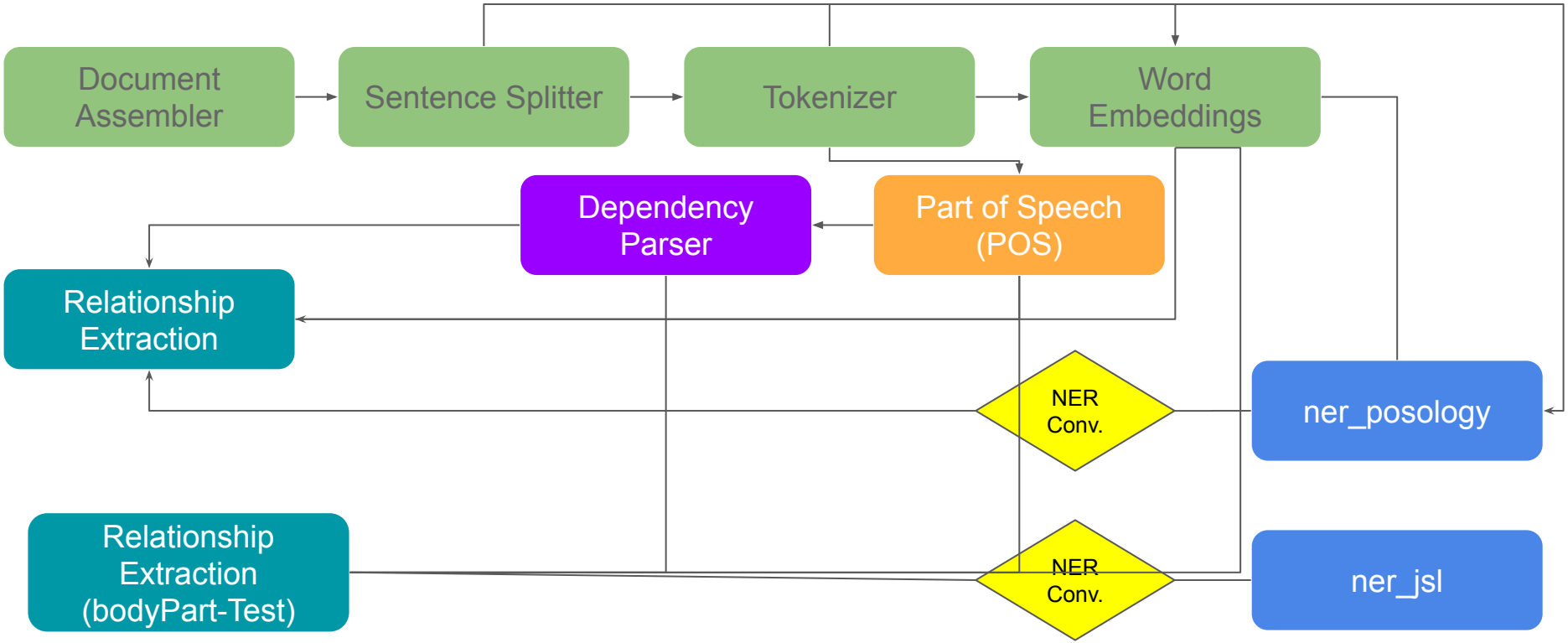
Clinical Relation Extraction

	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)**

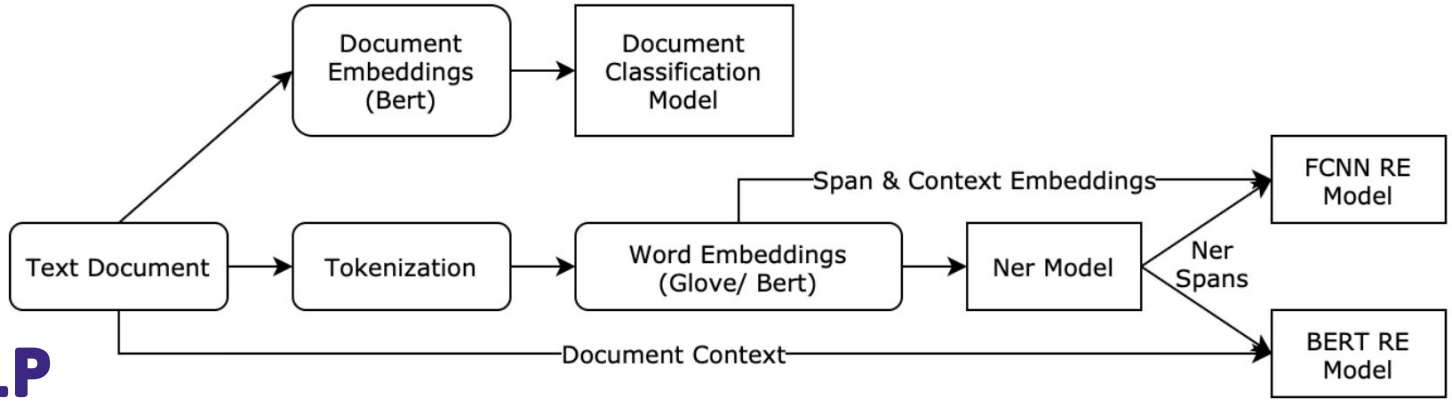
Adverse Drug Reactions (ADR)

Document	Class	ADE Entity	Drug Entity	relation
I feel a bit drowsy & have a little blurred vision after taking insulin.	ADE	drowsy blurred vision	insulin insulin	Positive Positive
@yho fluvastatin gave me cramps, but lipitor suits me!	ADE	cramps cramps	fluvastatin lipitor	Positive 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

NLP SUMMIT

Presented by John Snow LABS

Thank you !

Veysel Kocaman

Head of Data Science

John Snow Labs

Doc2Chunk / Chunk2Doc

- ✓ Transform the data from one AnnotatorType to another.
- ✓ Doc2Chunk
  - Converts DOCUMENT type annotations into CHUNK type with the contents of a chunkCol.
- ✓ Chunk2Doc
  - Converts a CHUNK type column back into DOCUMENT.
  - Useful when trying to re-tokenize or do further analysis on a CHUNK result.

```
chunkAssembler = Doc2Chunk() \
    .setInputCols("document") \
    .setChunkCol("target") \
```

```
chunkToDoc = Chunk2Doc()\
    .setInputCols("chunk")\
    .setOutputCol("chunkConverted")
```

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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Healthcare NLP Summit ‘22

1. 

End-to-End No-Code Development of NER model for Text with Annotation Lab
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2. 

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
John Snow Labs

4. 

End-to-End No-Code Development of Visual NER Models for PDFs and Images
John Snow Labs

5. 

A Hierarchical Approach for Automated ICD-10 Coding Using Phrase-level Attention
John Snow Labs

6. 

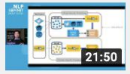
End-to-End No-Code Development of AI Models for Text and Images
John Snow Labs

7. 

Opportunities and Challenges of Applying Advances in NLP to Healthcare
John Snow Labs

8. 

Current State-of-the-Art Accuracy for Key Medical Natural Language Processing Benchmarks
John Snow Labs

9. 

Machine Reading for Precision Medicine
John Snow Labs

10. 

Collaborative Healthcare NLP: Customisable NLP platforms for health and related research
John Snow Labs

11. 

Using Spark NLP in R: a Drug Standardization Case Study
John Snow Labs

12. 

How to sign up for a free trial and how to use your license on COLAB
John Snow Labs

13. 

Few-Shot Text Classification in the Real-World
John Snow Labs

14. 

Medical NLP: Domain Expertise and Data Quality are Vital For Success
John Snow Labs

15. 

Automatic mining of adverse drug reactions from social media posts and unstructured chats
John Snow Labs

16. 

Data Centric AI for Healthcare
John Snow Labs

17. 

Radiology Report Summarization
John Snow Labs

18. 

Entropy and Sentiment: the Anna Karenina Principle in Patient Experience Data
John Snow Labs

19. 

1 Line of Code to Use 600+ State-of-the-Art Clinical & Biomedical NLP Models
John Snow Labs

20. 

Cleanlab: Making AI Work with Messy, Real-World Healthcare and NLP Data
John Snow Labs

21. 

Natural Language Technologies: Current Status and Future Evolution
John Snow Labs

22. 

The Quest for Proactive and Reactive Healthcare
John Snow Labs

23. 

The Unified NLP Platform
John Snow Labs

24. 

Industry Survey Analysis: AI in Healthcare 2022
John Snow Labs

25. 

Using NLP at Scale to Process Patient Charts for Identifying Patient Encounters
John Snow Labs

26. 

Transfer Learning From Existing Diseases Via Hierarchical Multi-Modal BERT Models to Predict COVID19
John Snow Labs

27. 

Supporting Mental Healthcare Delivery Using NLP
John Snow Labs

28. 

Using Spark NLP to De-Identify Doctor Notes in the German Language
John Snow Labs

29. 

Accelerating Use of the Digital Medical Record with Optimized Structured & Unstructured Data
John Snow Labs

30. 

Is it Enough to Simply Apply Language Model for Optimal Text Classification?
John Snow Labs