John Snow LABS

Spark NLP for Data Scientists

October 12-13, 2021

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4 days, 16 hrs live training

Certification exams in 2 weeks

Welcome - We have a lot of things ahead of us

Day-1	60 min	- Intro to John Snow Labs, Spark NLP and NLP Theory - Spark NLP Pretrained Pipelines basics and JVM/Spark concepts
	10 min	Break
	50 min	- Text Preprocessing and composing custom pipeline in Spark NLP
	10 min	Break
	50 min	- Use any of the 4000+ pretrained Models for 200+ languages in Spark NLP
		Break
	50 min	- Train NER and Classifier models - Upload to Modelshub

Welcome - We have a lot of things ahead of us

Day-2	50 min	- Unsupervised Keyword Extraction with YAKE - Sentence Detection - Spell Checking - Graph triplet extraction
	10 min	Break
	60 min	- Visualize Embeddings with Manifold and Matrix Decomposition Algorithms - Scalable Semantic Search and Similarity with Embeddings
	10 min	Break
	60 min	- Question Answering, Summarization and other T5 applications - Multi-Lingual NLP - Train on English only and predict for 100+ languages - Huggingface and Tensorflow Hub to Spark NLP export
	10 min	Break
	50 min	- The Python NLU library basics - NLU & Streamlit - NLP Server

Part - I (Day 1)

- NLP Theory and Introduction to John Snow Labs
- Pretrained Pipelines
- Spark, JVM and Spark NLP basic concepts
- Notebook 1 - Spark NLP Basics

Spark NLP for Data Scientists

Christian Kasim Loan
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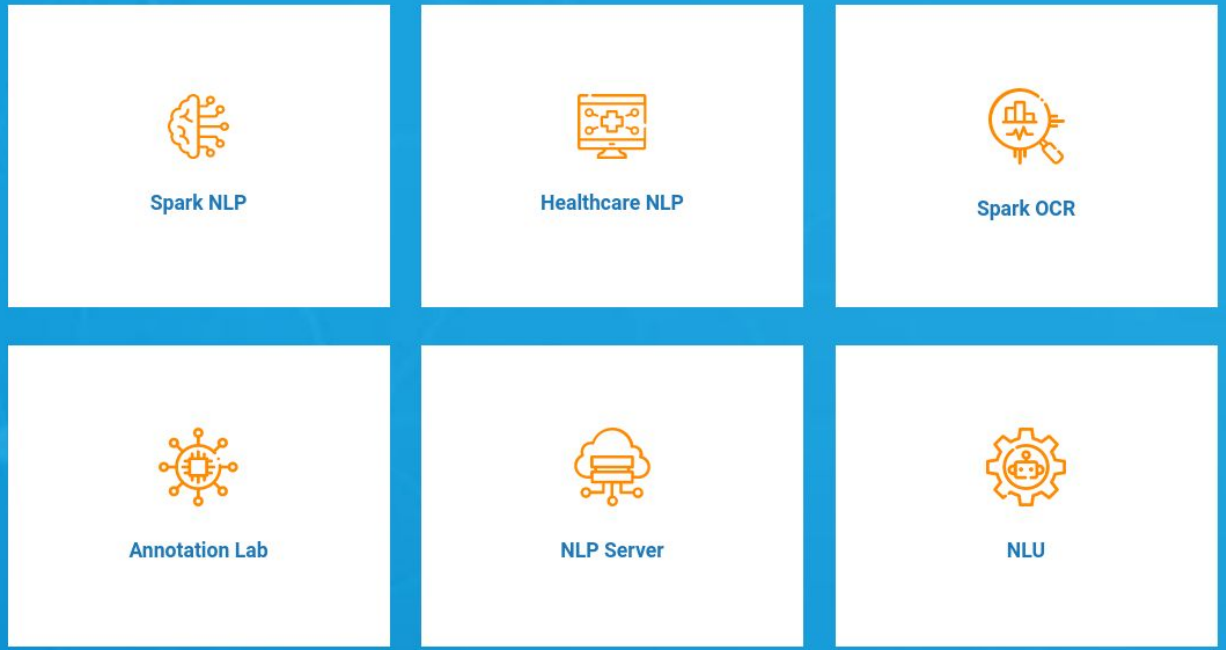
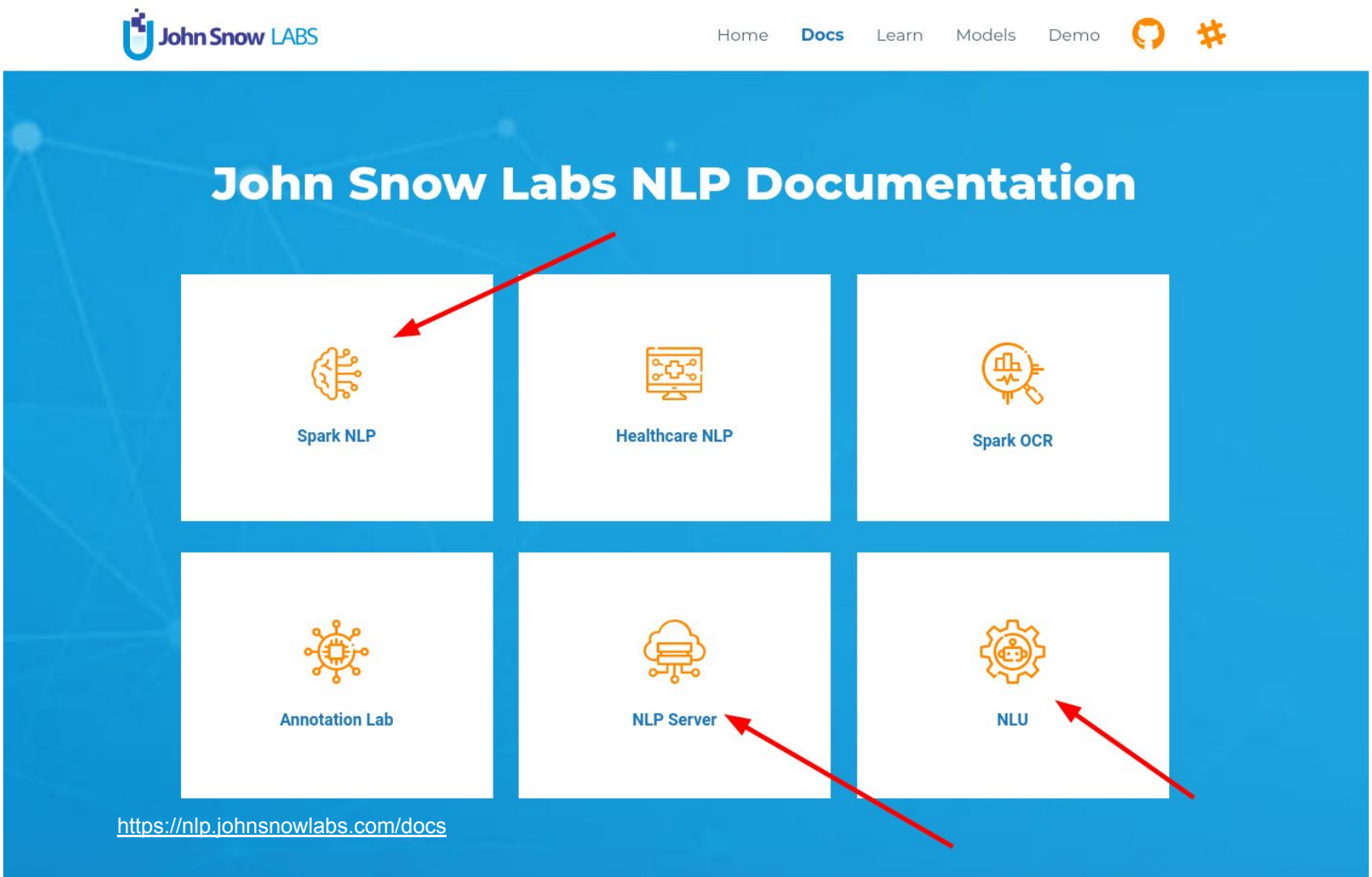
John Snow Labs NLP Documentation



https://nlp.johnsnowlabs.com/docs


John Snow LABS
Home
Docs
Learn
Models
Demo
John Snow Labs NLP Documentation
Spark NLP
Healthcare NLP
Spark OCR
Annotation Lab
NLP Server
NLU
https://nlp.johnsnowlabs.com/docs

Setup

pip install spark-nlp

RUNNING CODE:

https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/Certification_Trainings/Public

[How to set up Google Colab]

BOOKMARK:

https://nlp.johnsnowlabs.com/

https://nlp.johnsnowlabs.com/docs/en/quickstart

spark-nlp.slack.com

https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/1hr_workshop/SparkNLP_openSource_workshop_1hr.ipynb


```
[ ] !wget -q https://raw.githubusercontent.com/JohnSnowLabs/spark-nlp-workshop/master/colab_setup.sh
    !bash colab_setup.sh -p 2.4.4 -s 2.7.5
    # -p is for pyspark
    # -s is for spark-nlp
    # by default they are set to the latest

setup Colab for PySpark 2.4.4 and Spark NLP 2.7.5
     |████████████████████████████████| 215.7MB 78kB/s
     |████████████████████████████████| 143kB 53.1MB/s
     |████████████████████████████████| 204kB 42.7MB/s
  Building wheel for pyspark (setup.py) ... done
```

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

vkocaman Merge pull request #147 from JohnSnowLabs/summit_notebooks2021 — f6058ae 22 hours ago · History

..		
data	updates for nlp summit	3 months ago
databricks_notebooks	Dbc T5 added	2 days ago
slides	slides moved to a folder	3 months ago
utils	rebased	3 months ago
1.SparkNLP_Basics.ipynb	Pb NB1 updated	4 days ago
10.T5_Workshop_with_Spark_NLP.ipynb	add T5 nb	7 days ago
2.Text_Preprocessing_with_SparkNLP_Annotators_T...	Pb NB2-updated with RegTok,DocNorm	2 days ago
3.SparkNLP_Pretrained_Models.ipynb	Pb NB3-LangDetec Updated	yesterday
4.1_NerDL_Graph.ipynb	graph folder fro NerDL	4 months ago
4.NERDL_Training.ipynb	Pb NB4 updated	4 days ago
5.1_Text_classification_examples_in_SparkML_Spar...	updated for Spark 2.3	6 months ago
5.Text_Classification_with_ClassifierDL.ipynb	Pb NB5 updated	5 days ago
6.Playground_DataFrames.ipynb	updated for Spark 2.3	6 months ago
7.Context_Spell_Checker.ipynb	Pb NB7 updated	4 days ago
8.Keyword_Extraction_YAKE.ipynb	Pb NB8-Yake updated	4 days ago
9.SentenceDetectorDL.ipynb	Pb NB9 updated	4 days ago
README.md	readmes added	3 months ago

JOHN SNOW LABS

CIO Review ARTIFICIAL INTELLIGENCE SOLUTION PROVIDER OF THE YEAR - 2018

"John Snow Labs enables healthcare organizations to deploy state-of-the-art artificial intelligence (AI) platforms, models and data in production today."

AI PLATFORM OF THE YEAR

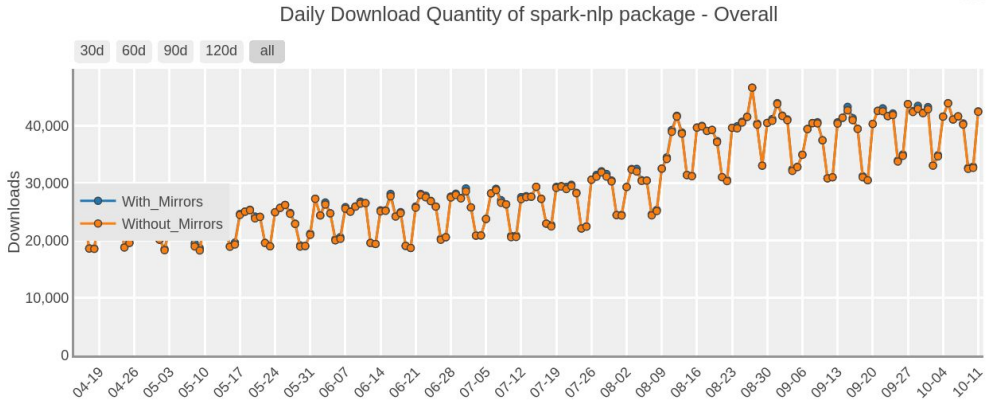
CIO APPLICATIONS 2019

"John Snow Labs wows in both proven customer success and verifiable state-of-the-art technology – making it a natural winner of the highly competitive 2019
AI Platform of the Year Award."

"Keep an eye on this company – as it represents where the industry and data science are headed."

Introducing Spark NLP

PyPI link	https://pypi.org/project/spark-nlp
Total downloads	9,997,656
Total downloads - 30 days	1,178,385
Total downloads - 7 days	275,300



- 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 (4 yrs in a row)
  - Delivering a mission-critical, enterprise grade NLP library (used by multiple Fortune 500)
  - Full-time development team (26 new releases in 2020, 30 new releases in 2019.)

https://medium.com/spark-nlp/introduction-to-spark-nlp-foundations-and-basic-components-part-i-c83b7629ed59

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indeed


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viacom


McKESSON


MERCK


Roche


selectdata


UiPath
Reboot Work.


ASCO
CANCER·LINQ
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UNIVERSITY

John Snow LABS

NLP SUMMIT HEALTHCARE

FREE & ONLINE

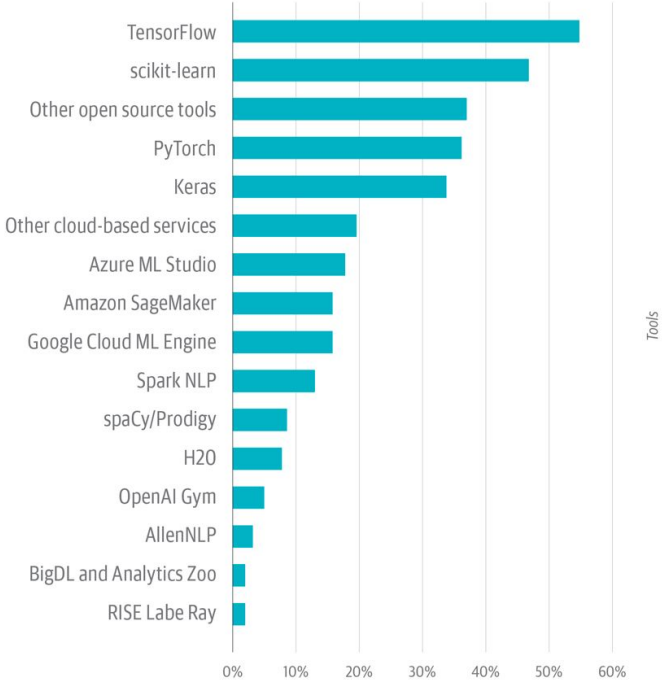
April 6th - 7th

Register

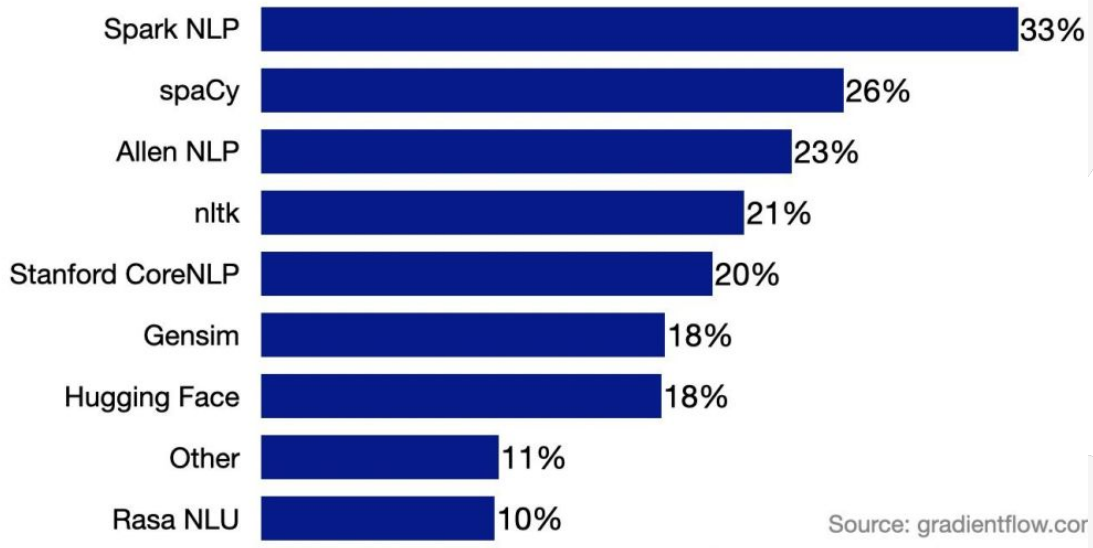
OFFICIALLY SUPPORTED RUNTIMES

Spark NLP in Industry

Which of the following AI tools do you use?



Which NLP libraries does your organization use?



NLP Industry Survey by Gradient Flow,
an independent data science research & insights company, September 2020

Spark NLP

- 73 total releases
- Release every two weeks for the past 3 years
- A single unified library for all your NLP/NLU need
- Active community on Slack and GitHub

NLP Feature	Spark NLP	spaCy	NLTK	CoreNLP	Hugging Face
Tokenization	**Yes**	Yes	Yes	Yes	Yes
Sentence segmentation	**Yes**	Yes	Yes	Yes	**No**
Steeming	**Yes**	Yes	Yes	Yes	**No**
Lemmatization	**Yes**	Yes	Yes	Yes	**No**
POS tagging	**Yes**	Yes	Yes	Yes	**No**
Entity recognition	**Yes**	Yes	Yes	Yes	Yes
Dep parser	**Yes**	Yes	Yes	Yes	**No**
Text matcher	**Yes**	Yes	**No**	**No**	**No**
Date matcher	**Yes**	**No**	**No**	**No**	**No**
Sentiment detector	**Yes**	**No**	Yes	Yes	Yes
Text classification	**Yes**	Yes	Yes	**No**	Yes
Spell checker	**Yes**	**No**	**No**	**No**	**No**
Language detector	**Yes**	**No**	**No**	**No**	**No**
Keyword extraction	**Yes**	**No**	**No**	**No**	**No**
Pretrained models	**Yes**	Yes	Yes	Yes	Yes
Trainable models	**Yes**	Yes	Yes	Yes	Yes

Biomedical Named Entity Recognition at Scale

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***Abstract*—Named entity recognition (NER) is a widely applicable natural language processing task and building block of question answering, topic modeling, information retrieval, etc. In the medical domain, NER plays a crucial role by extracting meaningful chunks from clinical notes and reports, which are then fed to downstream tasks like assertion status detection, entity resolution, relation extraction, and de-identification. Reimplementing a Bi-LSTM-CNN-Char deep learning architecture on top of Apache Spark, we present a single trainable NER model that obtains new state-of-the-art results on seven public biomedical benchmarks without using heavy contextual embeddings like BERT. This includes improving BC4CHEMD to 93.72% (4.1% gain), Species800 to 80.91% (4.6% gain), and JNLPBA to 81.29% (5.2% gain). In addition, this model is freely available within a production-grade code base as part of the open-source Spark NLP library; can scale up for training and inference in any Spark cluster; has GPU support and libraries for popular programming languages such as Python, R, Scala and Java; and can be extended to support other human languages with no code changes.**

I. Introduction

Electronic health records (EHRs) are the primary source of information for clinicians tracking the care of their patients. Information fed into these systems may be found in structured fields for which values are inputted electronically (e.g. laboratory test orders or results) [1] but most of the time information in these records is unstructured making it largely inaccessible

Spark NLP: Natural Language Understanding at Scale

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Accurate Clinical and Biomedical Named Entity Recognition at Scale

Anonymous NAACL-HLT 2021 submission

Abstract

Named entity recognition (NER) is one of the most important building blocks of NLP tasks in the medical domain by extracting meaningful chunks from clinical notes and reports, which are then fed to downstream tasks like assertion status detection, entity resolution, relation extraction, and de-identification. Due to the growing volume of healthcare data in unstructured format, an increasingly important challenge is providing high accuracy implementations of state-of-the-art deep learning (DL) algorithms at scale. In this study, we introduce a production-grade clinical and biomedical NER algorithm based on a modified BiLSTM-CNN-Char DL architecture built on top of Apache Spark. This algorithm establishes new state-of-the-art accuracy on 7 of 8 well-known biomedical NER benchmarks and 3 clinical concept extraction challenges: 2010 i2b2/VA clinical concept extraction, 2014 n2c2 de-identification, and 2018 n2c2 medication extraction. Moreover, clinical NER models trained using this implemen-

Improving Clinical Document Understanding on COVID-19 Research with Spark NLP

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Abstract

Following the global COVID-19 pandemic, the number of scientific papers studying the virus has grown massively, leading to increased interest in automated literate review. We present a clinical text mining system that improves on previous efforts in three ways. First, it can recognize over 100 different entity types including social determinants of health, anatomy, risk factors, and adverse events in addition to other commonly used clinical and biomedical entities. Second, the text processing pipeline includes assertion status detection, to distinguish between clinical facts that are present, absent, conditional, or about someone other than the patient. Third, the deep learning models used are more accurate than previously available, leveraging an integrated pipeline of state-of-the-art pre-trained named entity recognition models, and improving on the previous best performing benchmarks for assertion status detection. We illustrate extracting trends and insights - e.g. most frequent disorders and symptoms, and most common vital signs and EKG findings – from the COVID-19 Open Research Dataset (CORD-19). The system is built using the Spark NLP library which natively supports scaling to use distributed clusters, leveraging GPU's, configurable and reusable NLP pipelines, healthcare-specific embeddings, and the ability to train models to support new entity types or human languages with no code changes.

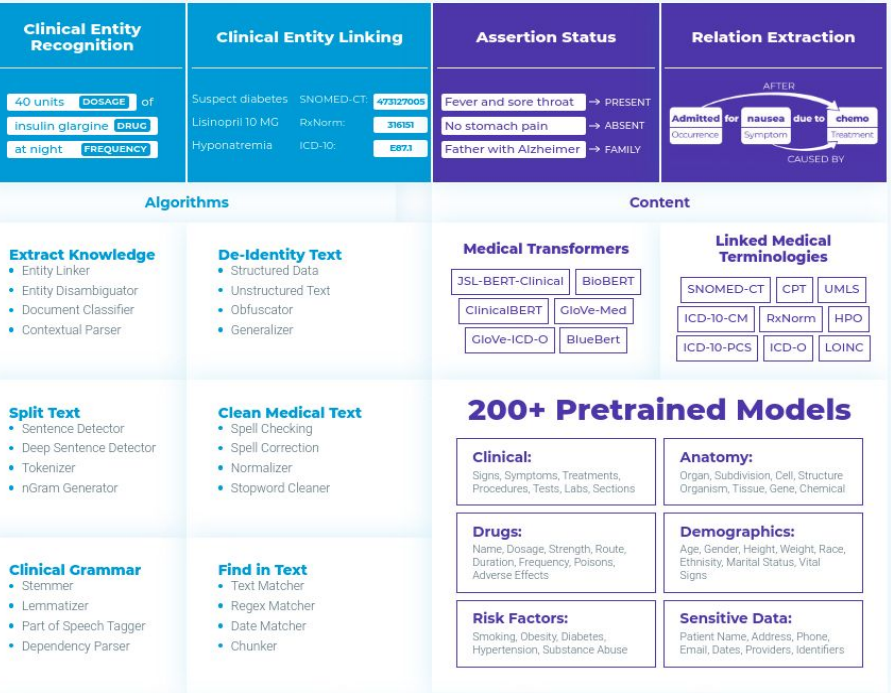
be found in structured fields for which values are inputted electronically (e.g. laboratory test orders or results) (Liede et al. 2015) but most of the time information in these records is unstructured making it largely inaccessible for statistical analysis (Murdoch and Detsky 2013). These records include information such as the reason for administering drugs, previous disorders of the patient or the outcome of past treatments, and they are the largest source of empirical data in biomedical research, allowing for major scientific findings in highly relevant disorders such as cancer and Alzheimer's disease (Perera et al. 2014).

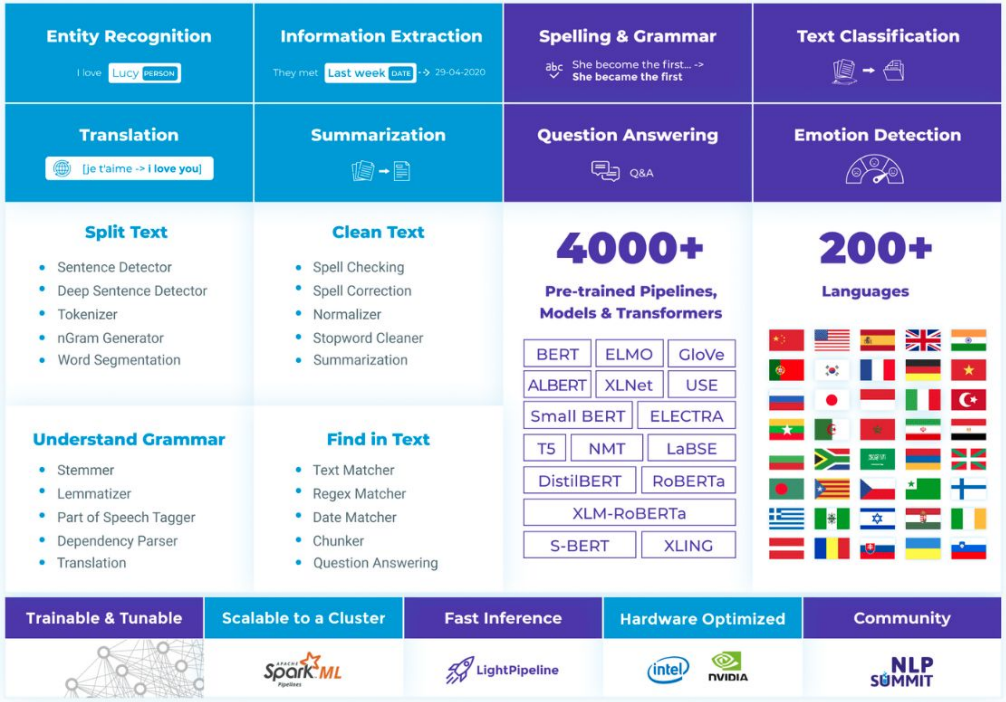
A primary building block in such text mining systems is named entity recognition (NER) - which is regarded as a critical precursor for question answering, topic modelling, information retrieval, etc (Yadav and Bethard 2019). In the medical domain, NER recognizes the first meaningful chunks out of a clinical note, which are then fed down the processing pipeline as an input to subsequent downstream tasks such as clinical assertion status detection (Uzuner et al. 2011), clinical entity resolution (Tzitzivacos 2007) and de-identification of sensitive data (Uzuner, Luo, and Szolovits 2007) (see Figure 1). However, segmentation of clinical and drug entities is considered to be a difficult task in biomedical NER systems because of complex orthographic structures of named entities

Peer-reviewed conference papers on Spark NLP NER

John Snow LABS

Spark NLP Modules

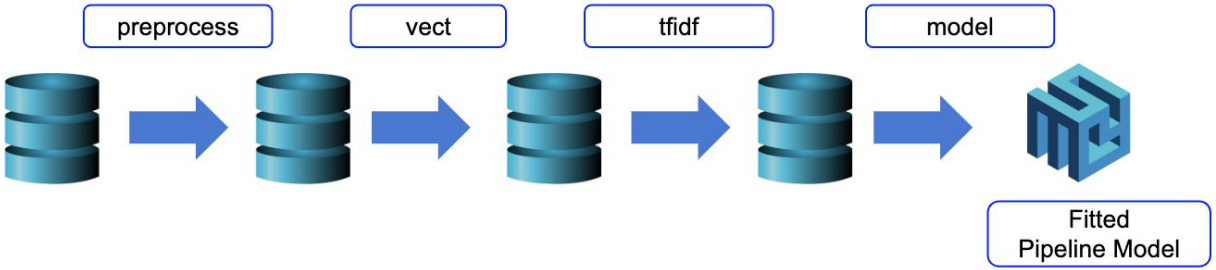




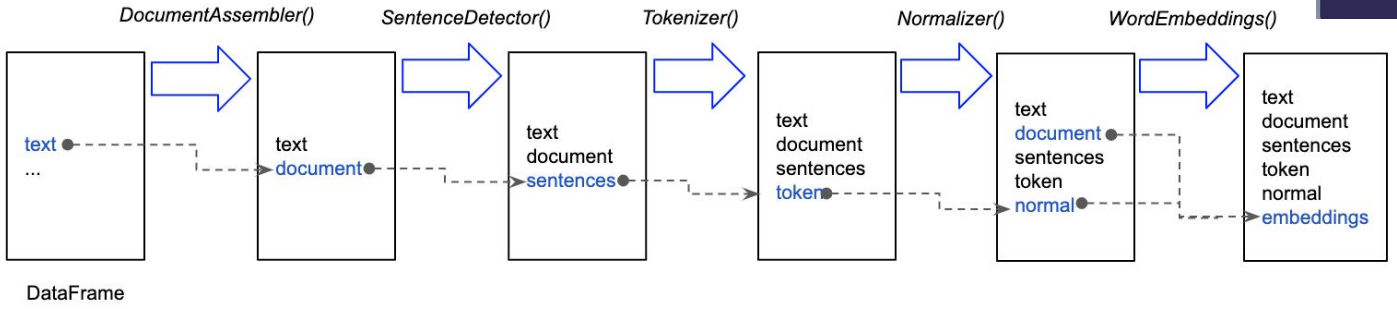
Spark NLP Modules (Enterprise and Public)

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).

Coding ...

1. Spark NLP Basics

2. Text Preprocessing with Spark NLP

3. Spark NLP Pretrained Models

(click on Colab icon or open in a new tab)

https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/Certification_Trainings/Public/1.SparkNLP_Basics.ipynb

https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/Certification_Trainings/Public/2.Text_Preprocessing_with_SparkNLP(Annotators_Transformers).ipynb

https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/Certification_Trainings/Public/3.SparkNLP_Pretrained_Models.ipynb

Spark NLP Basics and Pretrained Pipelines

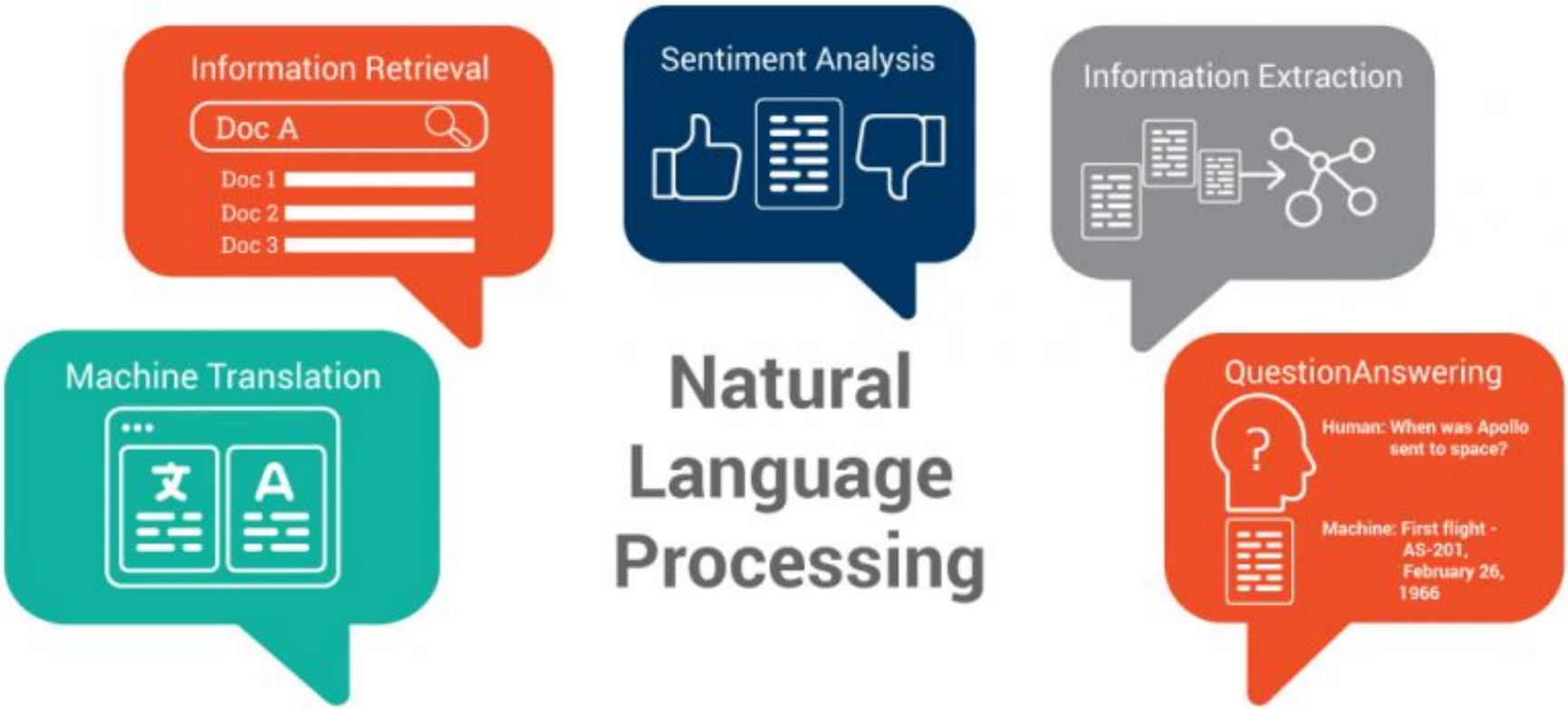
- Colab Setup
  - How to prevent Google Colab from disconnecting?
- Start Spark Session
- Using Pretrained Pipelines
  - Explain Document ML
  - Explain Document DL
  - Recognize Entities DL
  - Clean Stop Words
  - Clean Slang
  - Spell Checker
  - Spell Checker DL
  - Parsing a list of texts
  - Using fullAnnotate to get more details
  - Use pretrained match_chunk Pipeline for Individual Noun Phrase
  - Extract exact dates from referential date phrases
  - Sentiment Analysis
    - Vivek algo
    - DL version (trained on imdb)
    - DL version (trained on twitter dataset)

Text Preprocessing with Spark NLP

- Colab Setup
- Annotators and Transformer Concepts
  - Create Spark Dataframe
  - Transformers
- Document Assembler
- Sentence Detector
- Tokenizer
- Stacking Spark NLP Annotators in Spark ML Pipeline
- Normalizer
- Stopwords Cleaner
- Token Assembler
- Stemmer
- Lemmatizer
- NGram Generator
- TextMatcher
- RegexMatcher
- Text Cleaning with UDF
- Finisher
- LightPipeline

Spark NLP Pretrained Models

- Colab Setup
- LemmatizerModel
- PerceptronModel (POS - Part of speech tags)
- Chunker
- Dependency Parser
- SpellChecker
  - Norvig Spell Checker
  - Context SpellChecker
- Language Detector
- Embeddings
  - Word Embeddings (Glove)
    - Using your own Word embeddings in Spark NLP
  - Elmo Embeddings
  - Bert Embeddings
  - Albert Embeddings
  - XlnetEmbeddings
  - Chunk Embeddings
  - UniversalSentenceEncoder
- Loading Models from local
- Getting Sentence Embeddings from word embeddings
  - Cosine similarity between two embeddings (sentence similarity)
- NERDL Model
  - Public NER (CoNLL 2003)
  - NerDL OntoNotes 100D
  - NER with Bert (Onto)
  - Getting the NER chunks with NER Converter
- Highlight the entities


Information Retrieval
Doc A
Doc 1
Doc 2
Doc 3
Sentiment Analysis
Information Extraction
Machine Translation
文
A
Natural Language Processing
QuestionAnswering
Human: When was Apollo sent to space?
Machine: First flight - AS-201, February 26, 1966

NLP Basics

LEMMATIZATION

Find the **lemma** of each word:

- How does it show in the dictionary?

Uses a lookup from a full dictionary.

```
am, are, is    →    be

liver          →    liver

lives          →    live
```

STEMMING

Find the **stem** of each word.

Uses rules: e.g, remove common suffixes.

Form	Suffix	Stem
studies	-es	studi
studying	-ing	study
niñas	-as	niñ
niñez	-ez	niñ

- The goal of both stemming and lemmatization is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form for normalization purposes.
- Lemmatization always returns real words, stemming doesn't.

NLP Basics

Remove stop words and apply stemming

it was a bright cold day in april and the clocks were striking thirteen winston smith his chin nuzzled into his breast in an effort to escape the vile wind slipped quickly through the glass doors of victory mansions though not quickly enough to prevent a swirl of gritty dust from entering along with him

bright cold day april clocks striking thirteen winston smith chin nuzzled breast effort escape vile wind slipped quickly glass doors victory mansions though quickly enough prevent swirl gritty dust entering along

- For tasks like text classification, where the text is to be classified into different categories, **stopwords** are **removed** or excluded from the given text so that more focus can be given to those words which define the meaning of the text.

Stopwords

a
able
about
above
according
accordingly
across
actually
after
afterwards
again
against
ain
all
allow
allows
almost
alone
along
already
also

(520 stopwords)

Spell Checking & Correction


```
val pipeline = PretrainedPipeline("spell_check_ml", "en")
val result = pipeline.annotate("Harry Potter is a graet muvie")

println(result("spell"))
/* will print Seq[String](…, "is", "a", "great", "movie") */
```

- 3 trainable approaches
- **Norvig Approach**:
  - Retrieves tokens and auto-corrects based on a given dictionary
- **Symmetric Delete**:
  - Uses distance metrics to find possible words
- **Context Aware**:
  - Most accurate: Judges words in context
  - Deep learning based

Context Spell Checker

The Spell Checker can leverage the context of words for ranking different correction sequences. Let's take a look at some examples,

```
# check for the different occurrences of the word "siter"
example1 = ["I will call my siter.",\
    "Due to bad weather, we had to move to a different siter.",\
    "We travelled to three siter in the summer."]
beautify(lp.annotate(example1))
```

```
['I  will  call  my  sister  .\n',
 'Due  to  bad  weather  ,  we  had  to  move  to  a  different  site  .\n',
 'We  travelled  to  three  sites  in  the  summer  .\n']
```

```
# check for the different occurrences of the word "ueather"
example2 = ["During the summer we have the best ueather.",\
    "I have a black ueather jacket, so nice.",\
    "I introduce you to my sister, she is called ueather."]
beautify(lp.annotate(example2))
```

```
['During  the  summer  we  have  the  best  weather  .\n',
 'I  have  a  black  leather  jacket  ,  so  nice  .\n',
 'I  introduce  you  to  my  sister  ,  she  is  called  Heather  .\n']
```

Notice that in the first example, 'siter' is indeed a valid English word,
https://www.merriam-webster.com/dictionary/siter

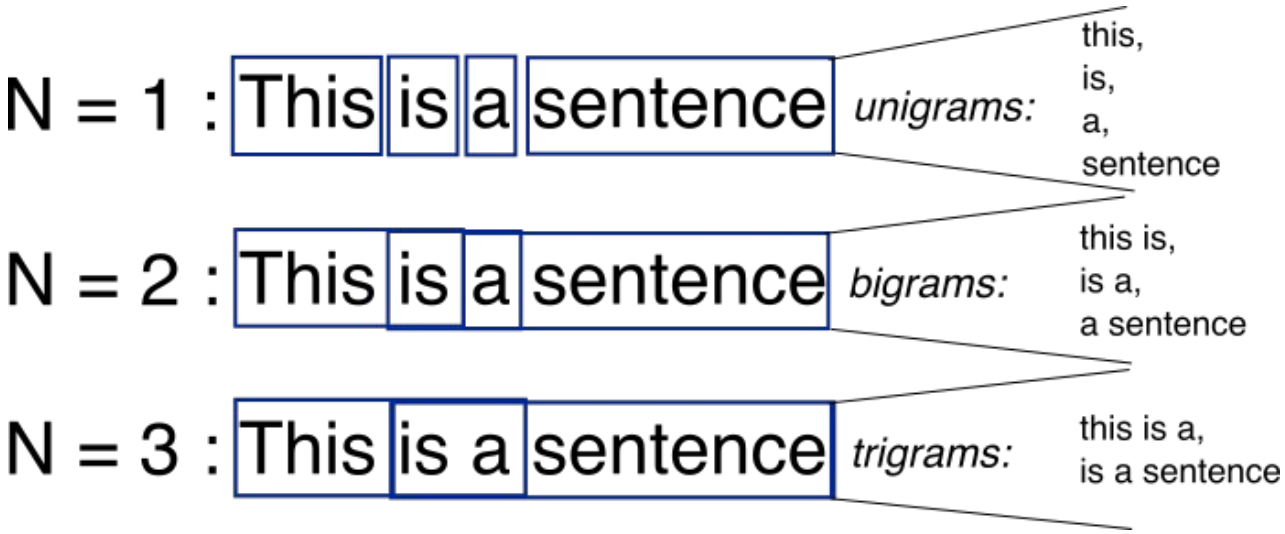
NORMALIZATION

Remove or replace undesirable characters or regular expressions:

from: `@Have a$ #2great birth) day>!`
to: `Have a great birth day!`

Spark NLP also comes with a Slang normalizer:

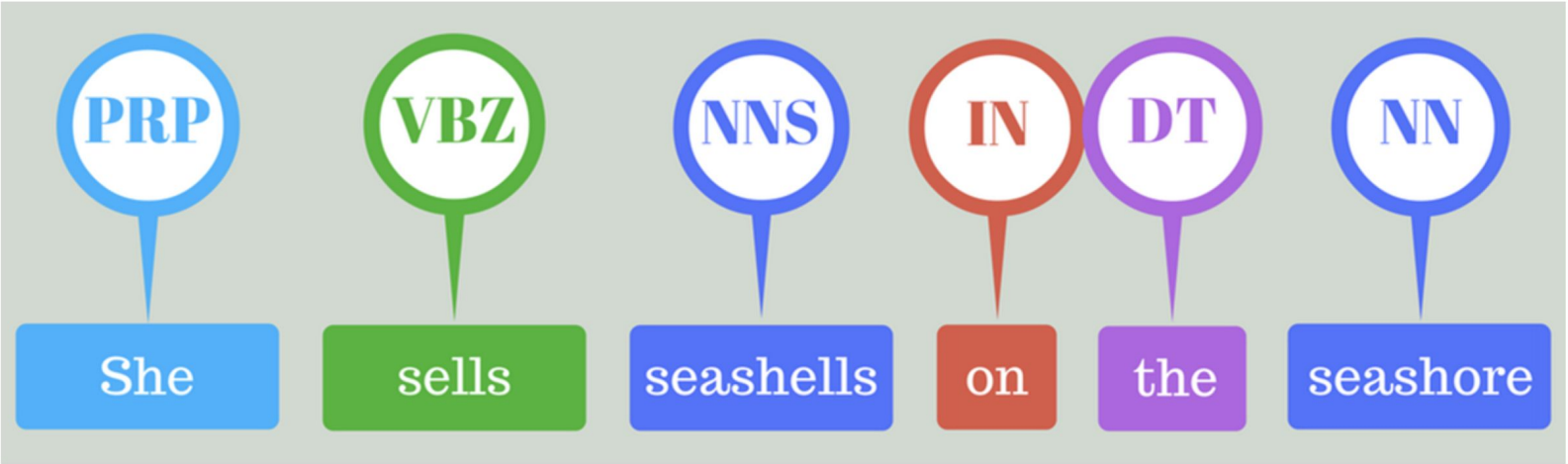
N-gram Tokenization



- Kind of tokenizers which split words or sentences into several tokens
- Each token has certain number of characters
- Number of character depends on the type of ngram tokenizer
- Unigram, bigram, trigram, etc.

PART OF SPEECH TAGGING

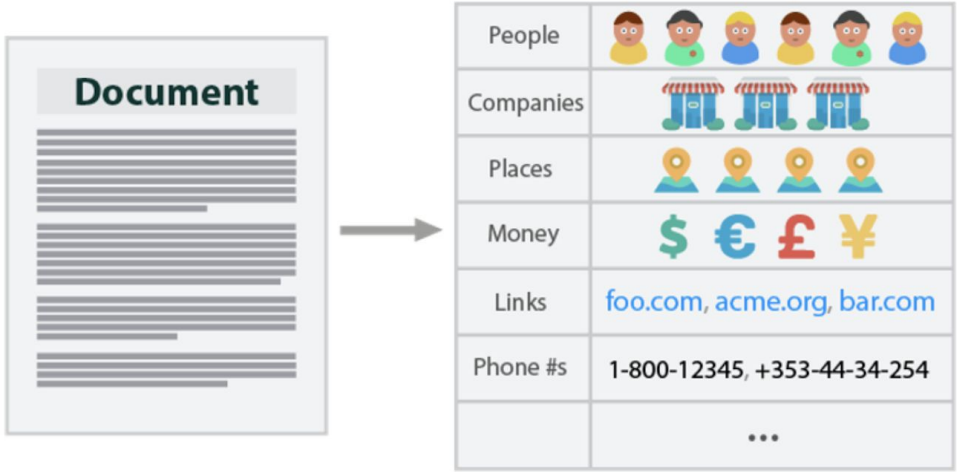
Often useful for recognizing named entities or word relationships.



A **POS tag** (or **part-of-speech tag**) is a special label assigned to each token (word) in a text corpus to indicate the **part of speech** and often also other grammatical categories such as tense, number (plural/singular), case etc.

Named Entity Recognition (NER)

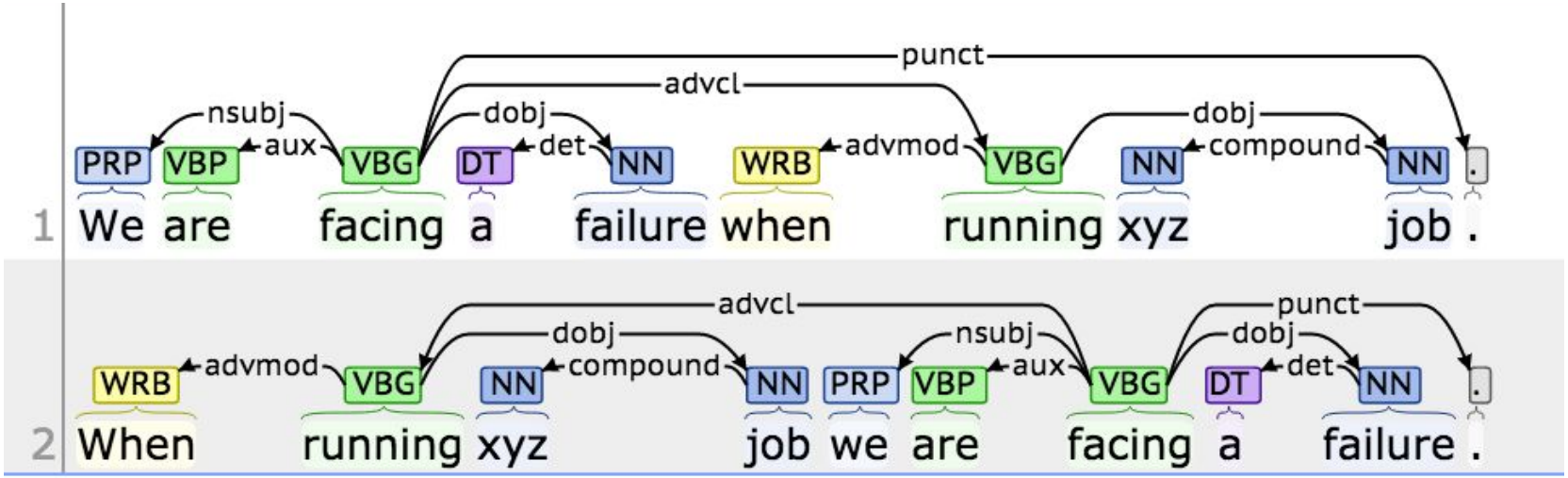
NER is a subtask of information extraction that seeks to locate and classify named entity mentioned in unstructured text into pre-defined categories such as person names, organizations, locations, medical codes, time expressions, quantities, monetary values, percentages, etc.



But Google ORG is starting from behind. The company made a late push into hardware, and Apple ORG 's Siri PRODUCT , available on iPhones PRODUCT , and Amazon ORG 's Alexa PRODUCT software, which runs on its Echo PRODUCT and Dot PRODUCT devices, have clear leads in consumer adoption.

DEPENDENCY PARSING

Useful for extracting relationships (i.e. building knowledge graphs):



Part - I (Day 1) - Coding Time

- Notebook 1 - Spark NLP Basics

Spark NLP
for Data Scientists

Christian Kasim Loan
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Part - II (Day 1)

- Text Preprocessing
- Composing Pipelines
- Working with Spark Dataframes
- Notebook 2 Text Preprocessing and composing Pipelines

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for Data Scientists

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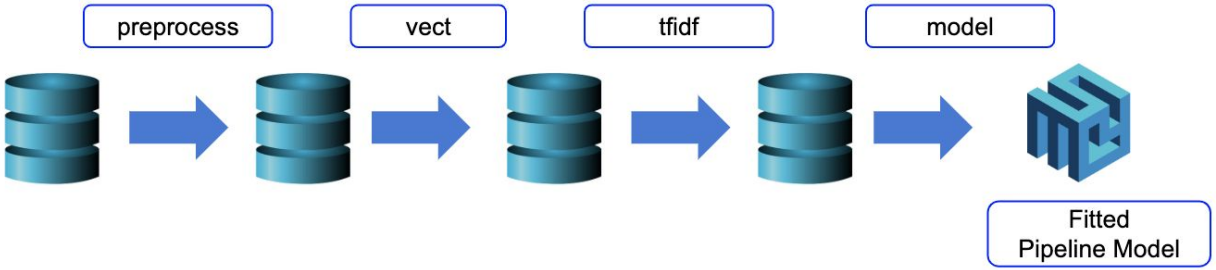
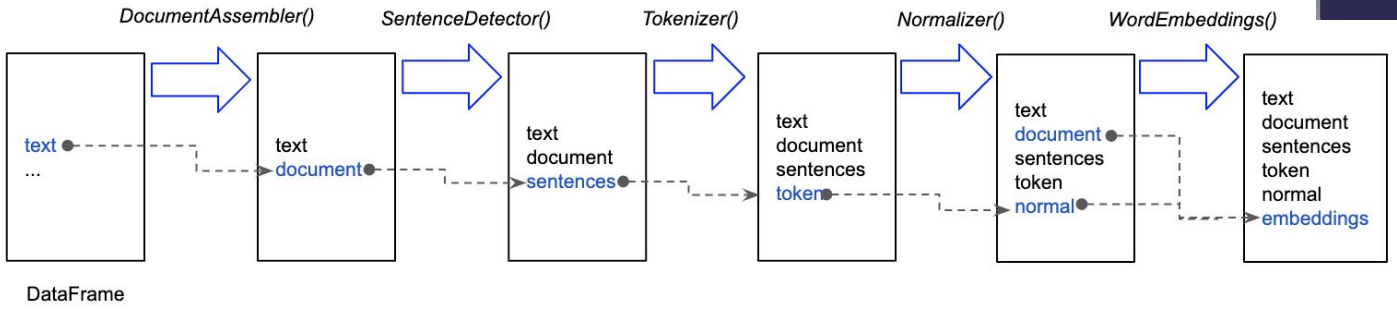
Pipeline Structure

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)
```



Part - II (Day 1) - Coding Time

- Notebook 2 Text Preprocessing and composing Pipelines

Spark NLP for Data Scientists

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Part - III (Day 1)

- Usage and overview of the 4000+ pretrained models for 200+ languages
- Notebook 3 Spark NLP pretrained models

Spark NLP
for Data Scientists

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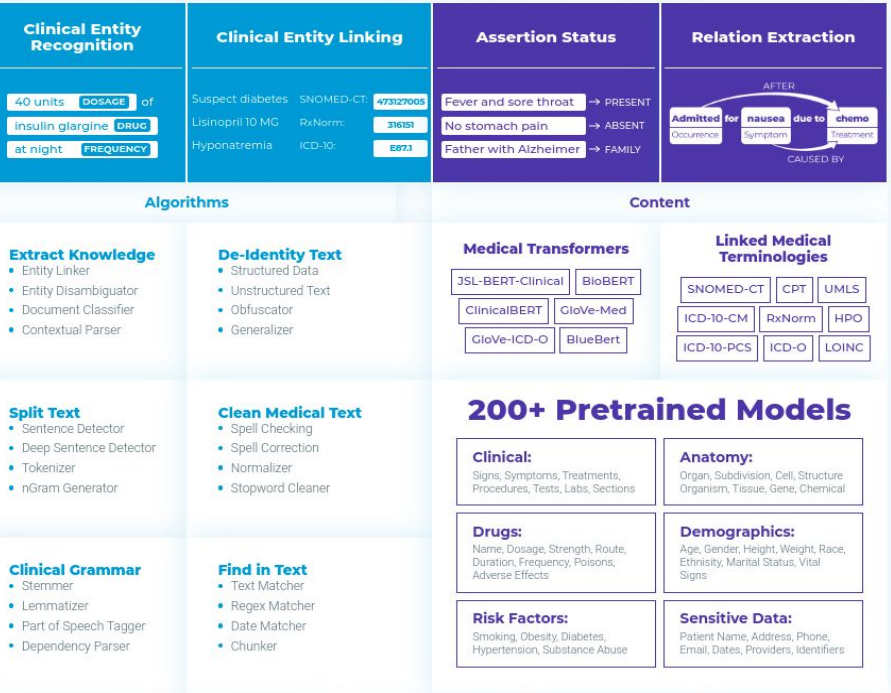
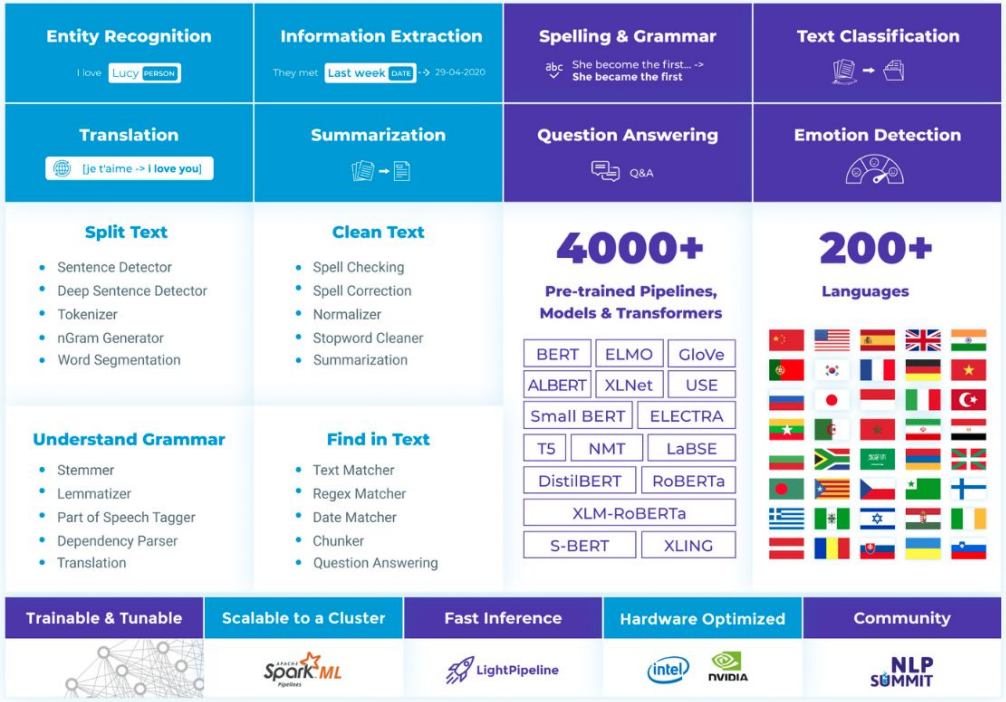
John Snow LABS

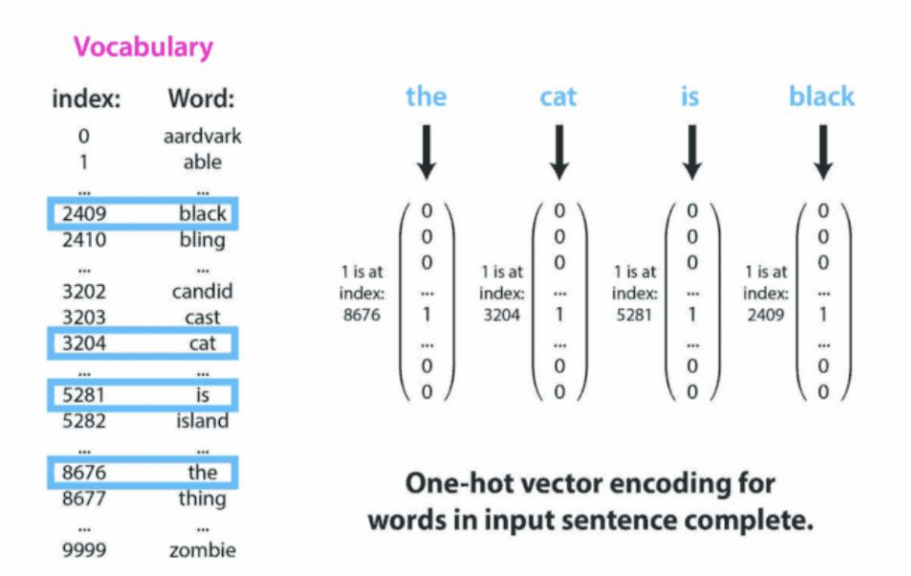
Spark NLP Modules





Spark NLP Modules (Enterprise and Public)

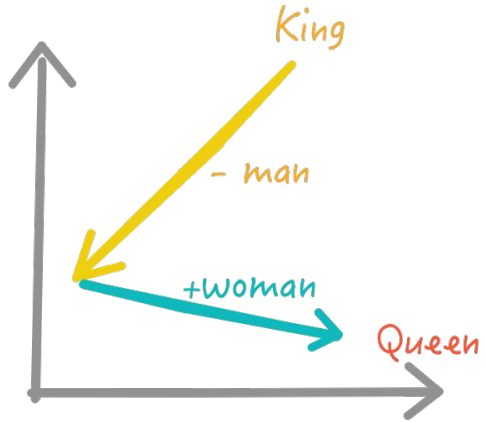
Word & Sentence Embeddings



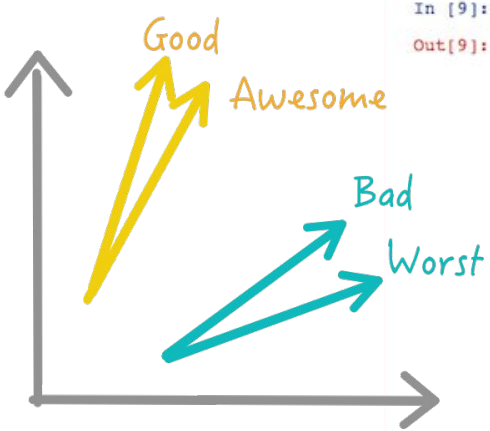

```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   , -0.16278  , -0.60306  ,
               -0.53766  ,  0.35711  ,  0.22882  ,  0.1171   ,  0.42983  ,
                0.16165  ,  0.407    ,  0.036476 ,  0.52636  , -0.13524  ,
               -0.016897 ,  0.029259 , -0.079115 , -0.32305  ,  0.052255 ,
               -0.3617   , -0.18355  , -0.34717  , -0.3691   ,  0.16881  ,
                0.21018  , -0.38376  , -0.096909 , -0.36296  , -0.37319  ,
                0.0021152,  0.32512  ,  0.063977 ,  0.36249  , -0.26935  ,
               -0.59341  , -0.13625  ,  0.016425 , -0.2474   , -0.07498  ,
                0.034708 , -0.01476  , -0.11648  ,  0.25559  , -0.35002  ,
               -0.52707  ,  0.21221  ,  0.062456 ,  0.26184  ,  0.53149  ,
                0.34957  , -0.22692  ,  0.44076  ,  0.4438   ,  0.6335   ,
               -0.049757 , -0.08134  ,  0.65618  , -0.4716   ,  0.090675 ,
               -0.084873 ,  0.31455  , -0.38495  , -0.19247  ,  0.48064  ,
                0.26688  ,  0.095743 ,  0.13024  ,  0.37023  ,  0.46269  ,
               -0.32844  ,  0.17375  , -0.36325  ,  0.30672  , -0.075042 ,
               -0.64684  , -0.49822  ,  0.12372  , -0.28547  ,  0.61811  ,
               -0.19228  ,  0.0040473,  0.1774   ,  0.033154 , -0.54862  ,
                0.34695  , -0.53506  , -0.013381 ,  0.085712 , -0.054447 ,
               -0.64673  ,  0.016749 ,  0.47676  ,  0.037803 , -0.10066  ,
               -0.4165   , -0.20252  ,  0.2794   ,  0.10852  , -0.40154  ,
```

- Words that are used in similar contexts will be given similar representations. That is, words that are used in similar ways will be placed close together within the high-dimensional semantic space–these points will cluster together, and their distance to each other will be low.

Word & Sentence Embeddings



a) Learns Analogy



b) Similar Words have same angles

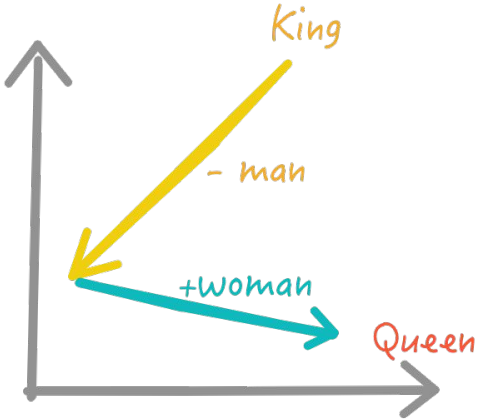
```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   , -0.16278  , -0.60306  ,
               -0.53766  ,  0.35711  ,  0.22882  ,  0.1171   ,  0.42983  ,
                0.16165  ,  0.407    ,  0.036476 ,  0.52636  , -0.13524  ,
               -0.016897 ,  0.029259 , -0.079115 , -0.32305  ,  0.052255 ,
               -0.3617   , -0.18355  , -0.34717  , -0.3691   ,  0.16881  ,
                0.21018  , -0.38376  , -0.096909 , -0.36296  , -0.37319  ,
                0.0021152,  0.32512  ,  0.063977 ,  0.36249  , -0.26935  ,
               -0.59341  , -0.13625  ,  0.016425 , -0.2474   , -0.07498  ,
                0.034708 , -0.01476  , -0.11648  ,  0.25559  , -0.35002  ,
               -0.52707  ,  0.21221  ,  0.062456 ,  0.26184  ,  0.53149  ,
                0.34957  , -0.22692  ,  0.44076  ,  0.4438   ,  0.6335   ,
               -0.049757 , -0.08134  ,  0.65618  , -0.4716   ,  0.090675 ,
               -0.084873 ,  0.31455  , -0.38495  , -0.19247  ,  0.48064  ,
                0.26688  ,  0.095743 ,  0.13024  ,  0.37023  ,  0.46269  ,
               -0.32844  ,  0.17375  , -0.36325  ,  0.30672  , -0.075042 ,
               -0.64684  , -0.49822  ,  0.12372  , -0.28547  ,  0.61811  ,
               -0.19228  ,  0.0040473,  0.1774   ,  0.033154 , -0.54862  ,
                0.34695  , -0.53506  , -0.013381 ,  0.085712 , -0.054447 ,
               -0.64673  ,  0.016749 ,  0.47676  ,  0.037803 , -0.10066  ,
               -0.4165   , -0.20252  ,  0.2794   ,  0.10852  , -0.40154  ,
```

- Deep-Learning-based natural language processing systems.
- They encode **words** and **sentences** 📜 in fixed-length dense vectors 📐 to drastically improve the processing of textual data.
- Based on **The Distributional Hypothesis**: Words that occur in the same contexts tend to have similar meanings.

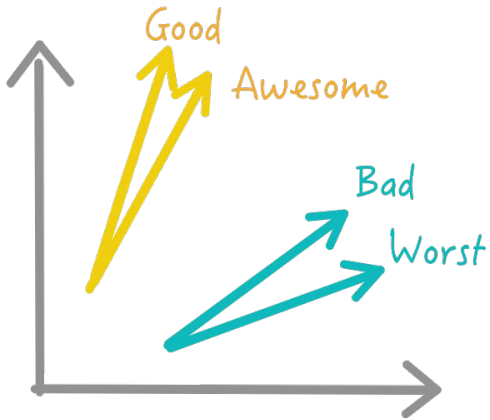
Word & Sentence Embeddings

Glove (100, 200, 300)	ELMO (512, 1024)	BERT (768d)	Universal Sentence Encoders (512)

Albert (768, 1024, 2048, 4096)	XLNet (768, 1024)	Electra (768)	Bert Sentence Embeddings (768)



a) Learns Analogy



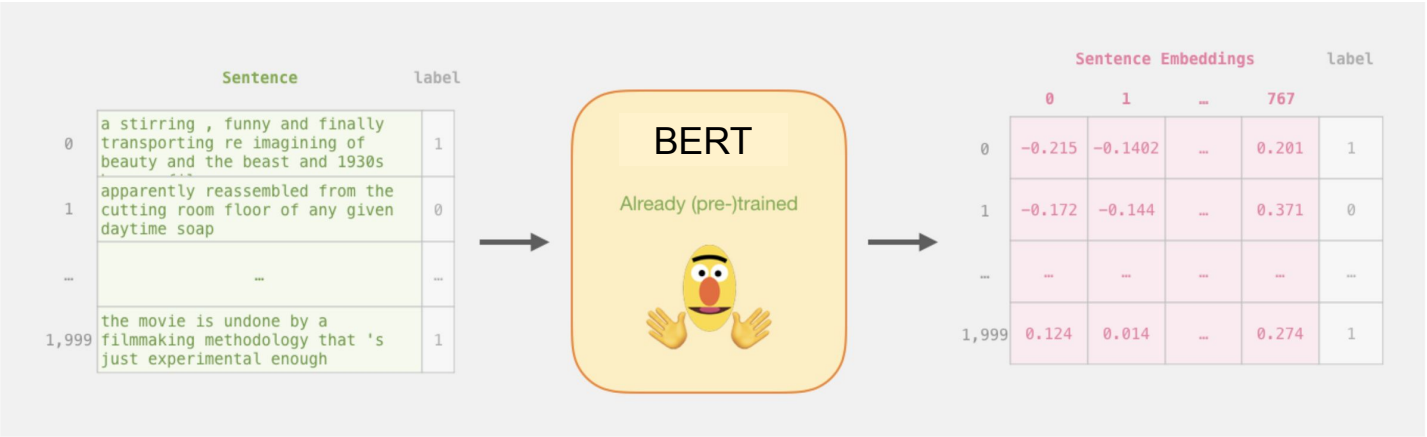
b) Similar Words have same angles

- Deep-Learning-based natural language processing systems.
- They encode **words** and **sentences** in fixed-length dense vectors 📐 to drastically improve the processing of textual data.
- Based on **The Distributional Hypothesis**: Words that occur in the same contexts tend to have similar meanings.
- Elmo and Bert-family embeddings are context-aware.

Text Classification with Word & Sentence Embeddings

Glove (100, 200, 300)	ELMO (512, 1024)	BERT (768d)	Universal Sentence Encoders (512)

Albert (768, 1024, 2048, 4096)	XLNet (768, 1024)	Electra (768)	Bert Sentence Embeddings (768)



Spark NLP

ClassifierDL

SentimentDL

MultiClassifierDL

Model	Name
WordEmbeddingsModel (GloVe)	`glove_100d`
BertEmbeddings	`electra_small_uncased`
BertEmbeddings	`electra_base_uncased`
BertEmbeddings	`electra_large_uncased`
BertEmbeddings	`bert_base_uncased`
BertEmbeddings	`bert_base_cased`
BertEmbeddings	`bert_large_uncased`
BertEmbeddings	`bert_large_cased`
BertEmbeddings	`biobert_pubmed_base_cased`
BertEmbeddings	`biobert_pubmed_large_cased`
BertEmbeddings	`biobert_pmc_base_cased`
BertEmbeddings	`biobert_pubmed_pmc_base_cased`
BertEmbeddings	`biobert_clinical_base_cased`
BertEmbeddings	`biobert_discharge_base_cased`
BertEmbeddings	`covidbert_large_uncased`
BertEmbeddings	`small_bert_L2_128`
BertEmbeddings	`small_bert_L4_128`
BertEmbeddings	`small_bert_L6_128`
BertEmbeddings	`small_bert_L8_128`
BertEmbeddings	`small_bert_L10_128`
BertEmbeddings	`small_bert_L12_128`
BertEmbeddings	`small_bert_L2_256`
BertEmbeddings	`small_bert_L4_256`
BertEmbeddings	`small_bert_L6_256`
BertEmbeddings	`small_bert_L8_256`
BertEmbeddings	`small_bert_L10_256`
BertEmbeddings	`small_bert_L12_256`
BertEmbeddings	`small_bert_L2_512`
BertEmbeddings	`small_bert_L4_512`
BertEmbeddings	`small_bert_L6_512`
BertEmbeddings	`small_bert_L8_512`
BertEmbeddings	`small_bert_L10_512`
BertEmbeddings	`small_bert_L12_512`
BertEmbeddings	`small_bert_L2_768`
BertEmbeddings	`small_bert_L4_768`
BertEmbeddings	`small_bert_L6_768`
BertEmbeddings	`small_bert_L8_768`
BertEmbeddings	`small_bert_L10_768`
BertEmbeddings	`small_bert_L12_768`
BertEmbeddings	`elmo`
BertEmbeddings	`albert_base_uncased`
BertEmbeddings	`albert_large_uncased`
BertEmbeddings	`albert_xlarge_uncased`
BertEmbeddings	`albert_xxlarge_uncased`
BertEmbeddings	`xlnet_base_cased`
BertEmbeddings	`xlnet_large_cased`
BertEmbeddings	`tfhub_use`
BertEmbeddings	`tfhub_use_lg`
BertSentenceEmbeddings	`sent_small_bert_L6_128`
BertSentenceEmbeddings	`sent_small_bert_L8_128`
BertSentenceEmbeddings	`sent_small_bert_L10_128`
BertSentenceEmbeddings	`sent_small_bert_L12_128`
BertSentenceEmbeddings	`sent_small_bert_L2_256`
BertSentenceEmbeddings	`sent_small_bert_L4_256`
BertSentenceEmbeddings	`sent_small_bert_L6_256`
BertSentenceEmbeddings	`sent_small_bert_L8_256`
BertSentenceEmbeddings	`sent_small_bert_L10_256`
BertSentenceEmbeddings	`sent_small_bert_L12_256`
BertSentenceEmbeddings	`sent_small_bert_L2_512`
BertSentenceEmbeddings	`sent_small_bert_L4_512`
BertSentenceEmbeddings	`sent_small_bert_L6_512`
BertSentenceEmbeddings	`sent_small_bert_L8_512`
BertSentenceEmbeddings	`sent_small_bert_L10_512`
BertSentenceEmbeddings	`sent_small_bert_L12_512`
BertSentenceEmbeddings	`sent_small_bert_L2_768`
BertSentenceEmbeddings	`sent_small_bert_L4_768`
BertSentenceEmbeddings	`sent_small_bert_L6_768`
BertSentenceEmbeddings	`sent_small_bert_L8_768`
BertSentenceEmbeddings	`sent_small_bert_L10_768`
BertSentenceEmbeddings	`sent_small_bert_L12_768`

Word & Sentence Embeddings

albert_base = https://tfhub.dev/google/albert_base/3 | 768-embed-dim, 12-layer, 12-heads, 12M parameters

albert_large = https://tfhub.dev/google/albert_large/3 | 1024-embed-dim, 24-layer, 16-heads, 18M parameters

albert_xlarge = https://tfhub.dev/google/albert_xlarge/3 | 2048-embed-dim, 24-layer, 32-heads, 60M parameters

albert_xxlarge = https://tfhub.dev/google/albert_xxlarge/3 | 4096-embed-dim, 12-layer, 64-heads, 235M parameters

XLNet-Large = https://storage.googleapis.com/xlnet/released_models/cased_L-24_H-1024_A-16.zip | 24-layer, 1024-hidden, 16-heads

XLNet-Base = https://storage.googleapis.com/xlnet/released_models/cased_L-12_H-768_A-12.zip | 12-layer, 768-hidden, 12-heads.

BERT is a bi-directional transformer for pre-training over a lot of unlabeled textual data to learn a language representation that can be used to fine-tune for specific machine learning tasks. While BERT outperformed the NLP state-of-the-art on several challenging tasks, its performance improvement could be attributed to the bidirectional transformer, novel pre-training tasks of Masked Language Model and Next Structure Prediction along with a lot of data and Google's compute power.

XLNet is a large bidirectional transformer that uses improved training methodology, larger data and more computational power to achieve better than BERT prediction metrics on 20 language tasks.

To improve the training, XLNet introduces permutation language modeling, where all tokens are predicted but in random order. This is in contrast to BERT's masked language model where only the masked (15%) tokens are predicted.

Albert is a Google's new "ALBERT" language model and achieved state-of-the-art results on three popular benchmark tests for natural language understanding (NLU): GLUE, RACE, and SQuAD 2.0. ALBERT is a "lite" version of Google's 2018 NLU pretraining method BERT. Researchers introduced two parameter-reduction techniques in ALBERT to lower memory consumption and increase training speed.

https://nlp.johnsnowlabs.com/api/

Train your own embeddings and via Huggingface or TfHub and scale with Spark NLP

HuggingFace to Spark NLP

Spark NLP	HuggingFace Notebooks	Colab
BertEmbeddings	HuggingFace in Spark NLP - BERT	Open in Colab
BertSentenceEmbeddings	HuggingFace in Spark NLP - BERT Sentence	Open in Colab
DistilBertEmbeddings	HuggingFace in Spark NLP - DistilBERT	Open in Colab
RoBertaEmbeddings	HuggingFace in Spark NLP - RoBERTa	Open in Colab
XlmRoBertaEmbeddings	HuggingFace in Spark NLP - XLM-RoBERTa	Open in Colab
AlbertEmbeddings	HuggingFace in Spark NLP - ALBERT	Open in Colab
XlnetEmbeddings	HuggingFace in Spark NLP - XLNet	Open in Colab
LongformerEmbeddings	HuggingFace in Spark NLP - Longformer	Open in Colab
BertForTokenClassification	HuggingFace in Spark NLP - BertForTokenClassification	Open in Colab
DistilBertForTokenClassification	HuggingFace in Spark NLP - DistilBertForTokenClassification	Open in Colab
AlbertForTokenClassification	HuggingFace in Spark NLP - AlbertForTokenClassification	Open in Colab
RoBertaForTokenClassification	HuggingFace in Spark NLP - RoBertaForTokenClassification	Open in Colab
XlmRoBertaForTokenClassification	HuggingFace in Spark NLP - XlmRoBertaForTokenClassification	Open in Colab

TF Hub to Spark NLP

Spark NLP	TF Hub Notebooks	Colab
BertEmbeddings	TF Hub in Spark NLP - BERT	Open in Colab
BertSentenceEmbeddings	TF Hub in Spark NLP - BERT Sentence	Open in Colab
AlbertEmbeddings	TF Hub in Spark NLP - ALBERT	Open in Colab

TensorFlow Hub

Compatibility

Spark NLP: The equivalent annotator in Spark NLP **TF Hub**: Models from TF Hub **HuggingFace**: Models from HuggingFace **Model Architecture**: Which architecture is compatible with that annotator **Flags**:

- Fully supported ✅
- Partially supported (requires workarounds) ✔
- Under development ❎
- Not supported ❌

Spark NLP	TF Hub	HuggingFace	Model Architecture
BertEmbeddings	✅	✅	BERT - Small BERT - ELECTRA
BertSentenceEmbeddings	✅	✅	BERT - Small BERT - ELECTRA
DistilBertEmbeddings		✅	DistilBERT
RoBertaEmbeddings		✅	RoBERTa - DistilRoBERTa
XlmRoBertaEmbeddings		✅	XLM-RoBERTa
AlbertEmbeddings	✅	✅	ALBERT
XlnetEmbeddings		✅	XLNet
LongformerEmbeddings		✅	Longformer
ElmoEmbeddings	❎	❎	
UniversalSentenceEncoder	❎		
BertForTokenClassification		✅	TFBertForTokenClassification
DistilBertForTokenClassification		✅	TFDistilBertForTokenClassification
AlbertForTokenClassification		✅	TFAlbertForTokenClassification
RoBertaForTokenClassification		✅	TFRobertaForTokenClassification
XlmRoBertaForTokenClassification		✅	TFXLMRobertaForTokenClassification
XlnetForTokenClassification		✅	TFXLNetForTokenClassificationet
LongformerForTokenClassification		✅	TFLongformerForTokenClassification
T5Transformer		❌	
MarianTransformer		❌	

https://nlp.johnsnowlabs.com/docs/en/transformers#example-notebooks

100+ Languages supported by **Language-agnostic BERT Sentence Embedding (LABSE)** and **XLM-RoBERTa**

Train in **1 Language**, predict in **100+ different languages**

ISO	NAME	ISO	NAME	ISO	NAME
af	AFRIKAANS	ht	HAITIAN_CREOLE	pt	PORTUGUESE
am	AMHARIC	hu	HUNGARIAN	ro	ROMANIAN
ar	ARABIC	hy	ARMENIAN	ru	RUSSIAN
as	ASSAMESE	id	INDONESIAN	rw	KINYARWANDA
az	AZERBAIJANI	ig	IGBO	si	SINHALESE
be	BELARUSIAN	is	ICELANDIC	sk	SLOVAK
bg	BULGARIAN	it	ITALIAN	sl	SLOVENIAN
bn	BENGALI	ja	Japanese	sm	SAMOAN
bo	TIBETAN	jv	JAVANESE	sn	SHONA
bs	BOSNIAN	ka	GEORGIAN	so	SOMALI
ca	CATALAN	kk	KAZAKH	sq	ALBANIAN
ceb	CEBUANO	km	KHMER	sr	SERBIAN
co	CORSICAN	kn	KANNADA	st	SESOTHO
cs	CZECH	ko	KOREAN	su	SUNDANESE
cy	WELSH	ku	KURDISH	sv	SWEDISH
da	DANISH	ky	KYRGYZ	sw	SWAHILI
de	GERMAN	la	LATIN	ta	TAMIL
el	GREEK	lb	LUXEMBOURGISH	te	TELUGU
en	ENGLISH	lo	LAOTHIAN	tg	TAJIK
eo	ESPERANTO	lt	LITHUANIAN	th	THAI
es	SPANISH	lv	LATVIAN	tk	TURKMEN
et	ESTONIAN	mg	MALAGASY	tl	TAGALOG
eu	BASQUE	mi	MAORI	tr	TURKISH
fa	PERSIAN	mk	MACEDONIAN	tt	TATAR
fi	FINNISH	ml	MALAYALAM	ug	UIGHUR
fr	FRENCH	mn	MONGOLIAN	uk	UKRAINIAN
fy	FRISIAN	mr	MARATHI	ur	URDU
ga	IRISH	ms	MALAY	uz	UZBEK
gd	SCOTS_GAELIC	mt	MALTESE	vi	VIETNAMESE
gl	GALICIAN	my	BURMESE	wo	WOLOF
gu	GUJARATI	ne	NEPALI	xh	XHOSA
ha	HAUSA	nl	DUTCH	yi	YIDDISH
haw	HAWAIIAN	no	NORWEGIAN	yo	YORUBA
he	HEBREW	ny	NYANJA	zh	Chinese
hi	HINDI	or	ORIYA	zu	ZULU
hmn	HMONG	pa	PUNJABI		
hr	CROATIAN	pl	POLISH		

```
# Binary Class Classifier, 2 classes
nlu.load('xx.embed_sentence.labse train.sentiment').fit(train_df).predict(test_df)

# Multi Class Classifier, N classes
nlu.load('xx.embed_sentence.labse train.classifier').fit(train_df).predict(test_df)

# Multi Class Classifier with multiple labels example (i.e. Hashtags)
# N classes, where one row can be assigned up to N labels
nlu.load('xx.embed_sentence.labse train.multi_classifier').fit(train_df).predict(test_df)
```

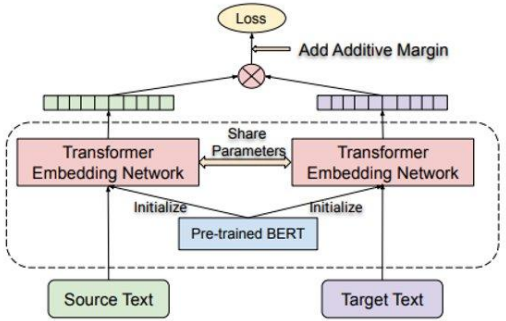
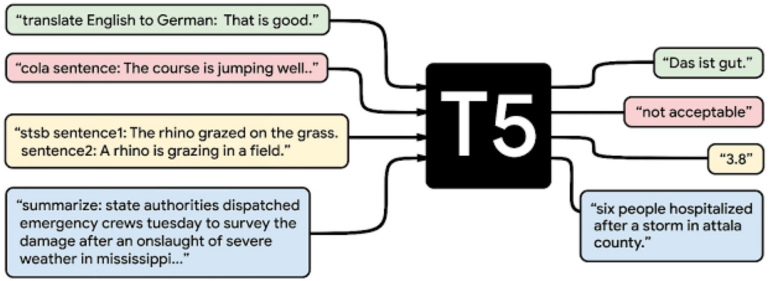


Figure 1: Dual encoder model with BERT based encoding modules.




```
# Closed book Question Answering
nlu.load('en.t5').predict('what is the capital of Germany?') # >>> Berlin
# Open Book Question answering
nlu.load('en.t5').predict('Who is president of Nigeria?') # >>> Muhammadu Buhari


# Open book Question Answering
context   = 'Peters last week was terrible! He had an accident and broke his leg while skiing!'
question1  = 'Why was peters week so bad?'
question2  = 'How did peter broke his leg?'
nlu.load('answer_question').predict(question1 + context) # >>> broke his leg
nlu.load('answer_question').predict(question2 + context) # >>> skiing



# Big T5 model for Summarization, Sentiment, Text Similarity and other SQUAD/GLUE tasks
pipe = nlu.load('t5')
pipe['t5'].settask('summarize')
pipe.predict(long_text)
```

[Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer]

1. Text summarization
2. Question answering
3. Translation
4. Sentiment analysis
5. Natural Language inference
6. Coreference resolution
7. Sentence Completion
8. Word sense disambiguation

Google

Every T5 Task with explanation:

Task Name	Explanation
1.CoLA	Classify if a sentence is grammatically correct
2.RTE	Classify whether a statement can be deducted from a sentence
3.MNLI	Classify for a hypothesis and premise whether they contradict or contradict each other or neither of both (3 class).
4.MRPC	Classify whether a pair of sentences is a re-phrasing of each other (semantically equivalent)
5.QNLI	Classify whether the answer to a question can be deducted from an answer candidate.
6.QQP	Classify whether a pair of questions is a re-phrasing of each other (semantically equivalent)
7.SST2	Classify the sentiment of a sentence as positive or negative
8.STSB	Classify the sentiment of a sentence on a scale from 1 to 5 (21 Sentiment classes)
9.CB	Classify for a premise and a hypothesis whether they contradict each other or not (binary).
10.COPA	Classify for a question, premise, and 2 choices which choice the correct choice is (binary).
11.MultiRc	Classify for a question, a paragraph of text, and an answer candidate, if the answer is correct (binary),
12.WiC	Classify for a pair of sentences and a disambigous word if the word has the same meaning in both sentences.
13.WSC/DPR	Predict for an ambiguous pronoun in a sentence what it is referring to.
14.Summarization	Summarize text into a shorter representation.
15.SQuAD	Answer a question for a given context.
16.WMT1.	Translate English to German
17.WMT2.	Translate English to French
18.WMT3.	Translate English to Romanian

Microsoft

Translate between **200+ Languages**

With Marian: Fast Neural Machine Translation in C++

MARIANNMT

Fast Neural Machine Translation in C++


```
# Use ISO standards for the languages
nlu.load('<start_language>.translate_to.<target_language>')

#Translate Turkish to English:
nlu.load('tr.translate_to.en')

#Translate English to French:
nlu.load('en.translate_to.fr')

#Translate French to Hebrew
nlu.load('fr.translate_to.he')`

#Translate English to German
nlu.load('en.translate_to.de')`
```

Part - III (Day 1) - Coding Time

- Notebook 3 Spark NLP pretrained models
- Notebook 13 - NLU Crash course, every Spark NLP model in 1 line

Spark NLP for Data Scientists

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Sr. Data Scientist
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Part - IV (Day 1)

- Training a Named Entity Recognizer
- Training a Deep Learning classifier
- Upload/Download your own model via John Snow Labs Models Hub
- Notebook 4 NERDL Training
- Notebook 5 ClassifierDL, SentimentDL, MultiClassifierDL Training

Spark NLP
for Data Scientists

Christian Kasim Loan
Sr. Data Scientist
christian@johnsnowlabs.com

Not Secure | nlpprogress.com/eng...

CoNLL 2003 (English)

The CoNLL 2003 NER task consists of newswire text from the Reuters RCV1 corpus tagged with four different entity types (PER, LOC, ORG, MISC). Models are evaluated based on span-based F1 on the test set. ♦ used both the train and development splits for training.

Model	F1	Paper / Source	Code
CNN Large + fine-tune (Baevski et al., 2019)	93.5	Cloze-driven Pretraining of Self-attention Networks	
RNN-CRF+Flair	93.47	Improved Differentiable Architecture Search for Language Modeling and Named Entity Recognition	
LSTM-CRF+ELMo+BERT+Flair	93.38	Neural Architectures for Nested NER through Linearization	Official
Flair embeddings (Akbik et al., 2018)♦	93.09	Contextual String Embeddings for Sequence Labeling	Flair framework
BERT Large (Devlin et al., 2018)	92.8	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	
CVT + Multi-Task (Clark et al., 2018)	92.61	Semi-Supervised Sequence Modeling with Cross-View Training	Official
BERT Base (Devlin et al., 2018)	92.4	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	
BiLSTM-CRF+ELMo (Peters et al., 2018)	92.22	Deep contextualized word representations	AllenNLP Project AllenNLP GitHub
Peters et al. (2017) ♦	91.93	Semi-supervised sequence tagging with bidirectional language models	
CRF + AutoEncoder (Wu et al., 2018)	91.87	Evaluating the Utility of Hand-crafted Features in Sequence Labelling	Official
Bi-LSTM-CRF + Lexical Features (Ghaddar and Langlais 2018)	91.73	Robust Lexical Features for Improved Neural Network Named-Entity Recognition	Official
BiLSTM-CRF + IntNet (Xin et al., 2018)	91.64	Learning Better Internal Structure of Words for Sequence Labeling	
Chiu and Nichols (2016) ♦	91.62	Named entity recognition with bidirectional LSTM-CNNs	

NER-DL in Spark NLP

SYSTEM	YEAR	LANGUAGE	ACCURACY
Spark NLP v2.4	2020	Python/Scala/Java/R	**93.3 (test F1) - 95.9 (dev F1)**
Spark NLP v2.x	2019	Python/Scala/Java/R	**93**
Spark NLP v1.x	2018	Python/Scala/Java/R	92
spaCy v2.x	2017	Python/Cython	92.6
spaCy v1.x	2015	Python/Cython	91.8
ClearNLP	2015	Java	91.7
CoreNLP	2015	Java	89.6
MATE	2015	Java	92.5
Turbo	2015	C++	92.4

The best NER score in production

93.3 %
Test Set

Bert

NerDLApproach

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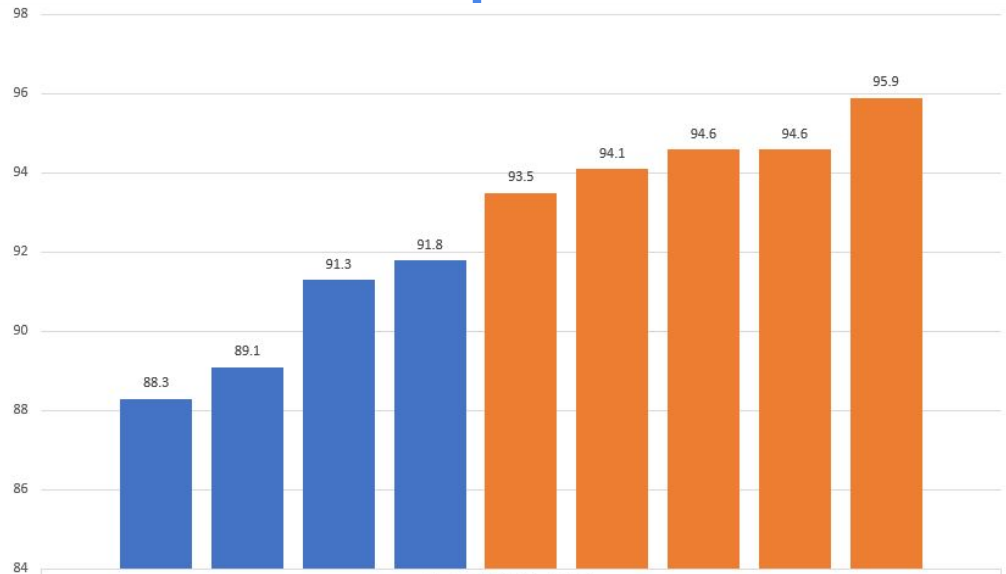
NER-DL in Spark NLP



	CoNLL 2003 - F1 Dev
spaCy 2.2	88.3
spaCy 2.2 + en_trf_bertbaseuncased_lg	89.1
spaCy 2.2 + en_core_web_md	91.3
spaCy 2.2 + en_core_web_lg	91.8
Spark NLP + GloVe 100d	93.5
Spark NLP + GloVe 300d	94.1
Spark NLP + ELMO	94.6
Spark NLP + BERT Base Cased	94.6
Spark NLP + BERT Large Cased	95.9

NER Systems

Feature-engineered machine learning systems	Dict	SP	DU	EN	GE
Carreras et al. (2002) binary AdaBoost classifiers	Yes	81.39	77.05	-	-
Malouf (2002) - Maximum Entropy (ME) + features	Yes	73.66	68.08	-	-
Li et al. (2005) SVM with class weights	Yes	-	-	88.3	-
Passos et al. (2014) CRF	Yes	-	-	90.90	-
Ando and Zhang (2005a) Semi-supervised state of the art	No	-	-	89.31	75.27
Agerri and Rigau (2016)	Yes	**84.16**	**85.04**	**91.36**	**76.42**
Feature-inferring neural network word models					
Collobert et al. (2011) Vanilla NN +SLL / Conv-CRF	No	-	-	81.47	-
Huang et al. (2015) Bi-LSTM+CRF	No	-	-	84.26	-
Yan et al. (2016) Win-BiLSTM (English), FF (German) (Many fets)	Yes	-	-	88.91	**76.12**
Collobert et al. (2011) Conv-CRF (SENNA+Gazetteer)	Yes	-	-	89.59	-
Huang et al. (2015) Bi-LSTM+CRF+ (SENNA+Gazetteer)	Yes	-	-	**90.10**	-
Feature-inferring neural network character models					
Gillick et al. (2015) – BTS	No	**82.95**	**82.84**	**86.50**	**76.22**
Kuru et al. (2016) CharNER	No	82.18	79.36	84.52	70.12
Feature-inferring neural network word + character models					
Yang et al. (2017)	Yes	85.77	**85.19**	91.26	-
Luo (2015)	Yes	-	-	91.20	-
Chiu and Nichols (2015)	Yes	-	-	**91.62**	-
Ma and Hovy (2016)	No	-	-	91.21	-
Santos and Guimaraes (2015)	No	82.21	-	-	-
Lample et al. (2016)	No	85.75	81.74	90.94	**78.76**
Bharadwaj et al. (2016)	Yes	**85.81**	-	-	-
Dernoncourt et al. (2017)	No	-	-	90.5	-
Feature-inferring neural network word + character + affix models					
Re-implementation of Lample et al. (2016) (100 Epochs)	No	85.34	85.27	90.24	78.44
Yadav et al. (2018)(100 Epochs)	No	86.92	87.50	90.69	78.56
Yadav et al. (2018) (150 Epochs)	No	**87.26**	**87.54**	90.86	**79.01**

1. Classical Approaches (rule based)
2. ML Approaches
   - Multi-class classification
   - Conditional Random Field (CRF)
3. DL Approaches
   - Bidirectional LSTM-CRF
   - Bidirectional LSTM-CNNs
   - Bidirectional LSTM-CNNS-CRF
   - Pre-trained language models (Bert, Elmo)
4. Hybrid Approaches (DL + ML)

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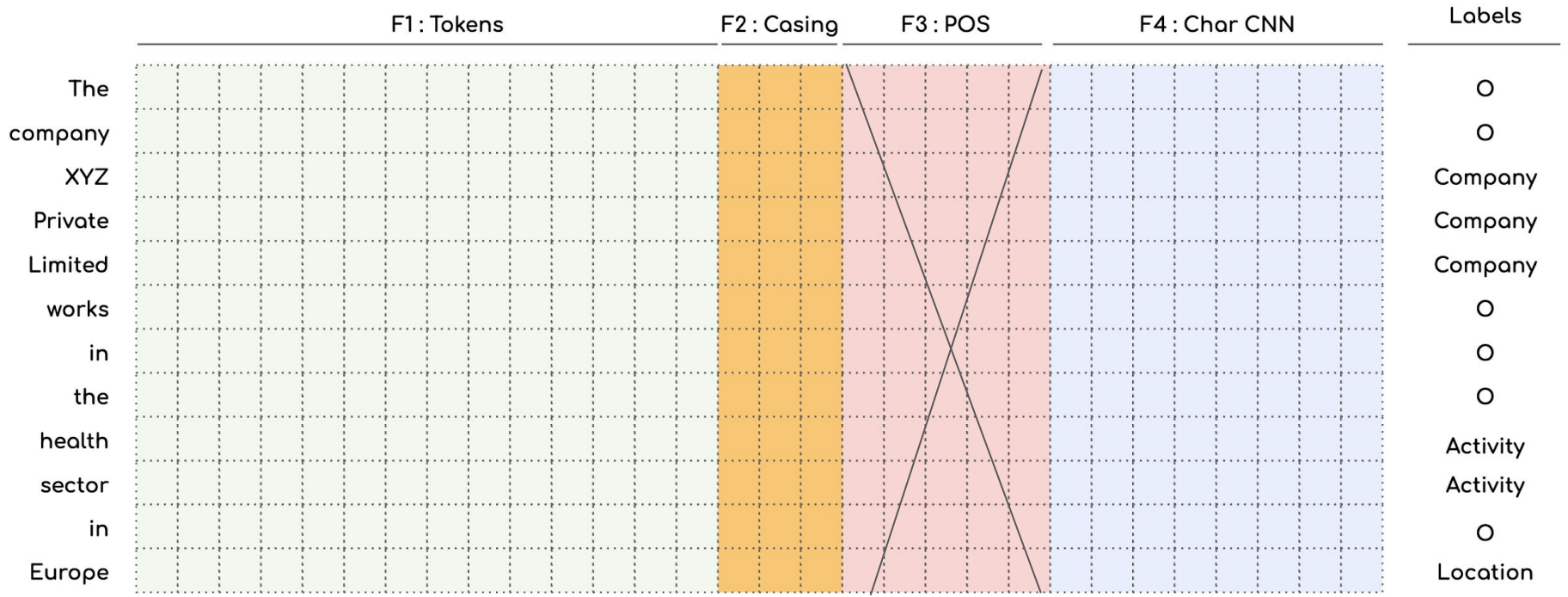
NER-DL in Spark NLP

Char-CNN-BiLSTM



NER-DL in Spark NLP

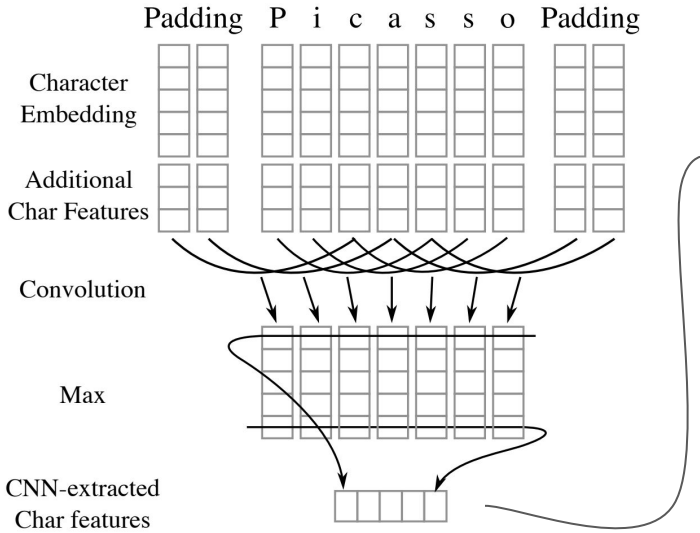


Figure 2: The convolutional neural network extracts character features from each word. The character embedding and (optionally) the character type feature vector are computed through lookup tables. Then, they are concatenated and passed into the CNN.

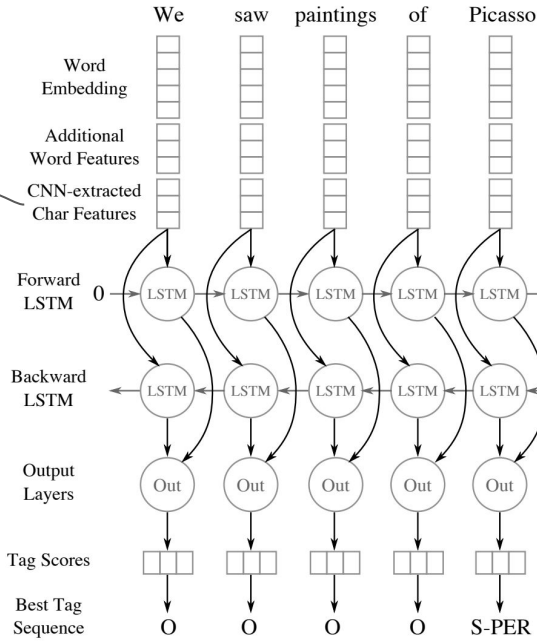


Figure 1: The (unrolled) BLSTM for tagging named entities. Multiple tables look up word-level feature vectors. The CNN (Figure 2) extracts a fixed length feature vector from character-level features. For each word, these vectors are concatenated and fed to the BLSTM network and then to the output layers (Figure 3).

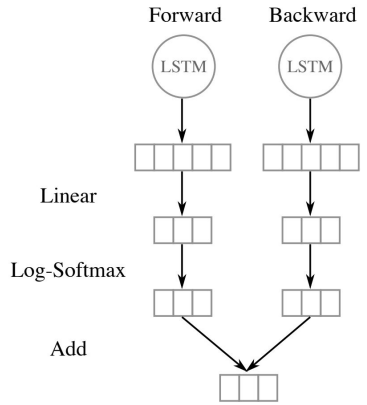


Figure 3: The output layers ("Out" in Figure 1) decode output into a score for each tag category.

Char-CNN-BiLSTM

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NER-DL in Spark NLP

CoNNL2003 format

All data files contain one word per line with empty lines representing sentence boundaries. At the end of each line there is a tag which states whether the current word is inside a named entity or not. The tag also encodes the type of named entity. Here is an example sentence:

U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	O	O

* Each line contains four fields: the word, its part-of-speech tag, its chunk tag and its named entity tag.

* **CoNLL**: Conference on Computational Natural Language Learning

BIO schema

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

John Smith ⇒ PERSON
New York ⇒ LOCATION

John Snow LABS

Coding ...

Open **4. NERDL Training** notebook in **Colab**

(click on Colab icon or open in a new tab)

https://github.com/JohnSnowLabs/spark-nlp-workshop/blob/master/tutorials/Certification_Trainings/Public/4.NERDL_Training.ipynb

Test set evaluation

In [ ]:
```
import pyspark.sql.functions as F

predictions.select(F.explode(F.arrays_zip('token.result','label.result','ner.result')).alias("cols")) \
.select(F.expr("cols['0']").alias("token"),
        F.expr("cols['1']").alias("ground_truth"),
        F.expr("cols['2']").alias("prediction")).show(truncate=False)
```

```
+--------------+------------+----------+
|token         |ground_truth|prediction|
+--------------+------------+----------+
|CRICKET       |O           |O         |
|-             |O           |O         |
|LEICESTERSHIRE|B-ORG       |B-ORG     |
|TAKE          |O           |O         |
|OVER          |O           |O         |
|AT            |O           |O         |
|TOP           |O           |O         |
|AFTER         |O           |O         |
|INNINGS       |O           |O         |
|VICTORY       |O           |O         |
|.             |O           |O         |
|LONDON        |B-LOC       |B-LOC     |
|1996-08-30    |O           |O         |
|West          |B-MISC      |B-MISC    |
|Indian        |I-MISC      |I-MISC    |
|all-rounder   |O           |O         |
|Phil          |B-PER       |B-PER     |
|Simmons       |I-PER       |I-PER     |
|took          |O           |O         |
|four          |O           |O         |
+--------------+------------+----------+
only showing top 20 rows
```

In [ ]:
```
from sklearn.metrics import classification_report

preds_df = predictions.select(F.explode(F.arrays_zip('token.result','label.result','ner.result')).alias("cols")) \
.select(F.expr("cols['0']").alias("token"),
        F.expr("cols['1']").alias("ground_truth"),
        F.expr("cols['2']").alias("prediction")).toPandas()


print (classification_report(preds_df['ground_truth'], preds_df['prediction']))
```

```
              precision    recall  f1-score   support

       B-LOC       0.88      0.93      0.90      1837
      B-MISC       0.80      0.82      0.81       922
       B-ORG       0.92      0.73      0.81      1341
       B-PER       0.94      0.95      0.95      1842
```

SentimentDL, ClassifierDL, and MultiClassifierDL

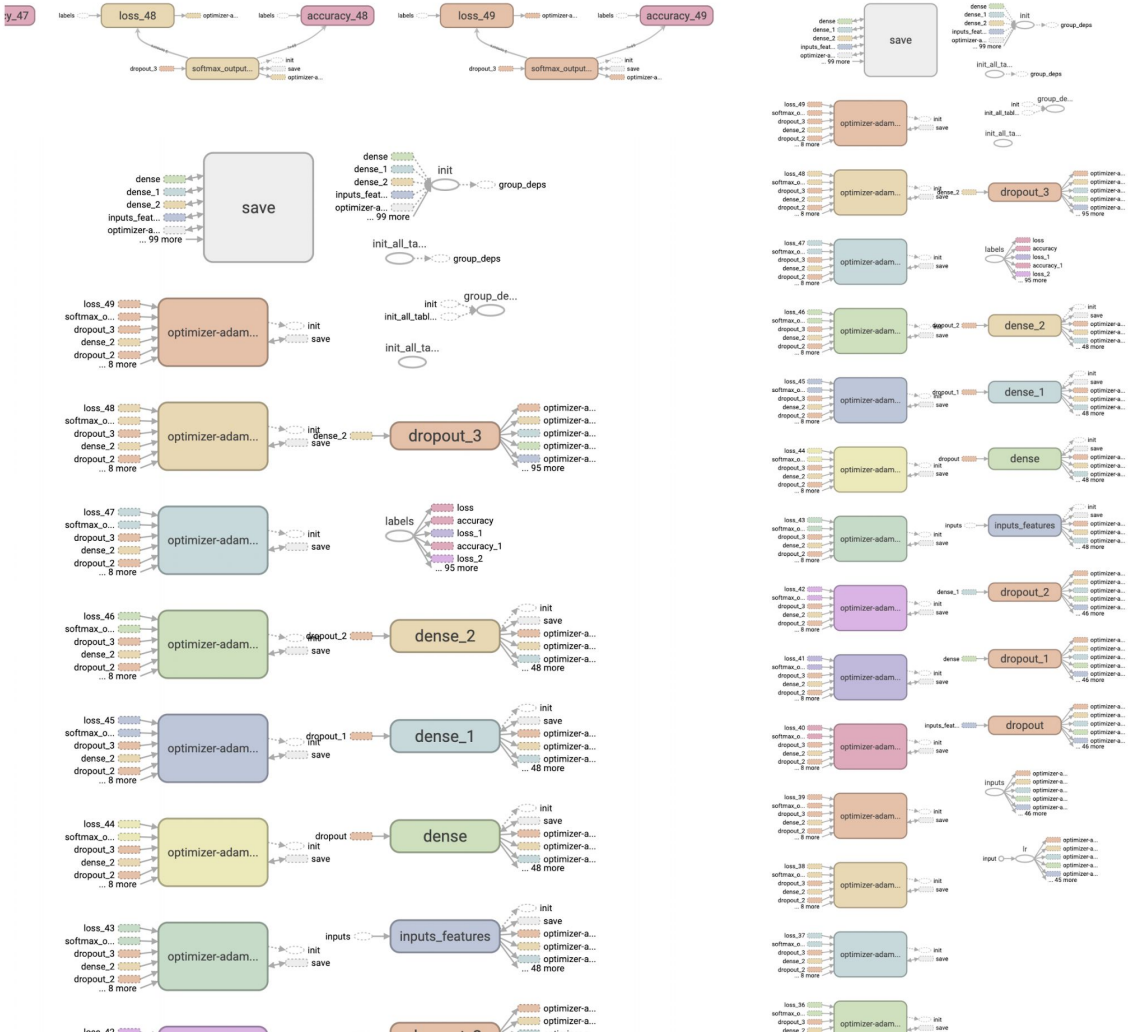
- BERT
- Small BERT
- BioBERT
- CovidBERT
- LaBSE
- ALBERT
- ELECTRA
- XLNet
- ELMO
- Universal Sentence Encoder
- GloVe

- 2 classes (positive/negative)
- 3 classes (0, 1, 2)
- 4 classes (Sports, Business, etc.)
- 5 classes (1.0, 2.0, 3.0, 4.0, 5.0)
- ... 100 classes!

- 100 dimensions
- 200 dimensions
- 128 dimensions
- 256 dimensions
- 300 dimensions
- 512 dimensions
- 768 dimensions
- 1024 dimensions

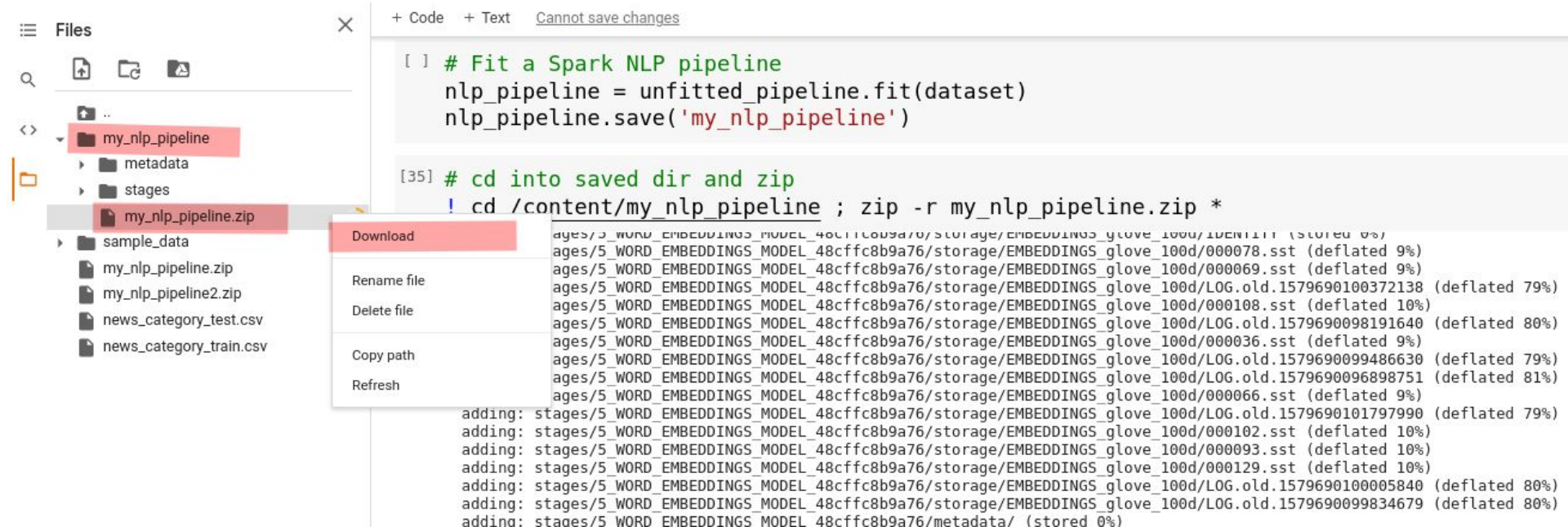
- tfhub_ues
- tfhub_use_lg
- glove_6B_100
- glove_6B_300
- glove_840B_300
- bert_base_cased
- bert_base_uncased
- bert_large_cased
- bert_large_uncased
- bert_multi_uncased
- electra_small_uncased
- elmo
- ... 100+ Word & Sentence models

Classifier DL Tensorflow Architecture



Upload trained models to Models Hub

- Trained models can be uploaded and shared via the modelshub
- Zip and Download the model
- Go to https://modelshub.johnsnowlabs.com/ and upload zip file



Part - IV (Day 1) - Coding Time

- Notebook 4 NERDL Training
- Notebook 5 ClassifierDL, SentimentDL, MultiClassifierDL Training

Spark NLP
for Data Scientists

Christian Kasim Loan
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End of Day 1
See you tomorrow same time same place :)

Spark NLP
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Part - I (Day 2)

- Notebook 7 Context Spell Checker
- Notebook 8 YAKE
- Notebook 9 Sentence Detection
- Notebook 12 RDF Graph Extraction

Spark NLP
for Data Scientists

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Spell Checking & Correction


```
val pipeline = PretrainedPipeline("spell_check_ml", "en")
val result = pipeline.annotate("Harry Potter is a graet muvie")

println(result("spell"))
/* will print Seq[String](…, "is", "a", "great", "movie") */
```

- 3 trainable approaches
- **Norvig Approach**:
  - Retrieves tokens and auto-corrects based on a given dictionary
- **Symmetric Delete**:
  - Uses distance metrics to find possible words
- **Context Aware**:
  - Most accurate: Judges words in context
  - Deep learning based

Context Spell Checker

The Spell Checker can leverage the context of words for ranking different correction sequences. Let's take a look at some examples,

```
# check for the different occurrences of the word "siter"
example1 = ["I will call my siter.",\
    "Due to bad weather, we had to move to a different siter.",\
    "We travelled to three siter in the summer."]
beautify(lp.annotate(example1))
```

```
['I  will  call  my  sister  .\n',
 'Due  to  bad  weather  ,  we  had  to  move  to  a  different  site  .\n',
 'We  travelled  to  three  sites  in  the  summer  .\n']
```

```
# check for the different occurrences of the word "ueather"
example2 = ["During the summer we have the best ueather.",\
    "I have a black ueather jacket, so nice.",\
    "I introduce you to my sister, she is called ueather."]
beautify(lp.annotate(example2))
```

```
['During  the  summer  we  have  the  best  weather  .\n',
 'I  have  a  black  leather  jacket  ,  so  nice  .\n',
 'I  introduce  you  to  my  sister  ,  she  is  called  Heather  .\n']
```

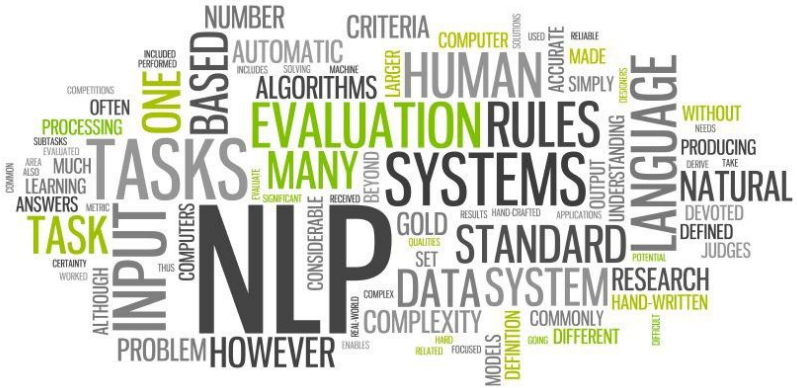
Notice that in the first example, 'siter' is indeed a valid English word,
https://www.merriam-webster.com/dictionary/siter

Notebook 7 Spell Checker

Unsupervised Keyword Extraction

YAKE! Is Yet Another Keyword Extraction Algorithm that can extract keywords without any by leveraging statistical properties of ngrams

Notebook 8 YAKE



Contextual Aware DL Sentence Detector

9 SentenceDetectorDL

`SentenceDetectorDL` (SDDL) is based on a general-purpose neural network model for sentence boundary detection. The task of sentence boundary detection is to identify sentences within a text. Many natural language processing tasks take a sentence as an input unit, such as part-of-speech tagging, dependency parsing, named entity recognition or machine translation.

In this model, we treated the sentence boundary detection task as a classification problem using a DL CNN architecture. We also modified the original implemenation a little bit to cover broken sentences and some impossible end of line chars.

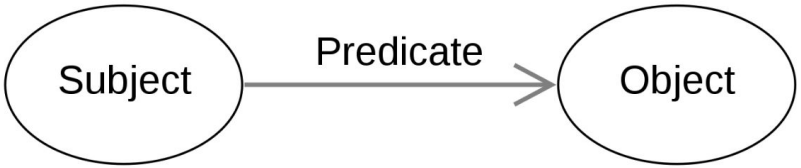
We are releasing two pretrained SDDL models: `english` and `multilanguage` that are trained on `SETimes corpus (Tyers and Alperen, 2010)` and `Europarl. Wong et al. (2014)` datasets.

Here are the test metrics on various languages for `multilang` model

Notebook 9 Sentence Detector DL

Language	Accuracy	Recall	Precision	F1
bg	0.96	1.00	0.93	0.96
bs	0.98	1.00	0.96	0.98
de	0.97	0.99	0.94	0.97
el	0.97	1.00	0.94	0.97
en	0.98	1.00	0.96	0.98
hr	0.98	1.00	0.96	0.98
mk	0.96	0.99	0.93	0.96
ro	0.97	1.00	0.95	0.97
sq	0.98	1.00	0.96	0.98
sr	0.98	1.00	0.95	0.97
tr	0.98	0.99	0.96	0.98

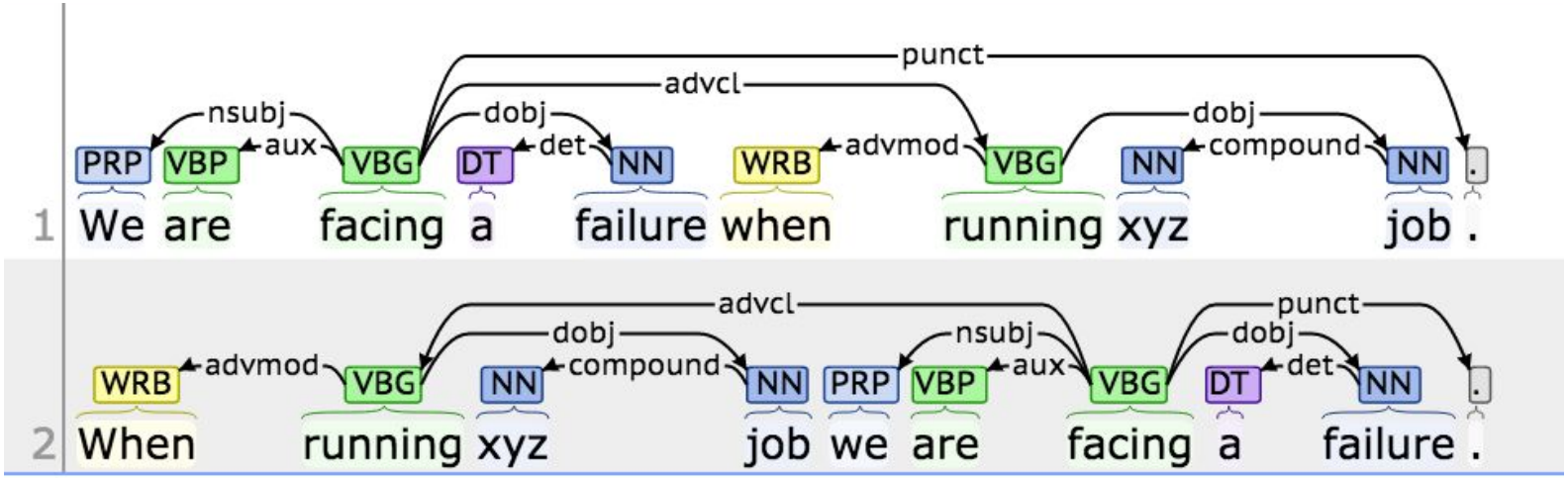
Extract RDF Semantic Triplets



Typed/Untyped Dependency Parsers define a **Predicate**

Relationship between **Subject** and **Object**

Notebook 12 Graph Extraction



Part - 1 (Day 2) - Coding Time

- Notebook 7 Context Spell Checker
- Notebook 8 YAKE
- Notebook 9 Sentence Detection
- Notebook 12 RDF Graph Extraction

Spark NLP
for Data Scientists

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Part - II (Day 2)

- Semantic Search and Similarity with Textual Embeddings
- Visualize Embeddings via Manifold and Decomposition Algorithms
- Notebook 11 Similarities and Dimension Reduction

Spark NLP
for Data Scientists

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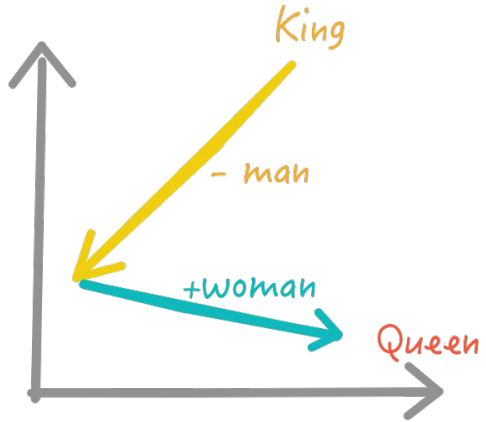
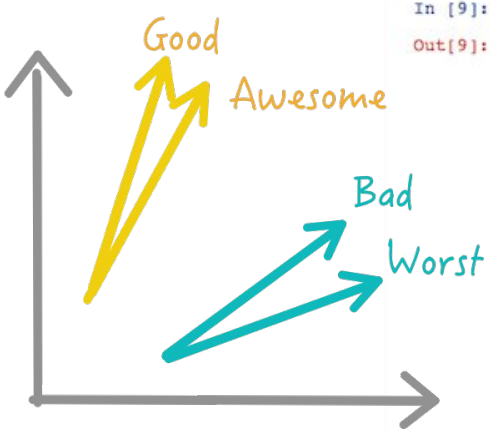
Word & Sentence Embeddings - reminder



a) Learns Analogy



b) Similar Words have same angles

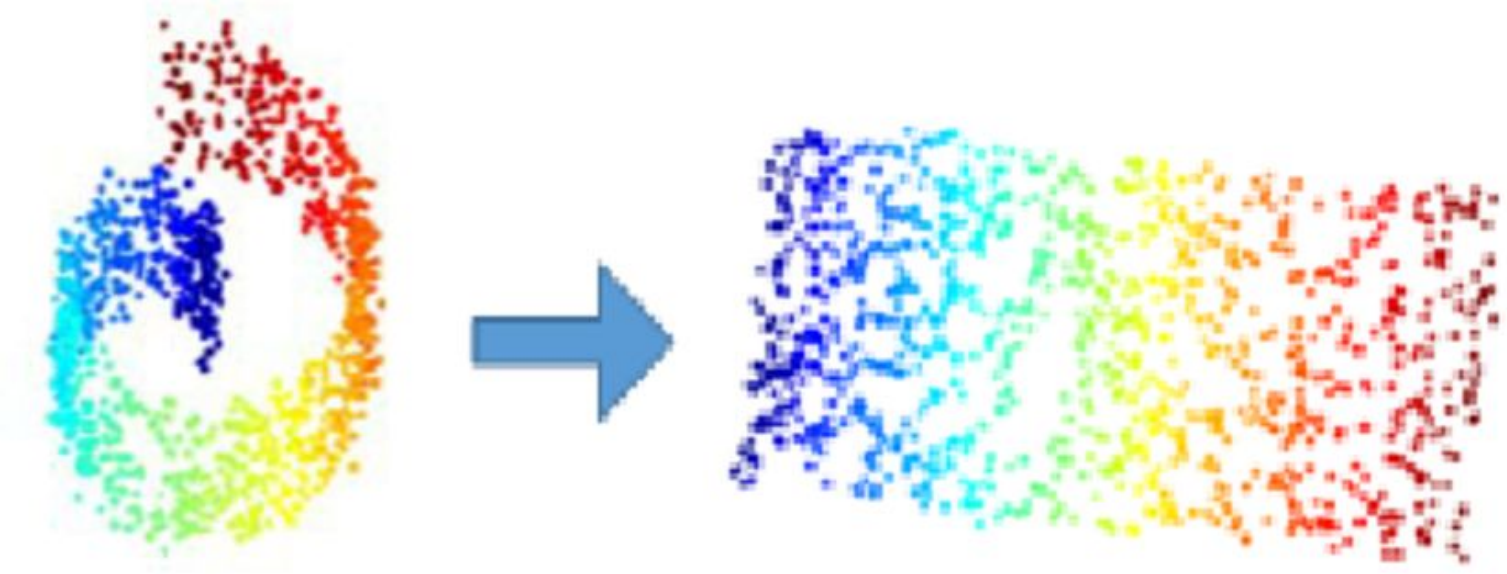
```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   , -0.16278  , -0.60306  ,
               -0.53766  ,  0.35711  ,  0.22882  ,  0.1171   ,  0.42983  ,
                0.16165  ,  0.407    ,  0.036476 ,  0.52636  , -0.13524  ,
               -0.016897 ,  0.029259 , -0.079115 , -0.32305  ,  0.052255 ,
               -0.3617   , -0.18355  , -0.34717  , -0.3691   ,  0.16881  ,
                0.21018  , -0.38376  , -0.096909 , -0.36296  , -0.37319  ,
                0.0021152,  0.32512  ,  0.063977 ,  0.36249  , -0.26935  ,
               -0.59341  , -0.13625  ,  0.016425 , -0.2474   , -0.07498  ,
                0.034708 , -0.01476  , -0.11648  ,  0.25559  , -0.35002  ,
               -0.52707  ,  0.21221  ,  0.062456 ,  0.26184  ,  0.53149  ,
                0.34957  , -0.22692  ,  0.44076  ,  0.4438   ,  0.6335   ,
               -0.049757 , -0.08134  ,  0.65618  , -0.4716   ,  0.090675 ,
               -0.084873 ,  0.31455  , -0.38495  , -0.19247  ,  0.48064  ,
                0.26688  ,  0.095743 ,  0.13024  ,  0.37023  ,  0.46269  ,
               -0.32844  ,  0.17375  , -0.36325  ,  0.30672  , -0.075042 ,
               -0.64684  , -0.49822  ,  0.12372  , -0.28547  ,  0.61811  ,
               -0.19228  ,  0.0040473,  0.1774   ,  0.033154 , -0.54862  ,
                0.34695  , -0.53506  , -0.013381 ,  0.085712 , -0.054447 ,
               -0.64673  ,  0.016749 ,  0.47676  ,  0.037803 , -0.10066  ,
               -0.4165   , -0.20252  ,  0.2794   ,  0.10852  , -0.40154  ,
```

- Deep-Learning-based natural language processing systems.
- They encode **words** and **sentences** 📜 in fixed-length dense vectors 📐 to drastically improve the processing of textual data.
- Based on **The Distributional Hypothesis**: Words that occur in the same contexts tend to have similar meanings.

Data Manifolds

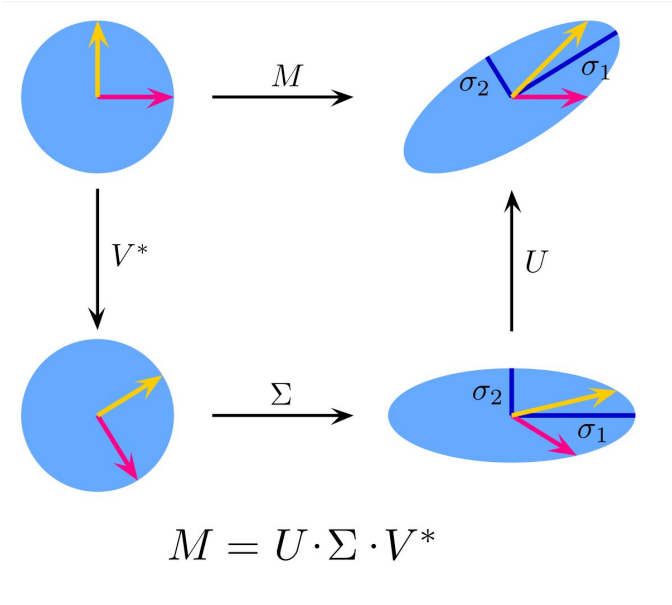
Reduce dimensionality by learning some lower dimensional structure

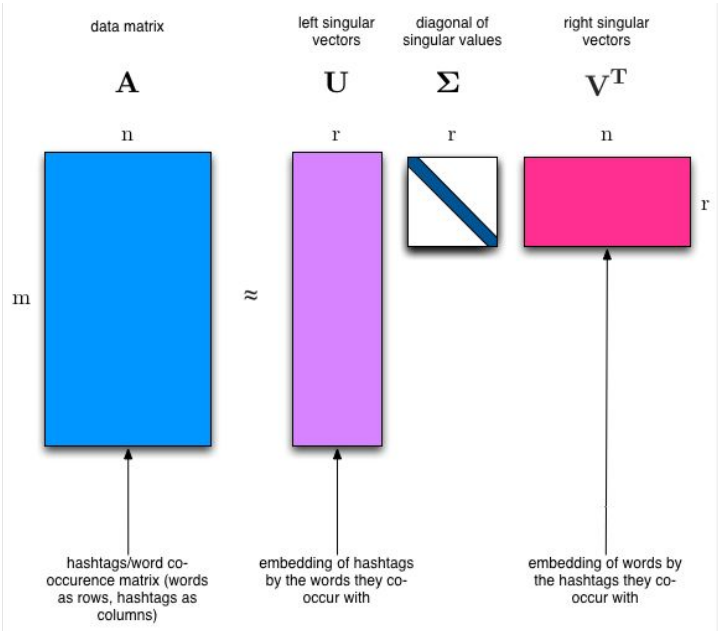
Which preserves relationship between of original hyperspace



Matrix Decompositions

Reduce dimensionality by decomposing Embedding Matrix into lower dimensions which partitions data shape, potentially revealing hidden structure





Part - II (Day 2) - Coding Time

- Notebook 11 Similarities and Dimension Reduction

Spark NLP for Data Scientists

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Part - III (Day 2)

- Question Answering, Summarization and more with T5
- Train a Multi-Lingual Classifier for over 100 languages
- Import embedding from Huggingface and TF-Hub to Spark NLP
- Notebook 5.2 training Multilingual Classifier
- Notebook 10 QUestion Answering and Summarization with T5

Spark NLP
for Data Scientists

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100+ Languages supported by **Language-agnostic BERT Sentence Embedding (LABSE)** and **XLM-RoBERTa**

Train in **1 Language**, predict in **100+ different languages**

ISO	NAME	ISO	NAME	ISO	NAME
af	AFRIKAANS	ht	HAITIAN_CREOLE	pt	PORTUGUESE
am	AMHARIC	hu	HUNGARIAN	ro	ROMANIAN
ar	ARABIC	hy	ARMENIAN	ru	RUSSIAN
as	ASSAMESE	id	INDONESIAN	rw	KINYARWANDA
az	AZERBAIJANI	ig	IGBO	si	SINHALESE
be	BELARUSIAN	is	ICELANDIC	sk	SLOVAK
bg	BULGARIAN	it	ITALIAN	sl	SLOVENIAN
bn	BENGALI	ja	Japanese	sm	SAMOAN
bo	TIBETAN	jv	JAVANESE	sn	SHONA
bs	BOSNIAN	ka	GEORGIAN	so	SOMALI
ca	CATALAN	kk	KAZAKH	sq	ALBANIAN
ceb	CEBUANO	km	KHMER	sr	SERBIAN
co	CORSICAN	kn	KANNADA	st	SESOTHO
cs	CZECH	ko	KOREAN	su	SUNDANESE
cy	WELSH	ku	KURDISH	sv	SWEDISH
da	DANISH	ky	KYRGYZ	sw	SWAHILI
de	GERMAN	la	LATIN	ta	TAMIL
el	GREEK	lb	LUXEMBOURGISH	te	TELUGU
en	ENGLISH	lo	LAOTHIAN	tg	TAJIK
eo	ESPERANTO	lt	LITHUANIAN	th	THAI
es	SPANISH	lv	LATVIAN	tk	TURKMEN
et	ESTONIAN	mg	MALAGASY	tl	TAGALOG
eu	BASQUE	mi	MAORI	tr	TURKISH
fa	PERSIAN	mk	MACEDONIAN	tt	TATAR
fi	FINNISH	ml	MALAYALAM	ug	UIGHUR
fr	FRENCH	mn	MONGOLIAN	uk	UKRAINIAN
fy	FRISIAN	mr	MARATHI	ur	URDU
ga	IRISH	ms	MALAY	uz	UZBEK
gd	SCOTS_GAELIC	mt	MALTESE	vi	VIETNAMESE
gl	GALICIAN	my	BURMESE	wo	WOLOF
gu	GUJARATI	ne	NEPALI	xh	XHOSA
ha	HAUSA	nl	DUTCH	yi	YIDDISH
haw	HAWAIIAN	no	NORWEGIAN	yo	YORUBA
he	HEBREW	ny	NYANJA	zh	Chinese
hi	HINDI	or	ORIYA	zu	ZULU
hmn	HMONG	pa	PUNJABI		
hr	CROATIAN	pl	POLISH		

```
# Binary Class Classifier, 2 classes
nlu.load('xx.embed_sentence.labse train.sentiment').fit(train_df).predict(test_df)

# Multi Class Classifier, N classes
nlu.load('xx.embed_sentence.labse train.classifier').fit(train_df).predict(test_df)

# Multi Class Classifier with multiple labels example (i.e. Hashtags)
# N classes, where one row can be assigned up to N labels
nlu.load('xx.embed_sentence.labse train.multi_classifier').fit(train_df).predict(test_df)
```

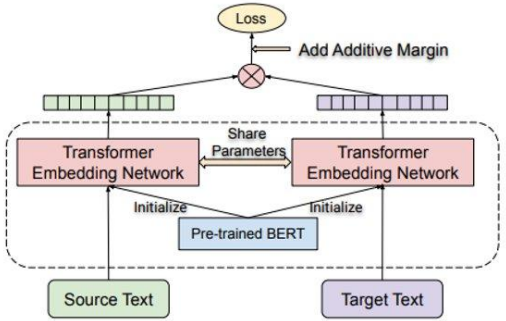
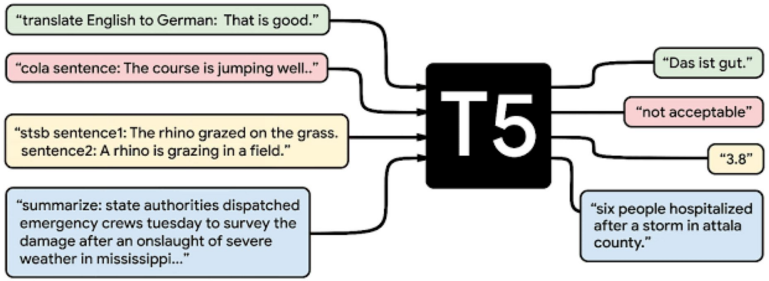


Figure 1: Dual encoder model with BERT based encoding modules.




```
# Closed book Question Answering
nlu.load('en.t5').predict('what is the capital of Germany?') # >>> Berlin
# Open Book Question answering
nlu.load('en.t5').predict('Who is president of Nigeria?') # >>> Muhammadu Buhari


# Open book Question Answering
context   = 'Peters last week was terrible! He had an accident and broke his leg while skiing!'
question1  = 'Why was peters week so bad?'
question2  = 'How did peter broke his leg?'
nlu.load('answer_question').predict(question1 + context) # >>> broke his leg
nlu.load('answer_question').predict(question2 + context) # >>> skiing



# Big T5 model for Summarization, Sentiment, Text Similarity and other SQUAD/GLUE tasks
pipe = nlu.load('t5')
pipe['t5'].settask('summarize')
pipe.predict(long_text)
```

[Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer]

1. Text summarization
2. Question answering
3. Translation
4. Sentiment analysis
5. Natural Language inference
6. Coreference resolution
7. Sentence Completion
8. Word sense disambiguation

Google

Every T5 Task with explanation:

Task Name	Explanation
1.CoLA	Classify if a sentence is grammatically correct
2.RTE	Classify whether a statement can be deducted from a sentence
3.MNLI	Classify for a hypothesis and premise whether they contradict or contradict each other or neither of both (3 class).
4.MRPC	Classify whether a pair of sentences is a re-phrasing of each other (semantically equivalent)
5.QNLI	Classify whether the answer to a question can be deducted from an answer candidate.
6.QQP	Classify whether a pair of questions is a re-phrasing of each other (semantically equivalent)
7.SST2	Classify the sentiment of a sentence as positive or negative
8.STSB	Classify the sentiment of a sentence on a scale from 1 to 5 (21 Sentiment classes)
9.CB	Classify for a premise and a hypothesis whether they contradict each other or not (binary).
10.COPA	Classify for a question, premise, and 2 choices which choice the correct choice is (binary).
11.MultiRc	Classify for a question, a paragraph of text, and an answer candidate, if the answer is correct (binary),
12.WiC	Classify for a pair of sentences and a disambigous word if the word has the same meaning in both sentences.
13.WSC/DPR	Predict for an ambiguous pronoun in a sentence what it is referring to.
14.Summarization	Summarize text into a shorter representation.
15.SQuAD	Answer a question for a given context.
16.WMT1.	Translate English to German
17.WMT2.	Translate English to French
18.WMT3.	Translate English to Romanian

Train your own embeddings and via Huggingface or TfHub and scale with Spark NLP

HuggingFace to Spark NLP

Spark NLP	HuggingFace Notebooks	Colab
BertEmbeddings	HuggingFace in Spark NLP - BERT	Open in Colab
BertSentenceEmbeddings	HuggingFace in Spark NLP - BERT Sentence	Open in Colab
DistilBertEmbeddings	HuggingFace in Spark NLP - DistilBERT	Open in Colab
RoBertaEmbeddings	HuggingFace in Spark NLP - RoBERTa	Open in Colab
XlmRoBertaEmbeddings	HuggingFace in Spark NLP - XLM-RoBERTa	Open in Colab
AlbertEmbeddings	HuggingFace in Spark NLP - ALBERT	Open in Colab
XlnetEmbeddings	HuggingFace in Spark NLP - XLNet	Open in Colab
LongformerEmbeddings	HuggingFace in Spark NLP - Longformer	Open in Colab
BertForTokenClassification	HuggingFace in Spark NLP - BertForTokenClassification	Open in Colab
DistilBertForTokenClassification	HuggingFace in Spark NLP - DistilBertForTokenClassification	Open in Colab
AlbertForTokenClassification	HuggingFace in Spark NLP - AlbertForTokenClassification	Open in Colab
RoBertaForTokenClassification	HuggingFace in Spark NLP - RoBertaForTokenClassification	Open in Colab
XlmRoBertaForTokenClassification	HuggingFace in Spark NLP - XlmRoBertaForTokenClassification	Open in Colab

TF Hub to Spark NLP

Spark NLP	TF Hub Notebooks	Colab
BertEmbeddings	TF Hub in Spark NLP - BERT	Open in Colab
BertSentenceEmbeddings	TF Hub in Spark NLP - BERT Sentence	Open in Colab
AlbertEmbeddings	TF Hub in Spark NLP - ALBERT	Open in Colab

TensorFlow Hub

Compatibility

Spark NLP: The equivalent annotator in Spark NLP **TF Hub**: Models from TF Hub **HuggingFace**: Models from HuggingFace **Model Architecture**: Which architecture is compatible with that annotator **Flags**:

- Fully supported ✅
- Partially supported (requires workarounds) ✔
- Under development ❎
- Not supported ❌

Spark NLP	TF Hub	HuggingFace	Model Architecture
BertEmbeddings	✅	✅	BERT - Small BERT - ELECTRA
BertSentenceEmbeddings	✅	✅	BERT - Small BERT - ELECTRA
DistilBertEmbeddings		✅	DistilBERT
RoBertaEmbeddings		✅	RoBERTa - DistilRoBERTa
XlmRoBertaEmbeddings		✅	XLM-RoBERTa
AlbertEmbeddings	✅	✅	ALBERT
XlnetEmbeddings		✅	XLNet
LongformerEmbeddings		✅	Longformer
ElmoEmbeddings	❎	❎	
UniversalSentenceEncoder	❎		
BertForTokenClassification		✅	TFBertForTokenClassification
DistilBertForTokenClassification		✅	TFDistilBertForTokenClassification
AlbertForTokenClassification		✅	TFAlbertForTokenClassification
RoBertaForTokenClassification		✅	TFRobertaForTokenClassification
XlmRoBertaForTokenClassification		✅	TFXLMRobertaForTokenClassification
XlnetForTokenClassification		✅	TFXLNetForTokenClassificationet
LongformerForTokenClassification		✅	TFLongformerForTokenClassification
T5Transformer		❌	
MarianTransformer		❌	

https://nlp.johnsnowlabs.com/docs/en/transformers#example-notebooks

Part - III (Day 2) - Coding Time

- Notebook 5.2 training Multilingual Classifier
- Notebook 10 QUestion Answering and Summarization with T5

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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

John Snow LABS

Part - IV (Day 2)

- Introduction to the Python NLU Library
- Introduction to NLP Server
- Notebook 13 - NLU Crash course, every Spark NLP model in 1 line

Spark NLP for Data Scientists

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What is NLU?

- All of the 4000+ Spark NLP models in 1 line of code
- Train models in 1 line of code
- Visualize with Streamlit or in Jupyter Notebook
- Automagically generates Spark NLP pipelines based on your request (Dependency Resolution)
- Works on Pandas/Spark/Modin Dataframes and returns same type of Dataframe

How does it work?

model= nlu.**load**(model)

- **Returns a nlu pipeline object**

model.**predict**(data)

- Returns a pandas DF

How does it work?

```
model = nlu.load('emotion')
```

- **Returns a nlu pipeline object**

```
model.predict('I love NLU!')
```

- Returns a pandas DF

EMOTION DETECTION

```
nlu.load('emotion').predict('I love NLU!')
```

sentence_embeddings	category_sentence	category_surprise	category_sadness	category_joy	category_fear	sentence	category	id
[0.027570432052016258, -0.052647676318883896, ...]	0	0.012899903	0.0015578865	0.9760173	0.0095249	I love NLU!	joy	1

TOKENIZATION & SPELL CHECKING

```
nlu.load('spell').predict('I liek pentut butr and jelli')
```

token	checked	id
I	I	1
liek	like	1
peantut	peanut	1
buttr	butter	1
and	and	1
jelli	jelly	1

NAMED ENTITY RECOGNITION

```
nlu.load('ner').predict('Angela Merkel from Germany and the American Donald Trump dont share many opinions')
```

embeddings	ner_tag	entities
[[-0.563759982585907, 0.26958999037742615, 0.3...	PER	Angela Merkel
[[-0.563759982585907, 0.26958999037742615, 0.3...	LOC	Germany
[[-0.563759982585907, 0.26958999037742615, 0.3...	MISC	American
[[-0.563759982585907, 0.26958999037742615, 0.3...	PER	Donald Trump

CALCULATING EMBEDDINGS

```
#watch out for your RAM, this could kill your machine

nlu.load('bert elmo albert xlnet use glove').predict('Get all of them at once! Watch your RAM tough!')
```

token	glove_embeddings	albert_embeddings	xlnet_embeddings	bert_embeddings	elmo_embeddings	use_embeddings	id
Get	[0.1443299949169159, 0.4395099878311157, 0.583...]	[-0.41224443912506104, -0.4611411392688751, 1...]	[-0.003953204490244389, -1.5821468830108643, -...]	[-0.7420049905776978, -0.8647691011428833, 0.1...]	[0.04002974182367325, -0.43536433577537537, -0...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
all	[-0.2182299941778183, 0.6919900178909302, 0.70...]	[1.1014549732208252, -0.43204769492149353, -0...]	[0.31148090958595276, -1.0986182689666748, 0.3...]	[-0.8933112025260925, 0.44822725653648376, -0...]	[0.17885173857212067, 0.045830272138118744, -0...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
of	[-0.15289999544620514, -0.24278999865055084, 0...]	[1.1535910367965698, 0.28440719842910767, 0.60...]	[-1.403516411781311, 0.3108177185058594, -0.32...]	[-0.5550722479820251, 0.2702311873435974, 0.04...]	[0.24783466756343842, -0.248960942029953, 0.02...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
them	[-0.10130999982357025, 0.10941000282764435, 0...]	[0.5475010871887207, 0.8660883903503418, 2.817...]	[-0.7559828758239746, -0.4712887704372406, -1...]	[-0.2922026813030243, -0.1301671266555786, -0...]	[-0.24157099425792694, -0.8055092692375183, -0...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
at	[0.17659999430179596, 0.0938510000705719, 0.24...]	[-0.5005946159362793, -0.4600788354873657, 0.5...]	[0.04092511534690857, -1.0951932668685913, -1...]	[-0.5613634586334229, -0.00903533399105072, -0...]	[-0.11999595910310745, 0.012994140386581421, -...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
once	[-0.23837999999523163, 0.221670001745224, 0.35...]	[-0.39100387692451477, -0.8297092914581299, 2...]	[-0.46001458168029785, -1.2062749862670898, 0...]	[0.2988640069961548, 0.3360409140586853, -0.37...]	[0.6701997518539429, 1.1368376016616821, 0.244...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
!	[0.38471999764442444, 0.49351000785827637, 0.4...]	[0.007945209741592407, -0.27733859419822693, 0...]	[-1.5816600322723389, -0.992130696773529, -0.1...]	[0.7550013065338135, -0.5257778167724609, -0.4...]	[-1.3351283073425293, 0.6296550035476685, -1.4...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
Watch	[-0.38264000415802, -0.08968199789524078, 0.02...]	[-0.10218311846256256, -0.4334276020526886, 0...]	[-1.3921688795089722, 0.6997514963150024, -0.8...]	[-0.24852752685546875, 1.222611427307129, -0.1...]	[0.04002974182367325, -0.43536433577537537, -0...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
your	[-0.5718399882316589, 0.046348001807928085, 0...]	[-0.4086211323738098, 1.0755341053009033, 1.78...]	[-0.8588163256645203, -2.3702170848846436, 0.0...]	[-0.035358428955078125, 0.7711482048034668, 0...]	[0.17885173857212067, 0.045830272138118744, -0...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
RAM	[-1.875599980354309, -0.40814998745918274, -0...]	[-0.09772858023643494, 0.3632940351963043, -0...]	[1.1277621984481812, -1.689896583557129, -0.19...]	[0.4528151750564575, -0.36768051981925964, -0...]	[0.24783466756343842, -0.248960942029953, 0.02...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
tough	[-0.5099300146102905, -0.1428000032901764, 0.5...]	[-0.22261293232440948, 0.21325691044330597, 0...]	[-1.3547197580337524, 0.43423181772232056, -1...]	[0.460737079381942 75, 0.05694812536239624, 0.5...]	[-0.24157099425792694, -0.8055092692375183, -0...]	[[-0.0019260947592556477, 0.009215019643306732...]	1
!	[0.38471999764442444, 0.49351000785827637, 0.4...]	[0.21658605337142944, -0.0493735149502754 2, 0...]	[-1.5816600322723389, -0.992130696773529, -0.1...]	[0.6830563545227051, -0.5751053094863892, -0.6...]	[-0.11999595910310745, 0.012994140386581421, -...]	[[-0.0019260947592556477, 0.009215019643306732...]	1

NLU WORKS DIRECTLY ON TYPICAL PYTHON DATASETS

Strings

```
import nlu
nlu.load('sentiment').predict('This is just one string')
```

Lists

```
import nlu
nlu.load('sentiment').predict(['This is an arrray', ' Of strings!'])
```

Pandas data frame

```
import nlu
import pandas as pd
data = {"text": ['This day sucks', 'I love this day', 'I dont like Sami']}
text_df = pd.DataFrame(data)
nlu.load('sentiment').predict(text_df)
```

Pandas series

```
import nlu
import pandas as pd
data = {"text": ['This day sucks', 'I love this day', 'I dont like Sami']}
text_df = pd.DataFrame(data)
nlu.load('sentiment').predict(text_df['text'])
```

Spark
Data Frame

Ray
Data Frame

Dask
Data Frame

NLU : Apache License 2.0

```
# Multiple binary sentiment classifiers trained on various datasets
nlu.load('classify.sentiment').predict('I love NLU and Python WebDev Conf 2021!')
nlu.load('classify.sentiment.imdb').predict('The Matrix was a pretty good movie')
nlu.load('classify.sentiment.twitter').predict('@elonmusk Tesla stock price is too high imo')

# Translate between 200 languages
nlu.load('en.translate_to.zh').predict('NLU can translate between 200 languages!')

# Spellchecking
nlu.load('spell').predict('I liek to live dangertus!')

# Extract Named Entities
nlu.load('ner').predict('Donald Trump and John Biden dont share many oppinions')

# Unsupervised Keyword Extraction
nlu.load('yake').predict('Weights extract keywords withouth requiring weights!')

# Over 50+ classifiers on various problems
nlu.load('classify.emotion').predict('He was suprised by the diversity of NLU')
nlu.load('classify.spam').predict('Hello you are the heir to a 100 Million fortune!')
nlu.load('classify.fakenews').predict('Unicorns landed on mars!')
nlu.load('classify.sarcasm').predict('love the teachers who give exams the day after halloween')
nlu.load('en.classify.question').predict('How expensive is the Watch?')
nlu.load('en.classify.toxic').predict('You are to stupid')
nlu.load('classify.cyberbullying').predict('Women belong in the kitchen!') #sorry

# Get BERTology and Transformer Embeddings for Sentences and Words
nlu.load('bert').predict('BERTolgy Word embeddings!')
nlu.load('bert elmo albert glove').predict('Multiple BERTolgy Word embeddings!')
nlu.load('embed_sentence.bert ').predict('BERTolgy Sentence embeddings!')

# Text cleaning and Pre-Processing
nlu.load('lemmatize').predict('Get me the lemmatized version of a string')
nlu.load('normalize').predict('Get me the lemmatized version of a string')
nlu.load('clean').predict('Get me the lemmatized version of a string')

# Grammatical Parts of Speech
nlu.load('pos').predict('Extract Parts of Speech')
```

- Tokenization
- Sentence Detector
- Stop Words Removal
- Normalizer
- Stemmer
- Lemmatizer
- NGrams
- Regex Matching
- Text Matching
- Chunking
- Date Matcher
- Part-of-speech tagging
- Dependency parsing
- Sentiment Detection (ML models)
- Spell Checker (ML and DL models)
- Word Embeddings

- BERT Embeddings
- ELMO Embeddings
- ALBERT Embeddings
- XLNet Embeddings
- Universal Sentence Encoder
- BERT Sentence Embeddings
- Sentence Embeddings
- Chunk Embeddings
- Unsupervised keywords extraction
- Language Detection & Identification
- Multi-class Text Classification
- Multi-label Text Classification
- Multi-class Sentiment Analysis
- Named entity recognition
- Easy TensorFlow integration
- Full integration with Spark ML functions
- +250 pre-trained models in 46 languages!
- +90 pre-trained pipelines in 13 languages!

```python
# Multiple binary sentiment classifiers trained on various datasets
nlu.load('classify.sentiment').predict('I love NLU and Python WebDev Conf 2021!')
nlu.load('classify.sentiment.imdb').predict('The Matrix was a pretty good movie')
nlu.load('classify.sentiment.twitter').predict('@elonmusk Tesla stock price is too high imo')

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nlu.load('clean').predict('Get me the lemmatized version of a string')

# Grammatical Parts of Speech
nlu.load('pos').predict('Extract Parts of Speech')
```
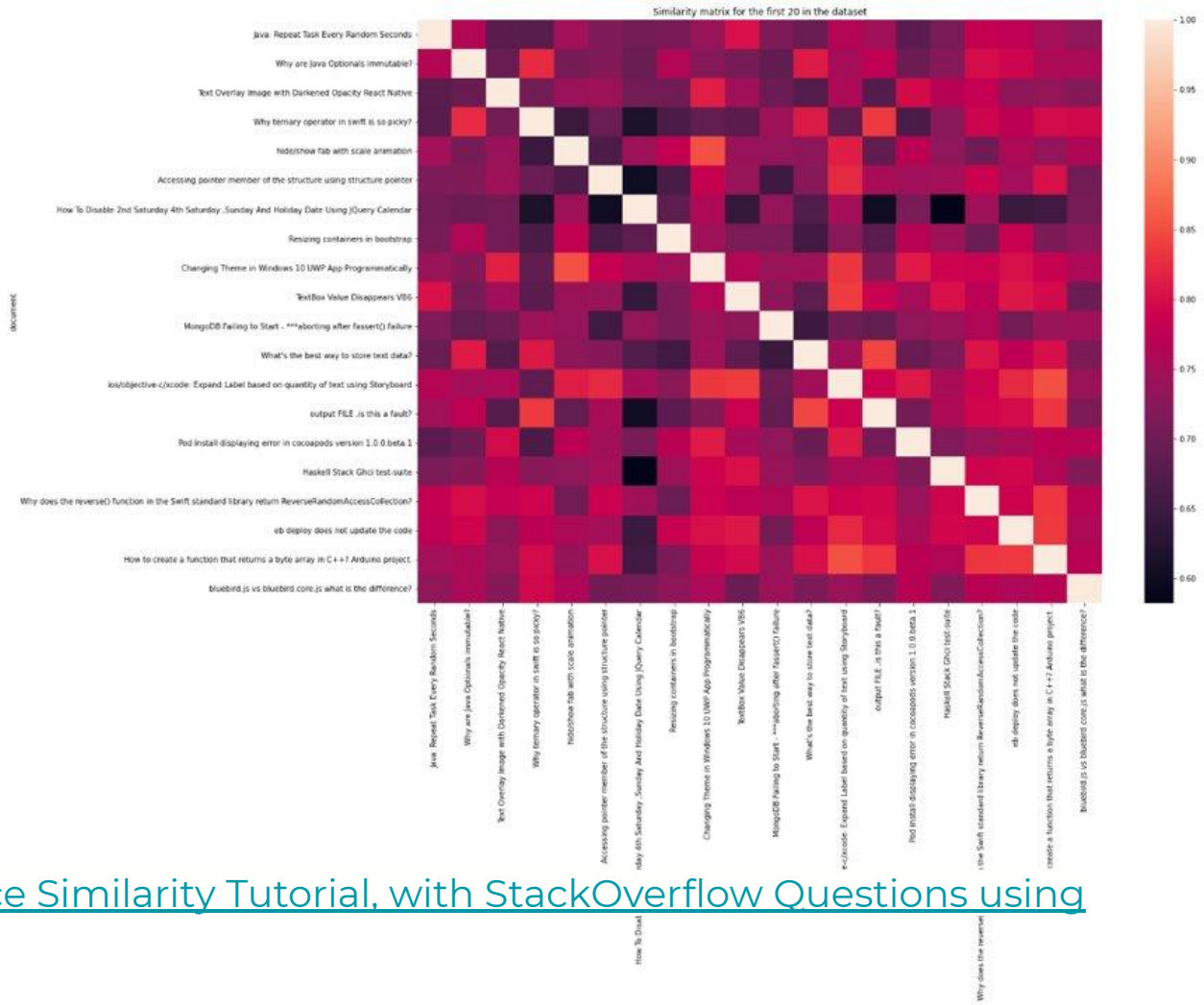

Sentence Similarity With BERTology Embeds or T5



[Indepth and Easy Sentence Similarity Tutorial, with StackOverflow Questions using BERTology embeddings]

t-SNE Visualizations with NLU

[1 line of Python code for BERT, ALBERT, ELMO, ELECTRA, XLNET, GLOVE, Part of Speech with NLU and t-SNE]

Visualize NER results

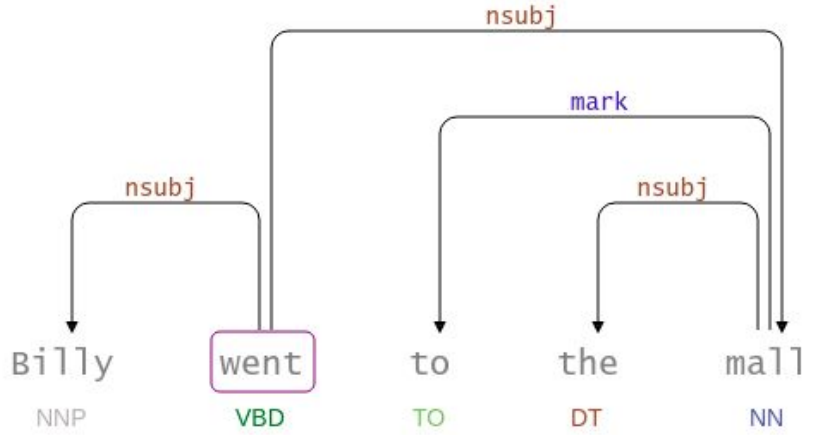
```
nlu.load('ner').viz("Donald Trump from America and Angela Merkel from Germany don't share many oppinions.")
```

```
onto_recognize_entities_sm download started this may take some time.
Approx size to download 160.1 MB
[OK!]
```

Visualize Dependency Trees

```
nlu.load('dep.typed').viz("Billy went to the mall")
```

```
dependency_typed_conllu download started this may take some time.
Approximate size to download 2.3 MB
[OK!]
dependency_conllu download started this may take some time.
Approximate size to download 16.7 MB
[OK!]
pos_anc download started this may take some time.
Approximate size to download 3.9 MB
[OK!]
sentence_detector_dl download started this may take some time.
Approximate size to download 354.6 KB
[OK!]
```



Visualize Assertion results

```
nlu.load('med_ner.clinical assert').viz("The MRI scan showed no signs of cancer in the left lung")
```

```
ner_clinical download started this may take some time.
Approximate size to download 13.9 MB
[OK!]
assertion_dl download started this may take some time.
Approximate size to download 1.3 MB
[OK!]
embeddings_clinical download started this may take some time.
Approximate size to download 1.6 GB
[OK!]
sentence_detector_dl download started this may take some time.
Approximate size to download 354.6 KB
[OK!]
```

Visualize Resolution

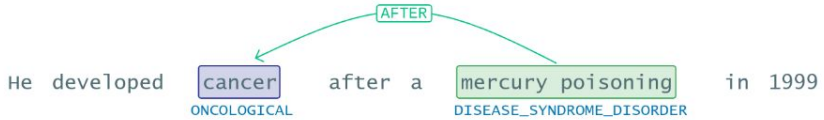
```
nlu.load('med_ner.jsl.wip.clinical resolve_chunk.rxnorm.in').viz("He took 2 pills of Aspirin daily")
```

```
jsl_ner_wip_clinical download started this may take some time.
Approximate size to download 14.5 MB
[OK!]
chunkresolve_rxnorm_in_clinical download started this may take some time.
Approximate size to download 26.9 MB
[OK!]
embeddings_clinical download started this may take some time.
Approximate size to download 1.6 GB
[OK!]
sentence_detector_dl download started this may take some time.
Approximate size to download 354.6 KB
[OK!]
```

Visualize Entity Relationships

```
nlu.load('med_ner.jsl.wip.clinical relation.temporal_events').viz('He developed cancer after a mercury poisoning in 1999 ')
```

```
jsl_ner_wip_clinical download started this may take some time.
Approximate size to download 14.5 MB
[OK!]
redl_temporal_events_biobert download started this may take some time.
Approximate size to download 383.3 MB
[OK!]
embeddings_clinical download started this may take some time.
Approximate size to download 1.6 GB
[OK!]
sentence_detector_dl download started this may take some time.
Approximate size to download 354.6 KB
[OK!]
```

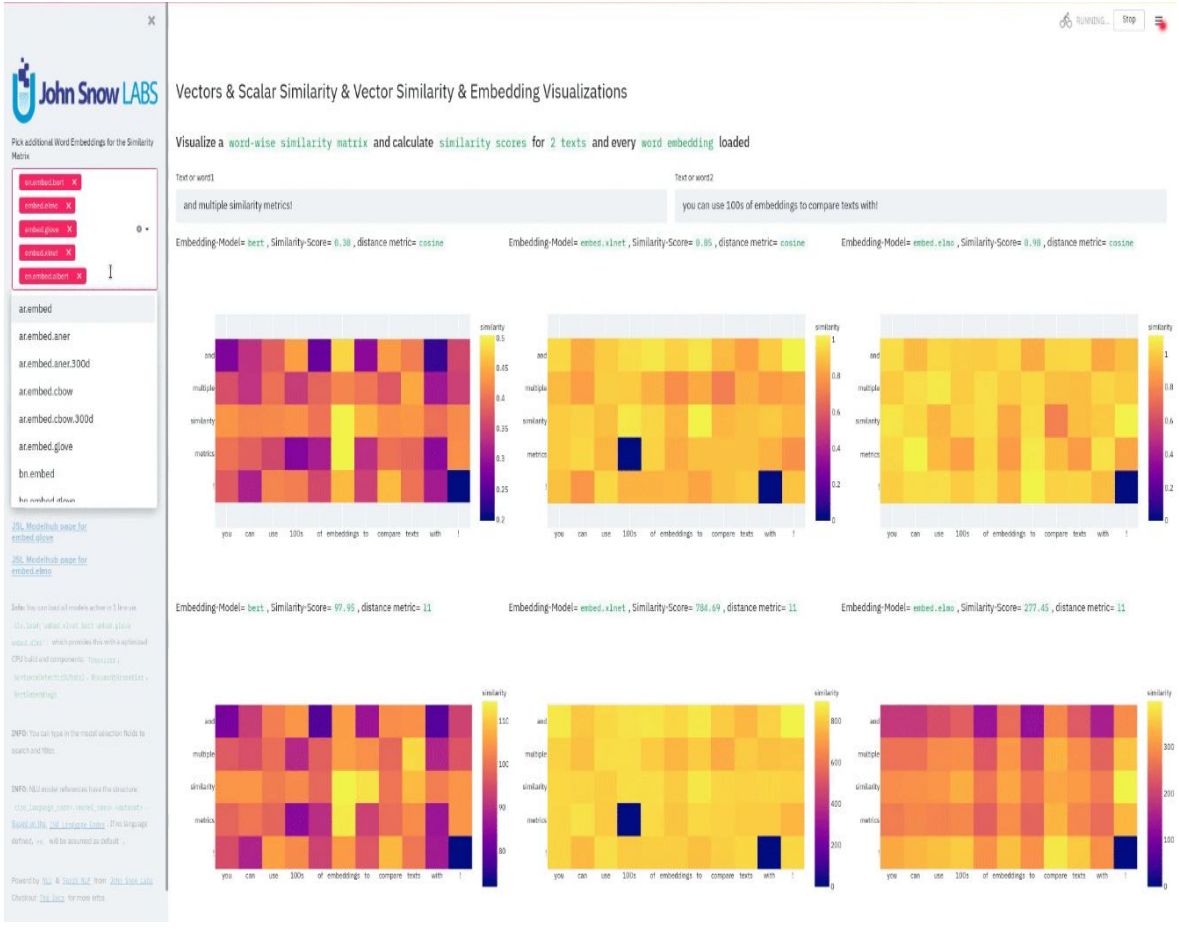


nlu_viz_cheatsheet.py

```python
data = 'I want some pretty visualizations please!'

# Viz detected entities
nlu.load('ner').viz(data)

# Viz labeled dependency tree and POS tags
nlu.load('dep.typed').viz(data)

# Viz asserted statuses
nlu.load('med_ner.clinical assert').viz(data)

# Viz resolved sentences
nlu.load('med_ner.jsl.wip.clinical resolve.icd10cm').viz(data)

# Viz resolved entities
nlu.load('med_ner.jsl.wip.clinical resolve_chunk.rxnorm.in').viz(data)

# Viz extracted relationships between entities
nlu.load('med_ner.jsl.wip.clinical relation.temporal_events').viz(data)
```

Explore 100+ Embeddings via 6 Similarity Metrics with 0 lines of code with NLU & Streamlit

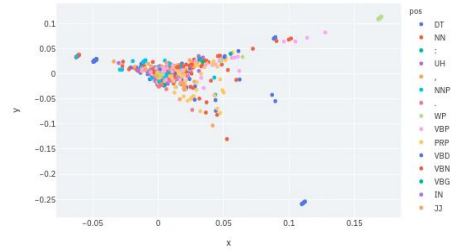
- Compare Multiple similarity Metrics And Embeddings at the same time
- Supported similarities :
  - Cosine
  - Cityblock
  - Euclidean
  - L2
  - L1
  - Manhattan



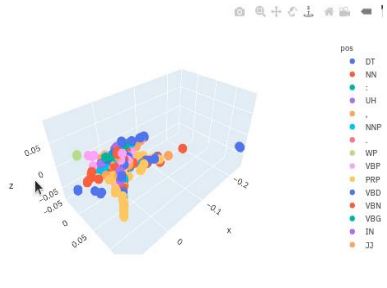
Explore 100+ Embeddings via 10+ Manifold and Matrix Decomposition with 0 lines of code with NLU & Streamlit

Compare multiple dimension reduction
Techniques and
Embeddings at the same time

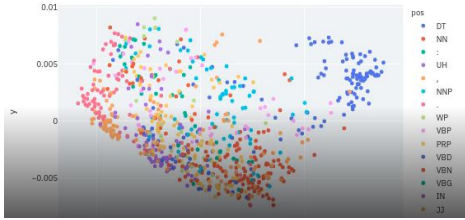
Word-Embeddings = `small_bert_L2_128` , Manifold-Algo = `LLE` for `D=2`



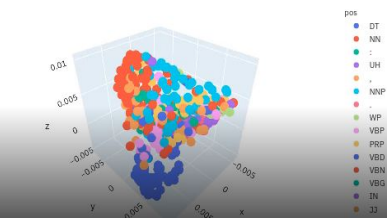
Word-Embeddings = `small_bert_L2_128` , Manifold-Algo = `LLE` for `D=3`

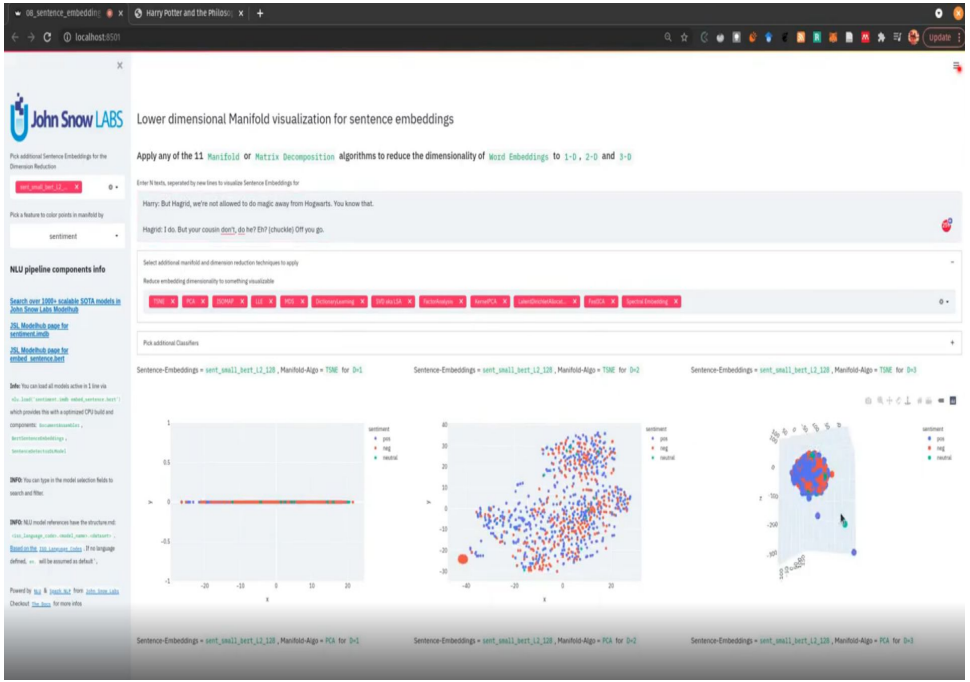


Word-Embeddings = `small_bert_L2_128` , Manifold-Algo = `Spectral Embedding` for `D=2`



Word-Embeddings = `small_bert_L2_128` , Manifold-Algo = `Spectral Embedding` for `D=3`





nlu_streamlit_cheatsheet.py

```python
# Input text data for visualizations
data = 'Billy from Berlin wants some pretty visualizations please!'

# Full UI with self generating Python code snippets for every feature
nlu.load('ner').viz_streamlit(data)

# Classification
nlu.load('sentiment').viz_streamlit_classes(data)

# Named Entity Recognition (NER)
nlu.load('ner').viz_streamlit_ner(data)

# Dependency Tree and Part of Speech (POS) Tags
nlu.load('dep.typed').viz_streamlit_dep_tree(data)

# Token features
nlu.load('stemm pos spell').viz_streamlit_token(data)

# Calculate similarity between two texts based on Word Embeddings
nlu.load('bert').viz_streamlit_word_similarity(['I love  NLU! <3','I also Streamlit! <3'])

# Raw visualizations in Streamlit
nlu.load('<Model>').viz(data, write_to_streamlit=True)

# Predict on any datatype and returns Pandas df
nlu.load('<Model>').predict(data)

# Enable caching
nlu.enable_streamlit_caching()
```

NER Domains and Models Overview

Domain	Description	Sample NLU Spells	Sample Entities	Sample Predicted Labels	Reference Links
ADE (Adverse Drug Events)	Find adverse drug event (ADE) related entities	ned_ner.ade_biobert	Aspirin , vomiting	DRUG , ADE	CADEC, Twimed
Anatomy	Find body parts, anatomical sites and reference related entities	ned_ner.anatomy	tubules , nasopharyngeal aspirates , embryoid bodies , NK cells , Mitochondrial , tracheoesophageal fistulas , heart , colon cancer , cervical , central nervous system	Tissue structure , Organism substance , Developing anatomical structure , Cell , Cellular component , Inmaterial anatomical_entity , organ , Pathological formation , Organism_subdivision , Anatomical_system	AnEM
Cellular/ Molecular Biology	Find Genes, Molecules, Cell or general Biology related entities	ned_ner.cellular.biobert	human T-cell leukemia virus type 1 Tax-responsive , primary T lymphocytes , E1A-immortalized , Spi-B mRNA , zeta-globin	DNA , Cell type , Cell line , RNA , Protein	JNLPBA
Chemical/Genes/ Proteins	Find Chemical, Gene and Protein related entities	ned_ner.chemprot.clinical	nitrogen , β-amyloid , NF-kappaB	CHEMICAL , GENE-Y , GENE-N	ChemProt
Chemical Compounds	Find general chemical compound related entities	ned_ner.chemicals	resveratrol , β-polyphenol	CHEM	Dataset by John Snow Labs
Drug Chemicals	Find chemical and drug related entities	ned_ner.drugs	potassium , anthracyclines , taxanes	DrugChem . DrugChem . DrugChem	i2b2 + FDA
Posology/Drugs	Find posology and drug related entities	ned_ner.posology.biobert	5000 units , Aspirin , 14 days , tablets , daily , topically , 30 mg	DOSAGE , DRUG , DURATION , FORM , FREQUENCY , ROUTE , STRENGTH .	i2b2 + FDA
Risk Factors	Find risk factor of patient related entities	ned_ner.risk_factors.biobert	coronary artery disease , hypertension , Smokes 2 packs of cigarettes per day , morbid obesity , Actos , Works in School , diabetic , diabetic	CAD , HYPERTENSION , SMOKER , OBESE , FAMILY HIST , MEDICATION , PHI , HYPERLIPIDEMIA , DIABETES	De-identification and Heart Disease Risk Factors Challenge datasets
cancer Genetics	Find cancer and genetics related entities	ned_ner.cancer	human , Kir 3.3 , GIRK3 , potassium , GIRK , chromosome 1q21-23 , pancreas , tissues , fat andskeletal muscle , KCNJ9 , Type II , breast cancer , patients , anthracyclines , taxanes , vinorelbine , patients , breast , vinorelbine inpatients , anthracyclines	Amino acid , Anatomical system , cancer , Cell , Cellular component , Developing anatomical Structure , Gene or gene product , Inmaterial anatomical_entity , Multi-tissue structure , Organ , Organism , Organism_subdivision , Simple_chemical , Tissue	CG TASK of BioNLP 2013
Diseases	Find disease related entities	ned_ner.diseases.biobert	the cyst , a large Prolene suture , a very small incisional hernia , the hernia cavity , omentum , the hernia , the wound lesion , The lesion , the existing scar , the cyst , the wound , this cyst down to its base , a small incisional hernia , The cyst	Disease	CG TASK of BioNLP 2013
Bacterial Species	Find bacterial species related entities	ned_ner.bacterial_species	Neisseria wadsworthii , N. bacilliformis , Spirochaeta litoralis	SPECIES	Dataset by John Snow Labs
Medical Problem/Test/Treatment	Find medical problem,test and treatment related entities	ned_ner.healthcare	respiratory tract infection , Ourexpression studies , atorvastatin	PROBLEM , TEST , TREATMENT	i2b2
Clinical Admission Events	Find clinical admission event related entities	ned_ner.admission_events	2007 , 12 AM , Headache , blood sample , presented , emergency room , daily	DATE , TIME , PROBLEM , TEST , TREATMENT , OCCURENCE , CLINICAL DEPT , EVIDENTIAL , DURATION , FREQUENCY , ADMISSION , DISCHARGE	Custom i2b2, enriched with Events
Genetic Variants	Find genetic variant related entities	en.med_ner.genetic_variants	rs1061170 , p.S45P , T13046C	DNAMutation , ProteinMutation , SNP	TMVAR
PHI (Protected Healthcare Information)	Find PHI(Protected Healthcare) related entities	en.med_ner.deid	2093-01-13 , David Hale , Hendrickson , </br> Ora , 7194334 , 01/13/93 , Oliveira , 25-year-old , 1-11-2000 , Cocke County Baptist Hospital , 0295 Keats Street. , (302) 786-5227 , Brothers Coal-Mine	MEDICALRECORD , ORGANIZATION , DOCTOR , USERNAME , PROFESSION , HEALTHPLAN , URL , CITY , DATE , LOCATION-OTHER , STATE , PATIENT , DEVICE , COUNTRY , ZIP , PHONE , HOSPITAL , EMAIL , IDNUM , SREET , BIOID , FAX , AGE	n2c2 i2b2-PHI
Social Determinants / Demographic Data	Find Social Determinants and Demographic Data Related Entities	ned_ner.jsl.enriched	21-day-old , male , congestion , mom , suctioning yellow discharge , she , problems with his breathing , perioral cyanosis , retractions , mom , Tylenol , His , his , respiratory congestion , He , tired , fussy , albuterol	Age , Diagnosis , Dosage , Drug_Name , Frequency , Gender , Lab_Name , Lab_Result , Symptom_Name	Dataset by John Snow Labs
General Clinical	Find General Clinical Entities	ned_ner.jsl.wip.clinical.modifier	28-year-old , female , gestational , diabetes , mellitus , eight , years , prior , type , two , diabetes , mellitus , T2DM , HTG-induced , pancreatitis , three , years , prior , acute , hepatitis , obesity , body , mass , index , BMI , kg/m2 , polyuria , polydipsia , poor , appetite , vomiting , Two , weeks , prior , she , five-day , course	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 ,	Dataset by John Snow Labs
			Bilateral breast ultrasound		

NER Domains and Models Overview

Radiology	Find Radiology related entities	`med_ner.radiology.wip_clinical`	`Bilateral, breast, ultrasound, ovoid mass, 0.5 x 0.5 x 0.4, cm, anteromedial aspect, left, shoulder, mass, isoechoic echotexture, muscle, internal color flow, benign fibrous tissue, lipoma`	`ImagingTest, Imaging Technique, ImagingFindings, OtherFindings, BodyPart, Direction, Test, Symptom, Disease Syndrome Disorder, Medical_Device, Procedure, Measurements, Units`	Dataset by John Snow Labs, MIMIC-CXR and MT Radiology texts
Radiology Clinical JSL-V1	Find radiology related entities in clinical setting	`med_ner.radiology.wip_greedy_biobert`	`Bilateral, breast, ultrasound, ovoid mass, 0.5 x 0.5 x 0.4, cm, anteromedial aspect, left, shoulder, mass, isoechoic echotexture, muscle, internal color flow, benign fibrous tissue, lipoma`	`Test Result, OtherFindings, BodyPart, ImagingFindings, Disease Syndrome Disorder, ImagingTest, Measurements, Procedure, Score, Test, Medical Device, Direction, Symptom, Imaging_Technique, ManualFix, Units`	Dataset by John Snow Labs,
Genes and Phenotypes	Find Genes and Phenotypes (the observable physical properties of an organism) related entities	`med_ner.human_phenotype.gene_biobert`	`APOC4 , polyhydramnios`	`GENE, PHENOTYPE`	PGR_1, PGR_2
Normalized Genes and Phenotypes	Find Normalized Genes and Phenotypes (the observable physical properties of an organism) related entities	`med_ner.human_phenotype.go_biobert`	`protein complex oligomerization , defective platelet aggregation`	`GO, HP`	PGR_1, PGR_2
Radiology Clinical JSL-V2	Find radiology related entities in clinical setting	`med_ner.jsl.wip.clinical.rd`		`Kidney Disease, HDL, Diet, Test, Imaging Technique, Triglycerides, Obesity, Duration, Weight, Social History Header, ImagingTest, Labour_Delivery, Disease Syndrome Disorder, Communicable Disease, Overweight, Units, Smoking, Score, Substance Quantity, Form, Race_Ethnicity, Modifier, Hyperlipidemia, ImagingFindings, Psychological Condition, OtherFindings, Cerebrovascular Disease, Date, Test_Result, VS Finding, Employment, Death Entity, Gender, Oncological, Heart Disease, Medical Device, Total Cholesterol, ManualFix, Time, Route, Pulse, Admission Discharge, RelativeDate , O2 Saturation, Frequency, RelativeTime, Hypertension, Alcohol, Allergen, Fetus NewBorn, Birth Entity, Age, Respiration, Medical History Header, Oxygen Therapy, Section Header, LDL, Treatment, Vital_Signs_Header, Direction, BMI, Pregnancy, Sexually Active or Sexual Orientation, Symptom, Clinical Dept, Measurements, Height, Family_History_Header, Substance, Strength, Injury or Poisoning, Relationship Status, Blood Pressure, Drug, Temperature, , EKG Findings, Diabetes, BodyPart, Vaccine, Procedure, Dosage`	Dataset by John Snow Labs,
General Medical Terms	Find general medical terms and medical entities.	`med_ner.medmentions`		`Qualitative Concept, Organization, Manufactured Object, Amino Acid, Peptide or Protein, Pharmacologic Substance, Professional or Occupational Group, Cell Component, Neoplastic Process, Substance, Laboratory Procedure, Nucleic Acid Nucleoside or Nucleotide, Research Activity, Gene or Genome, Indicator_Reagent_or_Diagnostic_Aid, Biologic Function, Chemical, Mammal, Molecular Function, Quantitative Concept, Prokaryote, Mental or Behavioral Dysfunction, Injury or Poisoning, Body Location or Region, Spatial Concept, Nucleotide Sequence, Tissue, Pathologic Function, Body Substance, Fungus, Mental Process, Medical Device, Plant, Health Care Activity, Clinical Attribute, Genetic Function, Food, Therapeutic_or_Preventive_Procedure, Body Part Organ, Organ Component, Geographic Area, Virus, Biomedical or Dental Material, Diagnostic_Procedure, Eukaryote, Anatomical Structure, Organism Attribute, Molecular Biology Research Technique, Organic_Chemical, Cell, Daily or Recreational Activity, Population Group, Disease or Syndrome, Group, Sign or Symptom, Body System`	MedMentions

Assertion Domains and Models Overview

Domain	Description	Spell	Predicted Entities	Examples	Reference Dataset
Radiology	Predict status of Radiology related entities	assert.radiology	Confirmed, Negative, Suspected	- Confirmed : X-Ray scan shows cancer in lung. - Negative : X-Ray scan shows no sign of cancer in lung. - Suspected :X-Ray raises suspicion of cancer in lung but does not confirm it.	Internal Dataset by Annotated by John Snow Labs
Healthcare/Clinical extended and Family JSL powerd	Predict status of, Healthcare/Clinical/Family related entities. Additional training with JSL Dataset	assert.jsl	Present, Absent, Possible, Planned, Someoneelse, Past, Family, Hypotetical	- Present : Patient diagnosed with cancer in 1999 - Absent : No sign of cancer was shown by the scans - Possible : Tests indicate patient might have cancer - Planned : CT-Scan is scheduled for 23.03.1999 - Someoneelse : The patient gave Aspirin to daugther. - Past : The patient has no more headaches since the operation - Family : The patients father has cancer . - Hypotetical : Death could be possible.	2010 I2b2 + Data provided by JSL
Healthcare/Clinical JSL powerd	Predict status of Healthcare/Clinical related entities. Additional training with JSL Dataset	assert.jsl_large	present, absent, possible, planned, someoneelse, past	- present : Patient diagnosed with cancer in 1999 - absent : No sign of cancer was shown by the scans - possible : Tests indicate patient might have cancer - planned : CT-Scan is scheduled for 23.03.1999 - someoneelse : The patient gave Aspirin to daugther - past : The patient has no more headaches since the operation	2010 I2b2 + Data provided by JSL
Healthcare/Clinical classic	Predict status of Healthcare/Clinical related entities	assert.biobert	present , absent, possible, conditional, associated_with_someone_else ,hypothetical	- present : Patient diagnosed with cancer in 1999 - absent : No sign of cancer was shown by the scans - possible : Tests indicate patient might have cancer - conditional If the test is positive, patient has AIDS - associated with someone_else : The patients father has cancer . - hypothetical : Death could be possible.	2010 I2b2

Resolution Domains Models Overview

Domain/Terminology	Description	Sample NLU Spells	Sample Entities	Sample Predicted Codes	Reference Links
ICD-10 / ICD-10-CM (International Classification of Diseases - Clinical Modification)	Get ICD-10-CM codes of Medical and Clinical Entities. The ICD-10 Clinical Modification (ICD-10-CM) is a modification of the ICD-10, authorized by the World Health Organization, used as a source for diagnosis codes in the U.S. Be aware, ICD10-CM is often referred to as ICD10	resolve.icd10cm.augmented	hypertension , gastritis	I10, K2970	ICD-10-CM , WHO ICD-10-CM
ICD-10-PCS (International Classification of Diseases - Procedure Coding System)	Get ICD-10-PCS codes of Medical and Clinical Entities. The International Classification of Diseases, Procedure Coding System (ICD-10-PCS), is a U.S. cataloging system for procedural code It is maintaining by Centers for Medicare & Medicaid Services	resolve.icd10pcs	hypertension , gastritis	DWY18ZZ, 0472326	ICD10-PCS, CMS ICD-10-PCS
ICD-O (International Classification of Diseases, Oncology) Topography & Morphology codes	Get ICD-0 codes of Medical and Clinical Entities. The International Classification of Diseases for Oncology (ICD-0), is a domain-specific extension of the International Statistical Classification of Diseases and Related Health Problems for tumor diseases.	resolve.icdo.base	metastatic lung cancer	9058/3+C38.3, 8801/3+C39.8	ICD-O Histology Behaviour dataset
HCC (Hierachical Conditional Categories)	Get HCC codes of Medical and Clinical Entities. Hierarchical condition category (HCC) relies on ICD-10 coding to assign risk scores to patients. Along with demographic factors (such as age and gender), Insurance companies use HCC coding to assign patients a risk adjustment factor (RAF) score.	resolve.hcc	hypertension , gastritis	139, 188	HCC
ICD-10-CM + HCC Billable	Get ICD-10-CM and HCC codes of Medical and Clinical Entities.	resolve.icd10cm.augmented_billable	metastatic lung cancer	C7800 + ['1', '1', '8']	ICD10-CM HCC
CPT (Current Procedural Terminology)	Get CPT codes of Medical and Clinical Entities. The Current Procedural Terminology(CPT) is developed by the American Medical Association (AMA) and used to assign codes to medical procedures/services/diagonstics. The codes are used to derive the amount of payment a healthcare provider may receives from insurance companies for the provided service.receives	resolve.cpt.procedures_measurements	calcium score, heart surgery	82310, 33257	CPT
LOINC (Logical Observation Identifiers Names and Codes)	Get LOINC codes of Medical and Clinical Entities. Logical Observation Identifiers Names and Codes (LOINC) developed by the U.S. organization Regenstrief Institute	resolve.loinc	acute hepatitis , obesity	28083-4, 58227-8	LOINC
HPO (Human Phenotype Ontology)	Get HPO codes of Medical and Clinical Entities.	resolve.HPO	cancer, bipolar disorder	0002664, 0007302, 0100753	HPO
UMLS (Unified Medical Language System) CUI	Get UMLS codes of Medical and Clinical Entities.	resolve.umls.findings	vomiting, polydipsia, hepatitis	C1963281, C3278316, C1963279	UMLS
SNOMED International (Systematized Nomenclature of Medicine)	Get SNOMED (INT) codes of Medical and Clinical Entities.	resolve.snomed.findings_int	hypertension	148439002	SNOMED
SNOMED CT (Clinical Terms)	Get SNOMED (CT) codes of Medical and Clinical Entities.	resolve.snomed.findings	hypertension	73578008	SNOMED
SNOMED Conditions	Get SNOMED Conditions codes of Medical and Clinical Entities.	resolve.snomed_conditions	schizophrenia	58214004	SNOMED
RxNorm and RxCUI (Concept Unique Indentifier)	Get Normalized RxNorm and RxCUI codes of Medical, Clinical and Drug Entities.	resolve.rxnorm	50 mg of eltrombopag oral	825427	[RxNorm Overview] [November 2020 RxNorm Clinical Drugs ontology graph]

Relation Extraction Domains and Models examples

Domain	Description	Sample NLU Spells	Predictable Relationships and Explanation
Dates and Clinical Entities	Predict binary temporal relationship between Date Entities and Clinical Entities	relation.date	- 1 for Date Entity and Clinical Entity are related. - 0 for Date Entity and Clinical Entity are not related
Body Parts and Directions	Predict binary direction relationship between Bodypart Entities and Direction Entities	relation.bodypart.direction	- 1 for Body Part and Direction are related - 0 for Body Part and Direction are not related
Body Parts and Problems	Predict binary location relationship between Bodypart Entities and Problem Entities	relation.bodypart.problem	- 1 for Body Part and Problem are related - 0 for Body Part and Problem are not related
Body Parts and Procedures	Predict binary application relationship between Bodypart Entities and Procedure Entities	relation.bodypart.procedure	- 1 for Body Part and Test/Procedure are related - 0 for Body Part and Test/Procedure are not related
Adverse Effects between drugs (ADE)	Predict binary effect relationship between Drugs Entities and Adverse Effects/Problem Entities	relation.ade	- 1 for Adverse Event Entity and Drug are related - 0 for Adverse Event Entity and Drug are not related
Phenotype abnormalities,Genes and Diseases	Predict binary caused by relationship between Phenotype Abnormality Entities, Gene Entities and Disease Entities	relation.humen_phenotype_gene	- 1 for Gene Entity and Phenotype Entity are related - 0 for Gene Entity and Phenotype Entity are not related
Temporal events	Predict multi-class temporal relationship between Time Entities and Event Entities	relation.temporal_events	- AFTER if Any Entity occured after Another Entity - BEFORE if Any Entity occured before Another Entity - OVERLAP if Any Entity during Another Entity
Dates and Tests/Results	Predict multi-class temporal cause,reasoning and conclusion relationship between Date Entities, Test Entities and Result Entities	relation.test_result_date	- relation.test result date - is finding of for Medical Entity is found because of Test Entity - is result of for Medical Entity reason for doing Test Entity - is_date of for Date Entity relates to time of Test/Result - 0 : No relationship
Clinical Problem, Treatment and Tests	Predict multi-class cause,reasoning and effect relationship between Treatment Entities, Problem Entities and Test Entities	relation.clinical	- TrIP : A certain treatment has improved/cured a medical problem - TrWP : A patient's medical problem has deteriorated or worsened because of treatment - TrCP : A treatment caused a medical problem - TrAP : A treatment administered for a medical problem - TrNAP : The administration of a treatment was avoided because of a medical problem - TeRP : A test has revealed some medical problem - TeCP : A test was performed to investigate a medical problem - PIP : Two problems are related to each other
DDI Effects of using Multiple Drugs (Drug Drug Interaction)	Predict multi-class effects, mechanisms and reasoning for DDI effects(Drug Drug Interaction) relationships between Drug Entities	relation.drug_drug_interaction	- DDI-advise when an advice/recommendation regarding a Drug Entity and Drug Entity is given - DDI-effect when Drug Entity and Drug Entity have an effect on the human body (pharmacodynamic mechanism). Including a clinical finding, signs or symptoms, an increased toxicity or therapeutic failure. - DDI-int when effect between Drug Entity and Drug Entity is already known and thus provides no additional information. - DDI-mechanism when Drug Entity and Drug Entity are affected by an organism (pharmacokinetic). Such as the changes in levels or concentration in a drug. Used for DDIs that are described by their PK mechanism - DDI-false when a Drug Entity and Drug Entity have no interaction mentioned in the text.
Posology (Drugs, Dosage, Duration, Frequency, Strength)	Predict multi-class posology relationships between Drug Entities, Dosage Entities, Strength Entities, Route Entities, Form Entities, Duration Entities and Frequency Entities	relation.posology	- DRUG-ADE if Problem Entity Adverse effect of Drug Entity - DRUG-DOSAGE if Dosage Entity refers to a Drug Entity - DRUG-DURATION if Duration Entity refers to a Drug Entity - DRUG-FORM if Mode/Form Entity refers to intake form of Drug Entity - DRUG-FREQUENCY if Frequency Entity refers to usage of Drug Entity - DRUG-REASON if Problem Entity is reason for taking Drug Entity - DRUG-ROUTE if Route Entity refer to administration method of Drug Entity - DRUG-STRENGTH if Strength Entity refers to Drug Entity
Chemicals and Proteins	Predict Regulator, Upregulator, Downregulator, Agonist, Antagonist, Modulator, Cofactor, Substrate relationships between Chemical Entities and Protein Entities	relation.chemprot	- CPR:1 if One ChemProt Entity is Part of of Another ChemProt Entity - CPR:2 if One ChemProt Entity is Regulator (Direct or Indirect) of Another ChemProt Entity - CPR:3 if One ChemProt Entity is Upregulator/Activator/Indirect Upregulator of Another ChemProt Entity - CPR:4 if One ChemProt Entity is Downregulator/Inhibitor/Indirect Downregulator of Another ChemProt Entity - CPR:5 if One ChemProt Entity is Agonist of Another ChemProt Entity - CPR:6 if One ChemProt Entity is Antagonist of Another ChemProt Entity - CPR:7 if One ChemProt Entity is Modulator (Activator/Inhibitor) of Another ChemProt Entity - CPR:8 if One ChemProt Entity is Cofactor of Another ChemProt Entity - CPR:9 if One ChemProt Entity is Substrate and product of of Another ChemProt Entity - CPR:10 if One ChemProt Entity is Not Related to Another ChemProt Entity

Relation Domain Examples

Domain	Sentence With Relationships	Predicted Relationships for Sample Sentence	Reference Links
Dates and Clinical Entities	This 73 y/o patient had CT on 1/12/95 , with cognitive decline since 8/11/94 .	- 1 for CT and 1/12/95 - 0 for cognitive decline and 1/12/95 - 1 for cognitive decline and 8/11/94	Internal Dataset by Annotated by John Snow Labs
Body Parts and Directions	MRI demonstrated infarction in the upper - brain stem , left cerebellum and right basil ganglia	- 1 for uppper and brain stem - 0 for upper and cerebellum - 1 for left and cerebellum	Internal Dataset by Annotated by John Snow Labs
Body Parts and Problems	Patient reported numbness in his left hand and bleeding from ear .	- 1 for numbness and hand - 0 for numbness and ear - 1 for bleeding and ear	Internal Dataset by Annotated by John Snow Labs
Body Parts and Procedures	The chest was scanned with portable ultrasound and amputation was performed on foot	- 1 for chest and portable ultrasound - 0 for chest and amputation - 1 for foot and amputation	Internal Dataset by Annotated by John Snow Labs
Adverse Effects between drugs (ADE)	Taking Lipitor for 15 years, experienced much sever fatigue ! Doctor moved me to voltaren 2 months ago , so far only experienced cramps	- 1 for sever fatique and Liptor - 0 for sever fatigue and voltaren - 0 for cramps and Liptor - 1 for cramps and voltaren	Internal Dataset by Annotated by John Snow Labs
Phenotype abnormalities,Genes and Diseases	She has a retinal degeneration, hearing loss and renal failure, short stature, Mutations in the SH3PXD2B gene coding for the Tks4 protein are responsible for the autosomal recessive.	- 1 for hearing loss and SH3PXD2B - 0 for retinal degeneration and hearing loss - 1 for retinal degeneration and autosomal recessive	PGR aclAntology
Temporal events	She is diagnosed with cancer in 1991 . Then she was admitted to Mayo Clinic in May 2000 and discharged in October 2001	- OVERLAP for cancer and 1991 - AFTER for additted and Mayo Clinic - BEFORE for admitted and discharged	Temporal JSL Dataset and n2c2
Dates and Tests/Results	On 23 March 1995 a X-Ray applied to patient because of headache , found tumor in brain	- is finding of for tumor and X-Ray - is result of for headache and X-Ray - is_date_of for 23 March 1995 and X-Ray	Internal Dataset by Annotated by John Snow Labs
Clinical Problem, Treatment and Tests	- TrIP : infection resolved with antibiotic course - TrWP : the tumor was growing despite the drain - TrCP : penicillin causes a rash - TrAP : Dexamphetamine for narcolepsy - TrNAP : Ralafen was not given because of ulcers - TeRP : an echocardiogram revealed a pericardial effusion - TeCP : chest x-ray for pneumonia - PIP : Azotemia presumed secondary to sepsis	- TrIP for infection and antibiotic course - TrWP for tumor and drain - TrCP for penicillin and rash - TrAP for Dexamphetamine and narcolepsy - TrNAP for Ralafen and ulcers - TeRP for echocardiogram and pericardial effusion - TeCP for chest x-ray and pneumonia - PIP for Azotemia and sepsis	2010 i2b2 relation challenge
DDI Effects of using Multiple Drugs (Drug Drug Interaction)	- DDI-advise : UROXATRAL should not be used in combination with other alpha-blockers - DDI-effect : Chlorthalidone may potentiate the action of other antihypertensive drugs - DDI-int : The interaction of omeprazole and ketoconazole has been established - DDI-mechanism : Grepafloxacin may inhibit the metabolism of theobromine - DDI-false : Aspirin does not interact with Chlorthalidone	- DDI-advise for UROXATRAL and alpha-blockers - DDI-effect for Chlorthalidone and antihypertensive drugs - DDI-int for omeprazole and ketoconazole - DDI-mechanism for Grepafloxacin and theobromine - DDI-false for Aspirin and Chlorthalidone	DDI Extraction corpus
Posology (Drugs, Dosage, Duration, Frequency, Strength)	- DRUG-ADE : had a headache after taking Paracetamol - DRUG-DOSAGE : took 0.5ML of Celstone - DRUG-DURATION : took Aspirin daily for two weeks - DRUG-FORM : took Aspirin as tablets - DRUG-FREQUENCY : Aspirin usage is weekly - DRUG-REASON : Took Aspirin because of headache - DRUG-ROUTE : Aspirin taken orally - DRUG-STRENGTH : 2mg of Aspirin	- DRUG-ADE for headache and Paracetamol - DRUG-DOSAGE for 0.5ML and Celstone - DRUG-DURATION for Aspirin and for two weeks - DRUG-FORM for Aspirin and tablets - DRUG-FREQUENCY for Aspirin and weekly - DRUG-REASON for Aspirin and headache - DRUG-ROUTE for Aspirin and orally - DRUG-STRENGTH for 2mg and Aspirin	Magge, Scotch, Gonzalez-Hernandez (2018)
Chemicals and Proteins	- CPR:1 (Part of) : The amino acid sequence of the rabbit alpha(2A)-adrenoceptor has many interesting properties. - CPR:2 (Regulator) : Triacsin inhibited ACS activity - CPR:3 (Upregulator) : Ibandronate increases the expression of the FAS gene - CPR:4 (Downregulator) : Vitamin C treatment resulted in reduced C-Rel nuclear translocation - CPR:5 (Agonist) : Reports show tricyclic antidepressants act as agonists at distinct opioid receptors - CPR:6 (Antagonist) : GDC-0152 is a drug triggers tumor cell apoptosis by selectively antagonizing LAPs - CPR:7 (Modulator) : Hydrogen sulfide is a allosteric modulator of ATP-sensitive potassium channels - CPR:8 (Cofactor) : polyinosinic:polycytidylic acid and the IFNα/β demonstrate capability of endogenous IFN. - CPR:9 (Substrate) : ZIP9 plays an important role in the transport and toxicity of Cd(2+) cells - CPR:10 (Not Related) : Studies indicate that GSK-3β inhibition by palinurin cannot be competed out by ATP	- CPR:1 (Part of) for amino acid and rabbit alpha(2A)-adrenoceptor - CPR:2 (Regulator) for Triacsin and ACS - CPR:3 (Upregulator) for Ibandronate and FAS gene - CPR:4 (Downregulator) for Vitamin C and C-Rel - CPR:5 (Agonist) for tricyclic antidepressants and opioid receptors - CPR:6 (Antagonist) (Antagonist) for GDC-0152 and LAPs - CPR:7 (Modulator) for Hydrogen sulfide and ATP-sensitive potassium channels - CPR:8 (Cofactor) for polyinosinic:polycytidylic acid and IFNα/β - CPR:9 (Substrate) for ZIP9 and Cd(2+) cells - CPR:10 (Not Related) for GSK-3β and ATP	ChemProt Paper

More NLU Ressources

- Join our Slack
- NLU Website
- NLU Githuab
- Many more NLU example tutorials
- Overview of every powerful nlu 1-liner
- Checkout the Modelshub for an overview of all models
- Checkout the NLU Namespace where you can find every model as a tabel
- Intro to NLU article
- Indepth and Easy Sentence Similarity Tutorial, with StackOverflow Questions using BERTology embeddings
- 1 line of Python code for BERT, ALBERT, ELMO, ELECTRA, XLNET, GLOVE, Part of Speech with NLU and t-SNE

Webinars and Videos

- NLU & Streamlit Tutorial
- Crash course of the 50 + Medical Domains and the 200+ Healtchare models in NLU
- Multi Lingual NLU Webinar - Tutorial on Chinese News dataset
- John Snow Labs NLU: Become a Data Science Superhero with One Line of Python code
- Python Web Def Conf - Python's NLU library: 4,000+ Models, 200+ Languages, State of the Art Accuracy, 1 Line of Code
- NYC/DC NLP Meetup with NLU

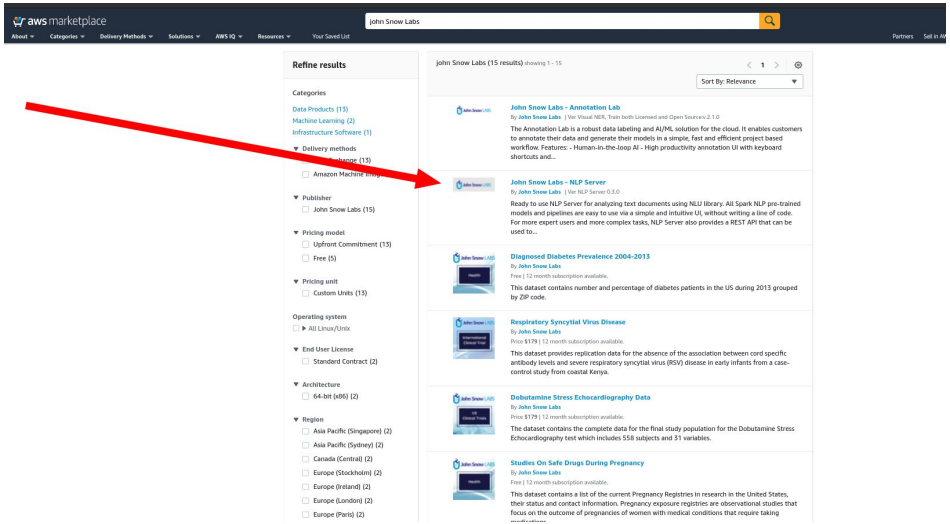
Part - IV (Day 2) - Coding Time

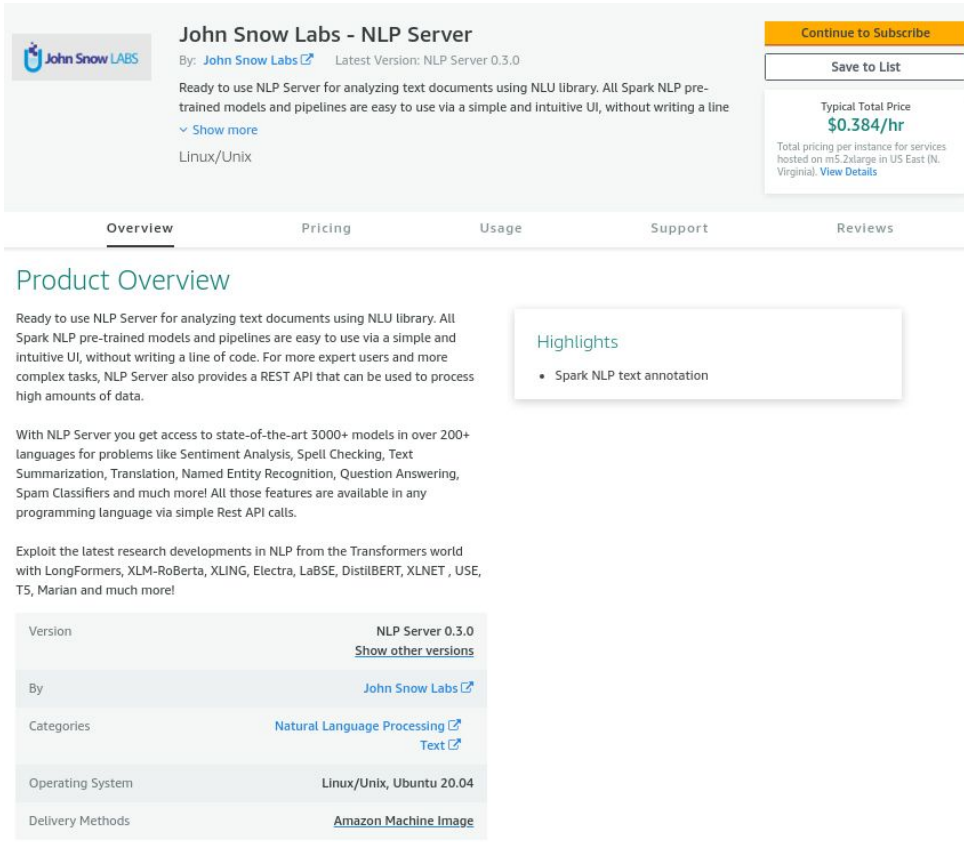
- Notebook 13 - NLU Crash course, every Spark NLP model in 1 line

Spark NLP
for Data Scientists

Christian Kasim Loan
Sr. Data Scientist
christian@johnsnowlabs.com

NLP Server - Powerful private deployable NLP Rest API

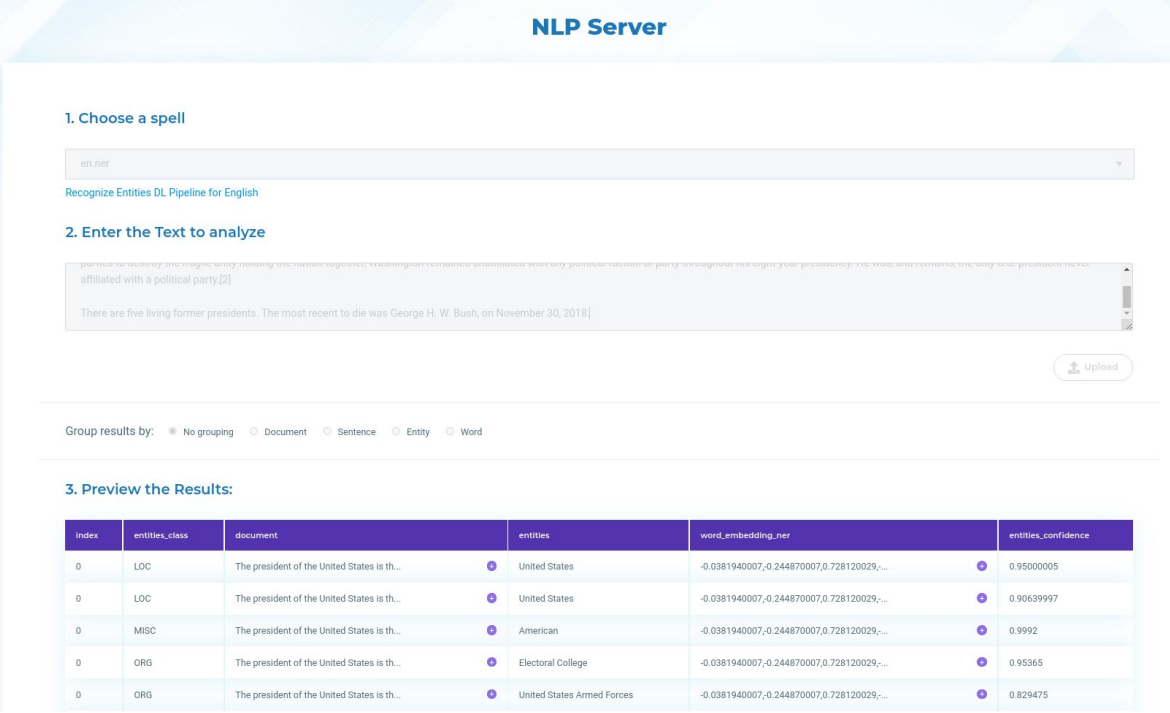




https://nlp.johnsnowlabs.com/docs/en/nlp_server/nlp_server

4000+ Models in 200 languages available as API and GUI with a few clicks in the AWS marketplace.

This enables you to use all of these Models with any programming Language by simple using REST API calls



API Usage in 3 Steps :

- Query - Send Data request
- Poll - Is server done processing?
- Get result - Get result when server done

Step 1 : Post a request

- Post a data processing request
- Returns UUID status

POST /api/results/

Request samples

Payload

Content type
application/json

Copy Expand all Collapse all

```
{
    "spell": "tokenize",
    "data": "I love NLU! <3"
}
```

Response samples

200 404 422

Content type
application/json

Copy Expand all Collapse all

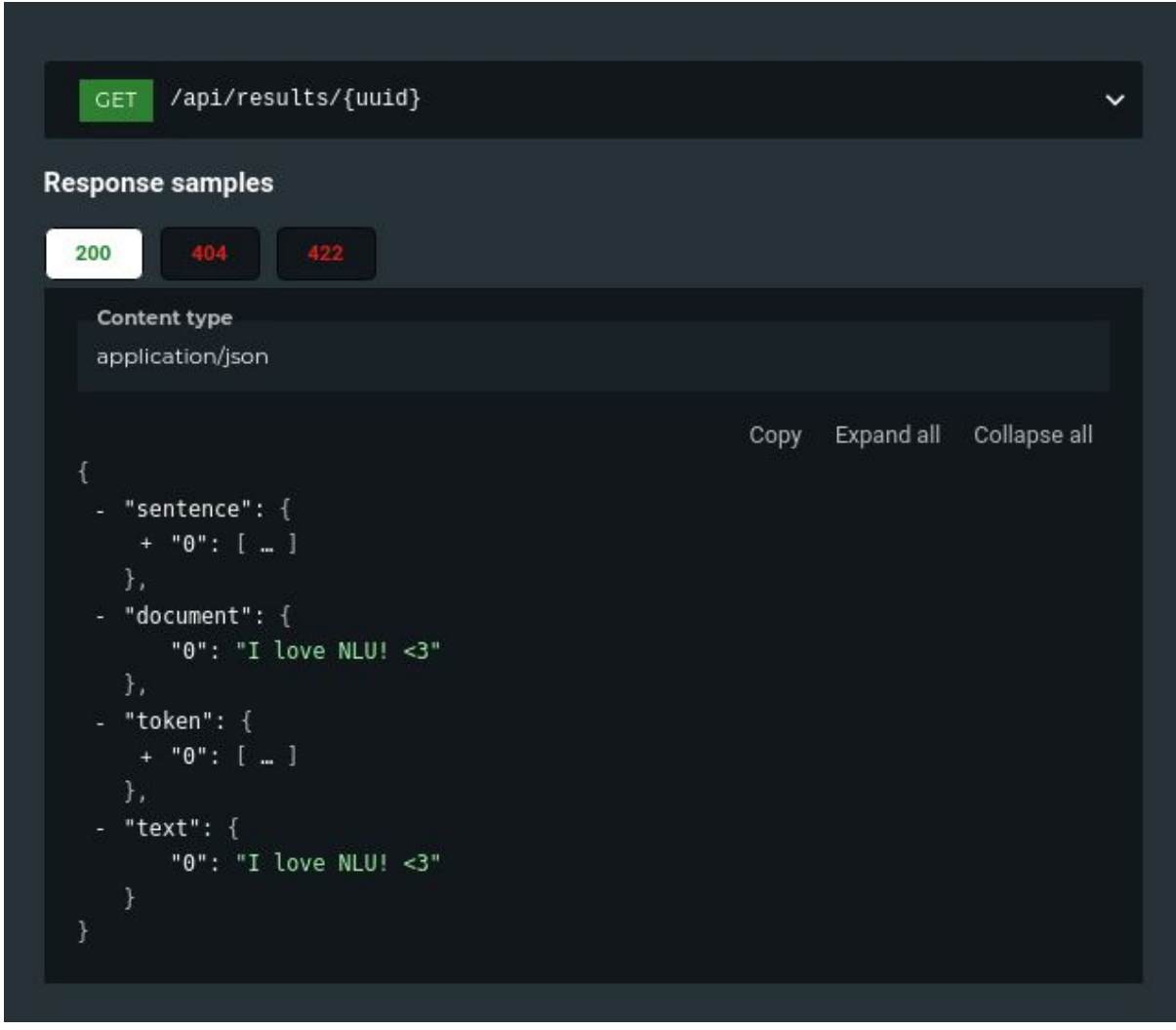
```
{
    "uuid": "njGeaDKl1VoRR7kjf002h"
}
```

Step 2 : Poll for result

- Poll Server for processing status

Step 3 : Get result as JSON

- Get result for UUID
- Contains NLP predictions



All of Spark NLP features behind a simple to use API. deployable in a few clicks on AWS

NLP_server_cheatsheet.py

```
import requests
# Invoke Processing with tokenization spell
r = requests.post(f'http://localhost:5000/api/results',json={"spell": "tokenize","data": "I love NLU!
<3"})
# Use the uuid to get your processed data
uuid = r.json()['uuid']

# Get status of processing
r = requests.get(f'http://localhost:5000/api/results/{uuid}/status').json
>>> {'status': {'code': 'success', 'message': None}}

# Get results
r = requests.get(f'http://localhost:5000/api/results/{uuid}').json()
>>> {'sentence': {'0': ['I love NLU! <3']}, 'document': {'0': 'I love NLU! <3'}, 'token': {'0': ['I',
'love', 'NLU', '!', '<3']}}
```

https://nlp.johnsnowlabs.com/docs/en/nlp_server/nlp_server

Thank you.


christian@JohnSnowLabs.com


@ckl_it


In/Christian-Kasim-Loan

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John Snow LABS

How to find your way in Spark NLP Universe?

A guidebook that contains all the helpful blogs, GitHub repos, documents, and demos of **Spark NLP**.

The Table of Contents

- Models Hub
- Streamlit Demos
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Models Hub

- Main Page
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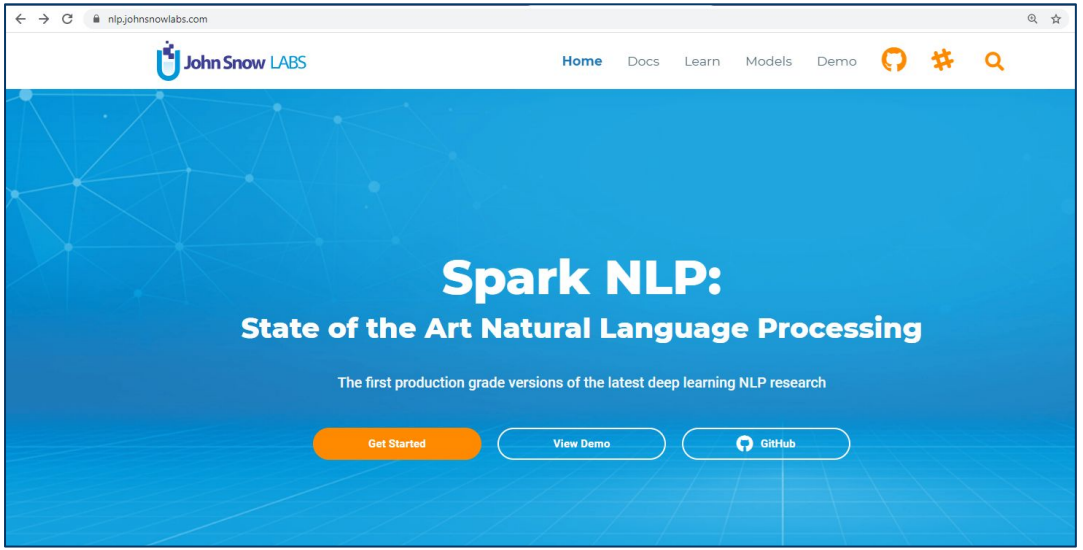
  - Colab Notebooks
  - Sample Code Snippets
  - Benchmarking (Metrics)



Main Page

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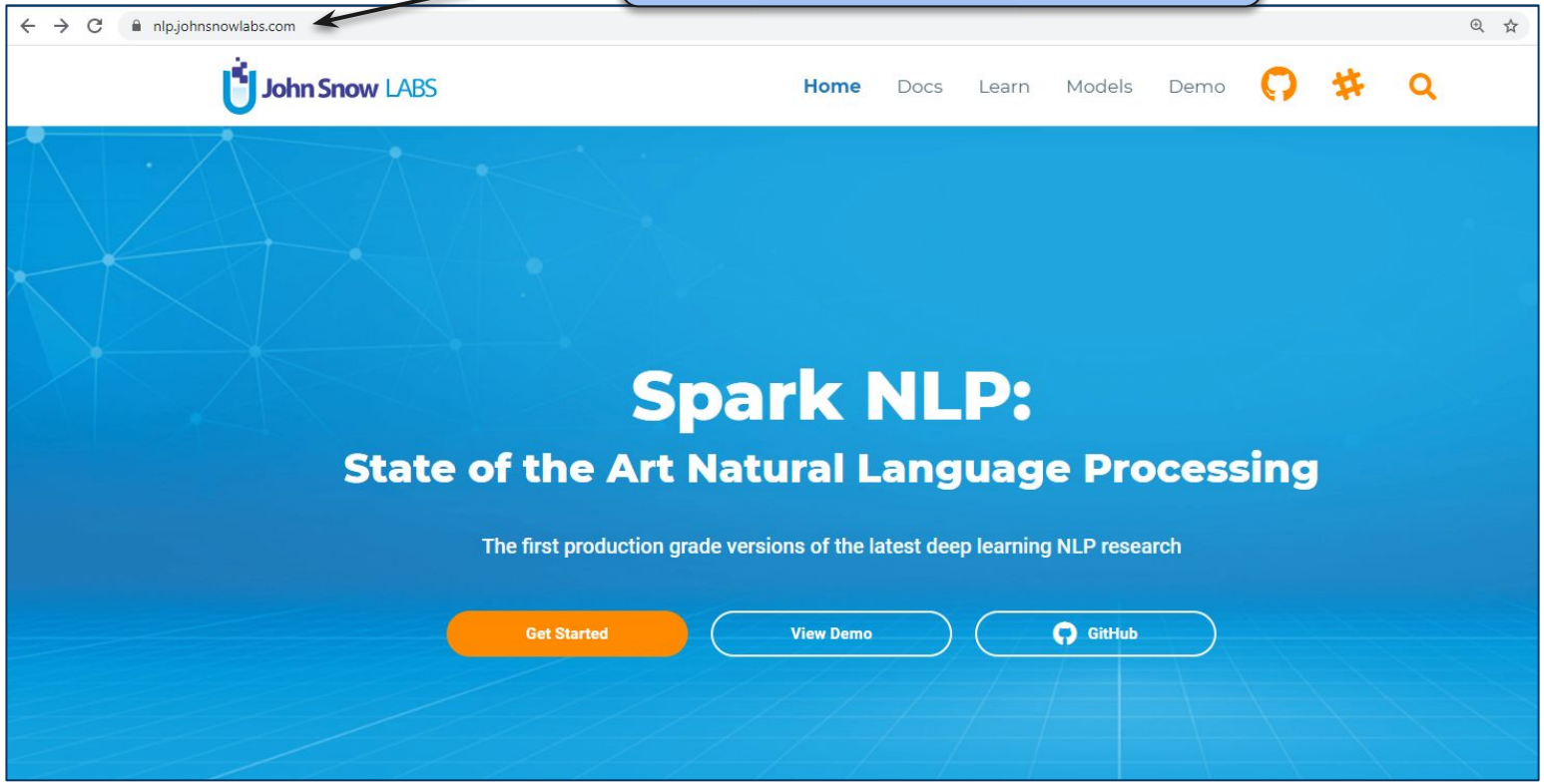

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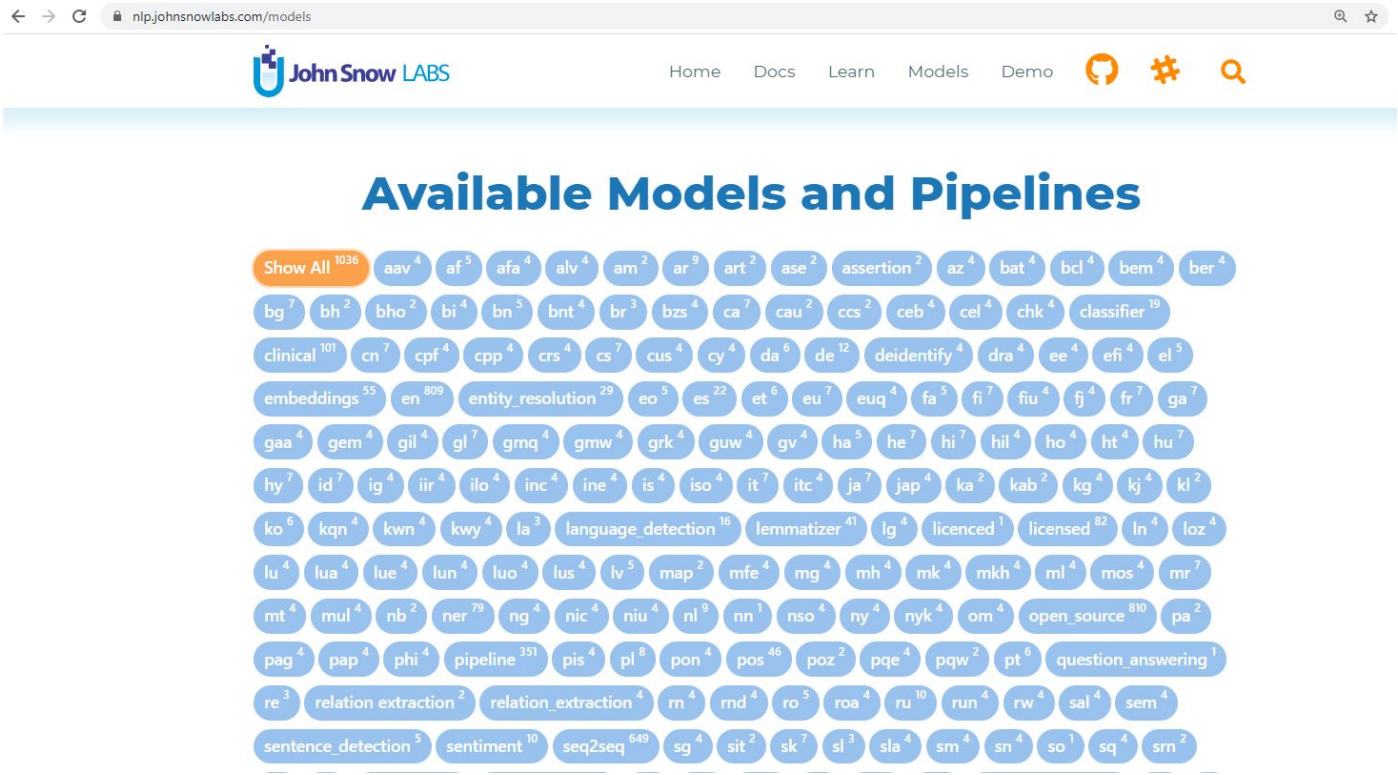
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gl 7
gmq 4
gmw 4
grk 4
guw 4
gv 4
ha 5
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hi 7
hil 4
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roa 4
ru 10
run 4
rw 4
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sentence_detection 5
sentiment 10
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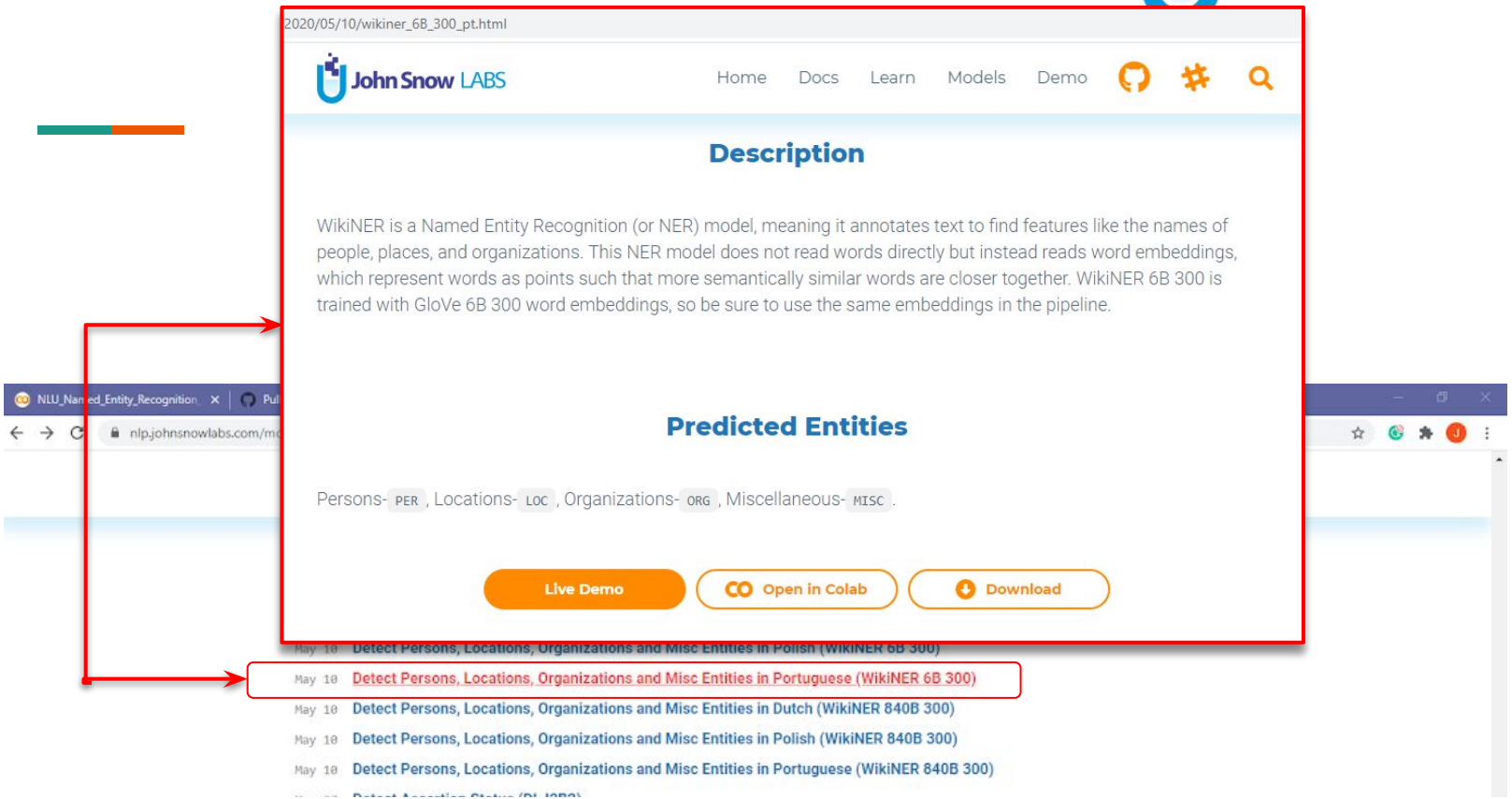
sk 7
sl 3
sla 4
sm 4
sn 4
so 1
sq 4
srn 2

Description Page



How to Use

How to use

Python | Scala

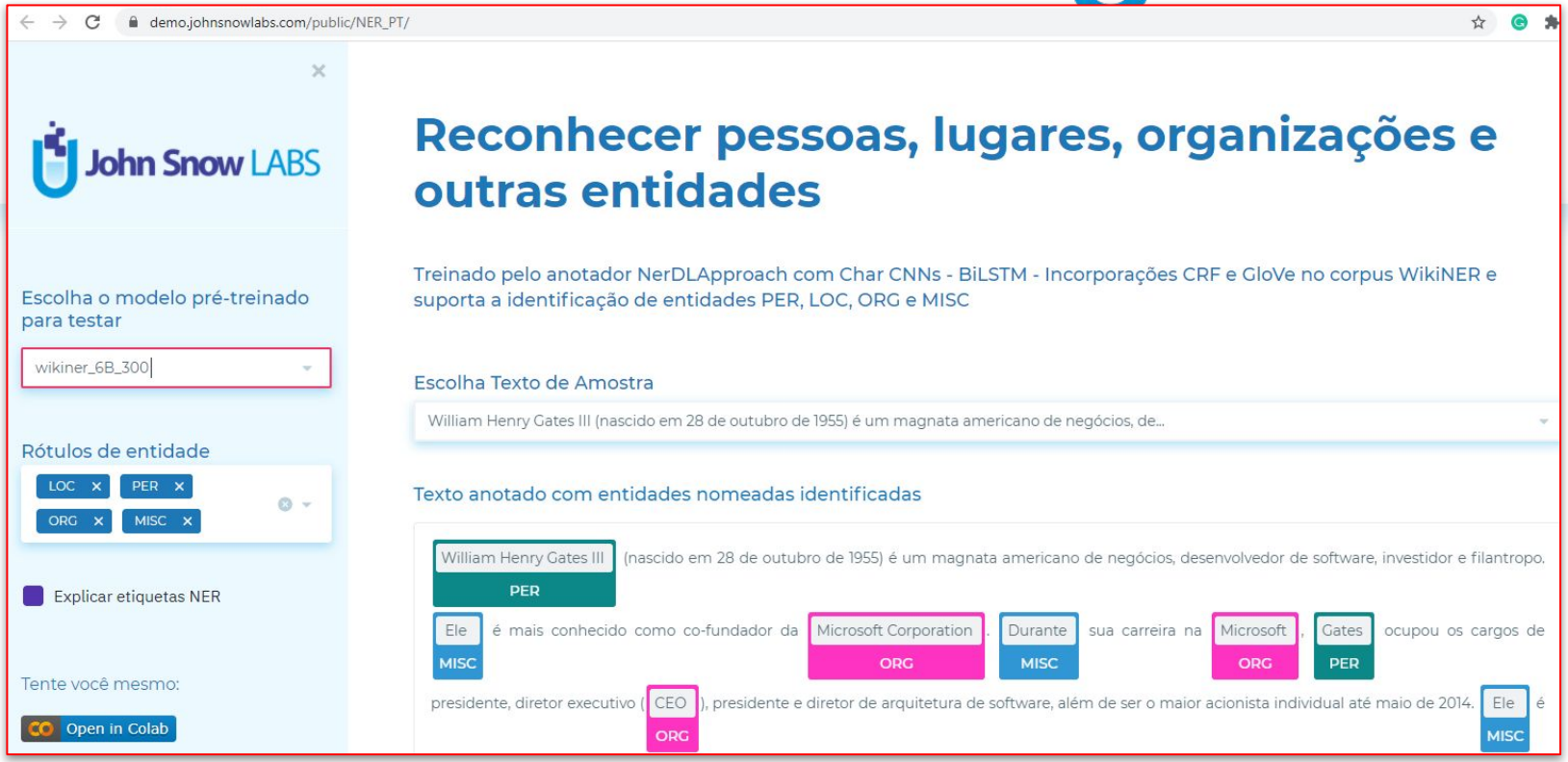
```
...
val ner_model = NerDLModel.pretrained("wikiner_6B_300", "pt")
        .setInputCols(Array("document", "token", "embeddings"))
        .setOutputCol("ner")
...
val pipeline = new Pipeline().setStages(Array(document_assembler, sentence_detector, tokenizer, embeddings, ner_model, ner
val result = pipeline.fit(Seq.empty["William Henry Gates III (nascido em 28 de outubro de 1955) é um magnata americano de
```

How to

Python | Scala

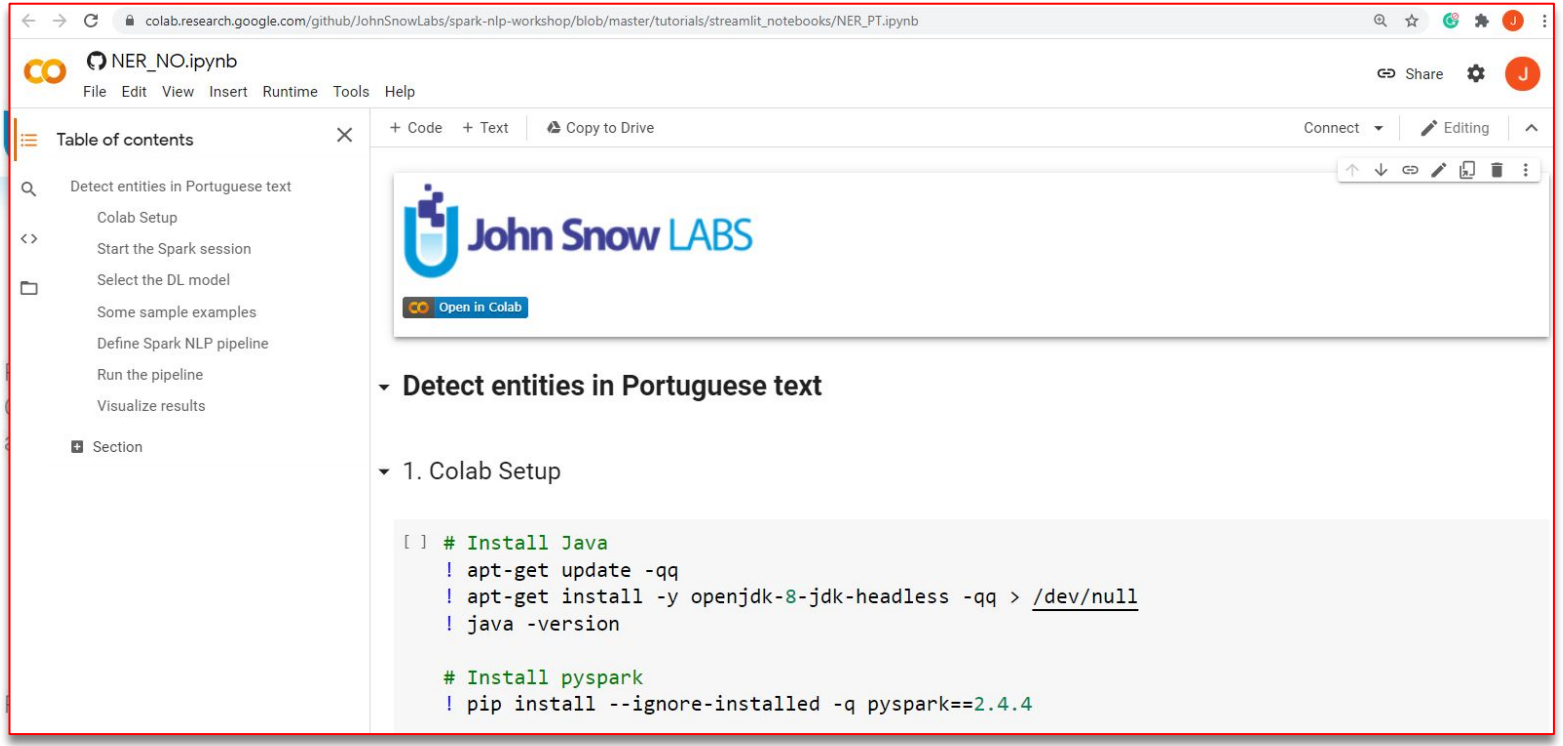
```
...
ner_model = NerDLModel.pretrained("wikiner_6B_300", "pt") \
        .setInputCols(["document", "token", "embeddings"]) \
        .setOutputCol("ner")
...
nlp_pipeline = Pipeline(stages=[document_assembler, sentence_detector, tokenizer, embeddings, ner_model, ner_converter])
pipeline_model = nlp_pipeline.fit(spark.createDataFrame([['']]).toDF('text'))

result = pipeline_model.transform(spark.createDataFrame(pd.DataFrame({'text': ["""William Henry Gates III (nascido em 28 d
```

Demo Page



Live Demo | Open in Colab | Download

Colab Notebooks



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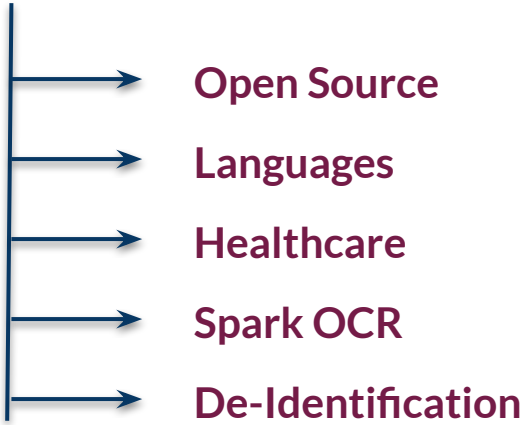
Benchmarking (Metrics)

Benchmarking

```
label    tp      fp      fn      prec            rec             f1
B-LOC    2081    157     142     0.9298481       0.93612236      0.9329747
I-ORG    1292    220     152     0.8544974       0.8947368       0.87415427
I-LOC    293     81      66      0.78342247      0.81615597      0.79945433
I-PER    1578    127     99      0.9255132       0.940966        0.9331757
B-ORG    1846    185     145     0.9089119       0.9271723       0.91795135
B-PER    3043    186     206     0.942397        0.93659586      0.9394875
tp: 10133 fp: 956 fn: 810 labels: 6
Macro-average    prec: 0.890765, rec: 0.9086249, f1: 0.8996063
Micro-average    prec: 0.91378844, rec: 0.9259801, f1: 0.9198439
```

Streamlit Demos



Main Page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State of the Art Natural Language
The first production grade versions of the latest deep learning NLP research
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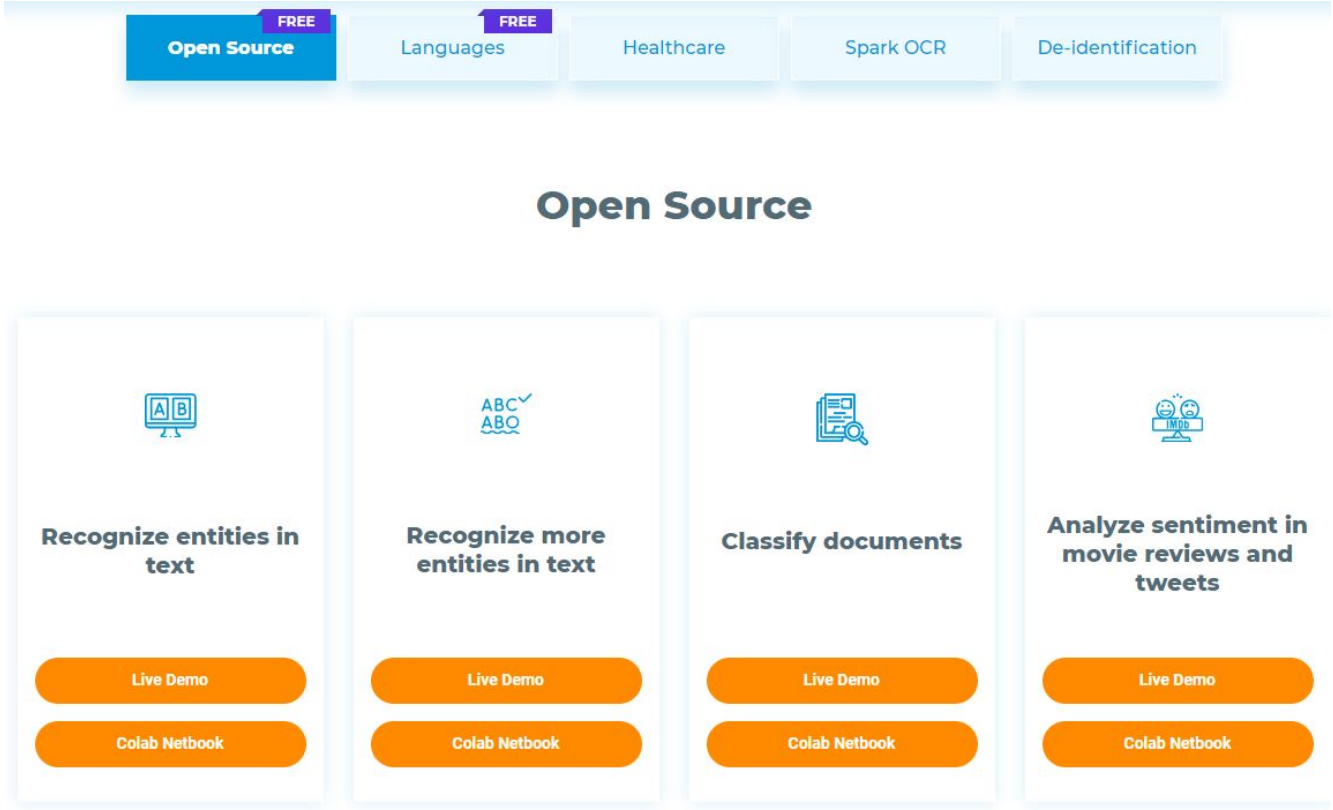
Streamlit Demos

Open Source


FREE
Open Source
FREE
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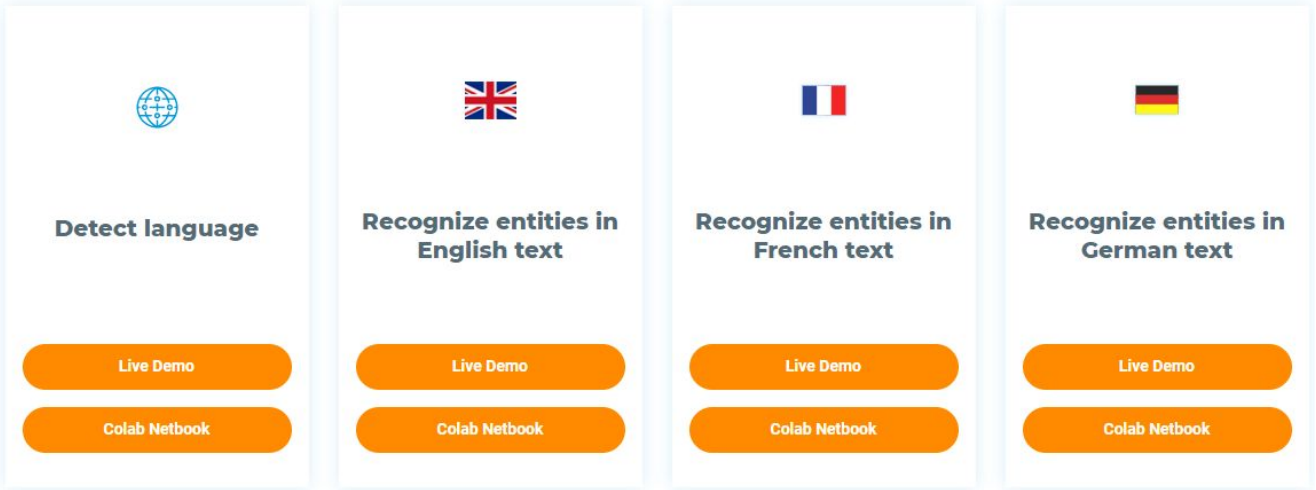
Healthcare
Spark OCR
De-identification
Open Source
Recognize entities in text
Live Demo
Colab Netbook
Recognize more entities in text
Live Demo
Colab Netbook
Classify documents
Live Demo
Colab Netbook
Analyze sentiment in movie reviews and tweets
Live Demo
Colab Netbook

Languages

Languages



Healthcare

Healthcare

Detect signs and symptoms

Live Demo

Colab Netbook

Detect diagnosis and procedures

Live Demo

Colab Netbook

Detect drugs and prescriptions

Live Demo

Colab Netbook

Detect risk factors

Live Demo

Colab Netbook

Spark OCR

Spark OCR

PDF to Text

Live Demo

Colab Netbook

DICOM to Text

Live Demo

Colab Netbook

Image to Text

Live Demo

Colab Netbook

Remove background noise from scanned documents

Live Demo

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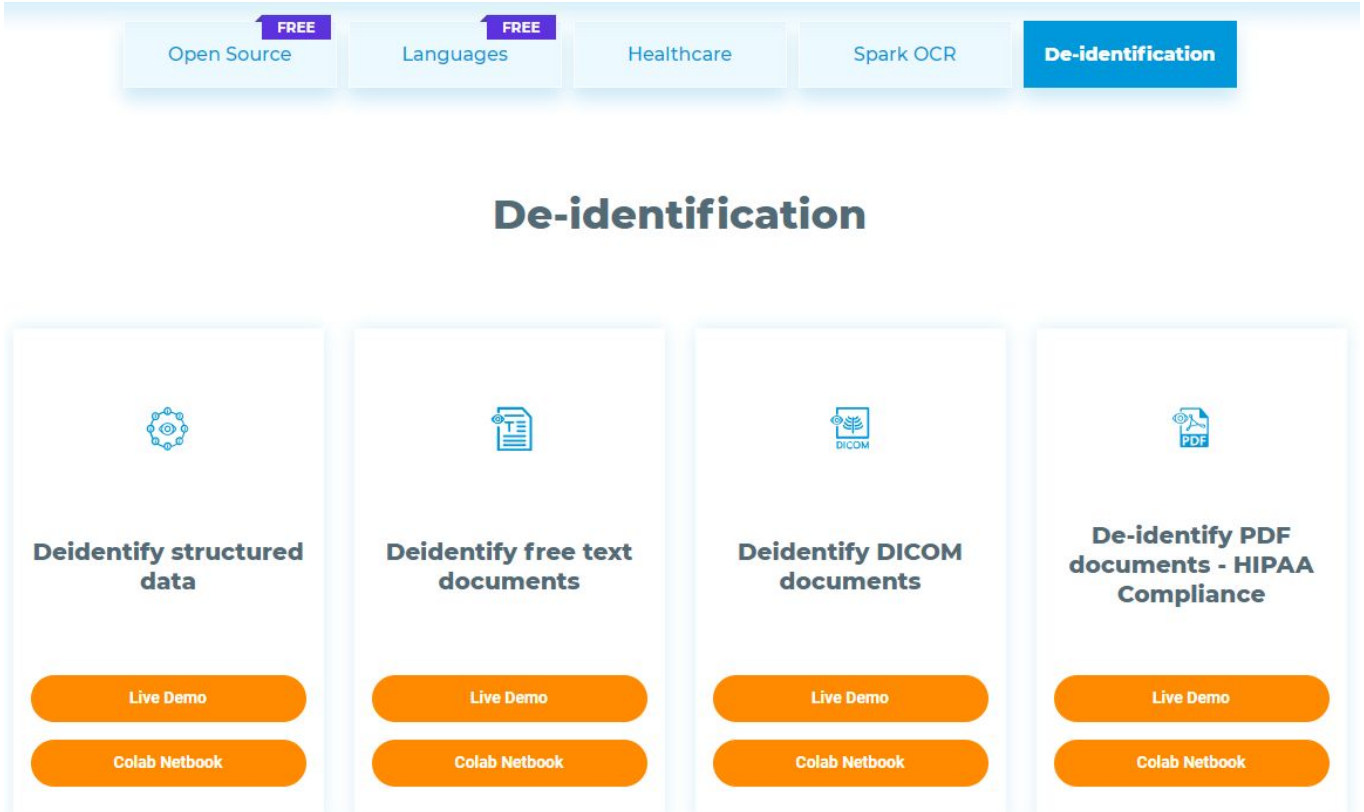
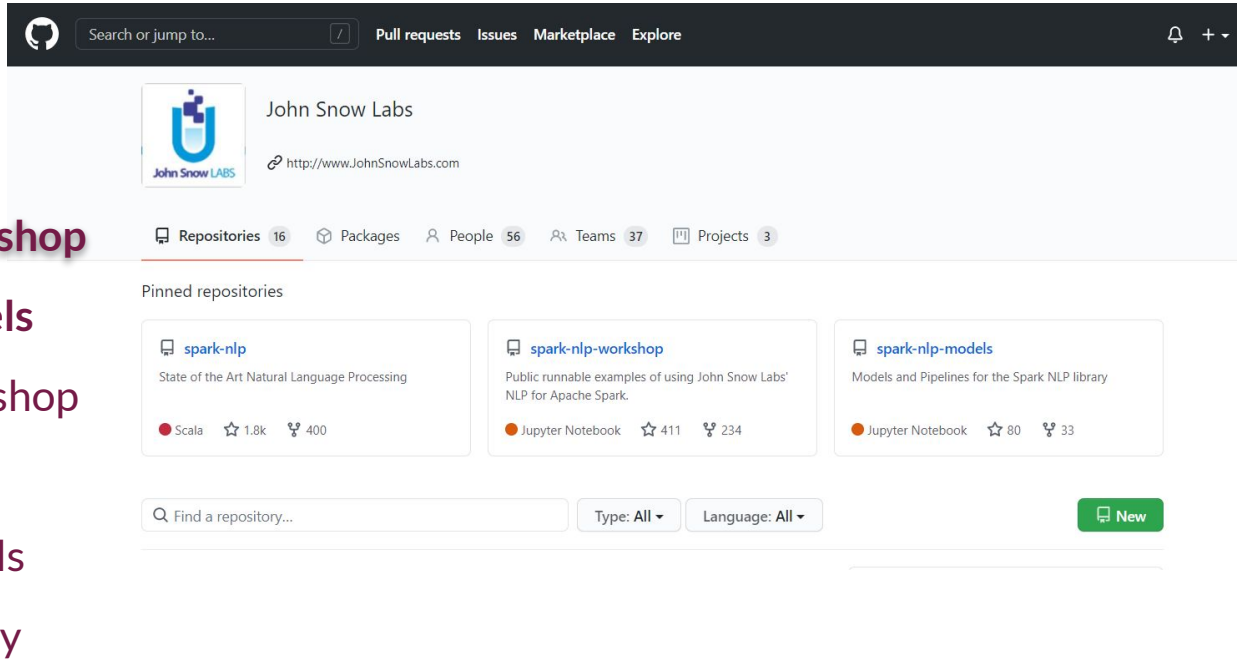
De-Identification

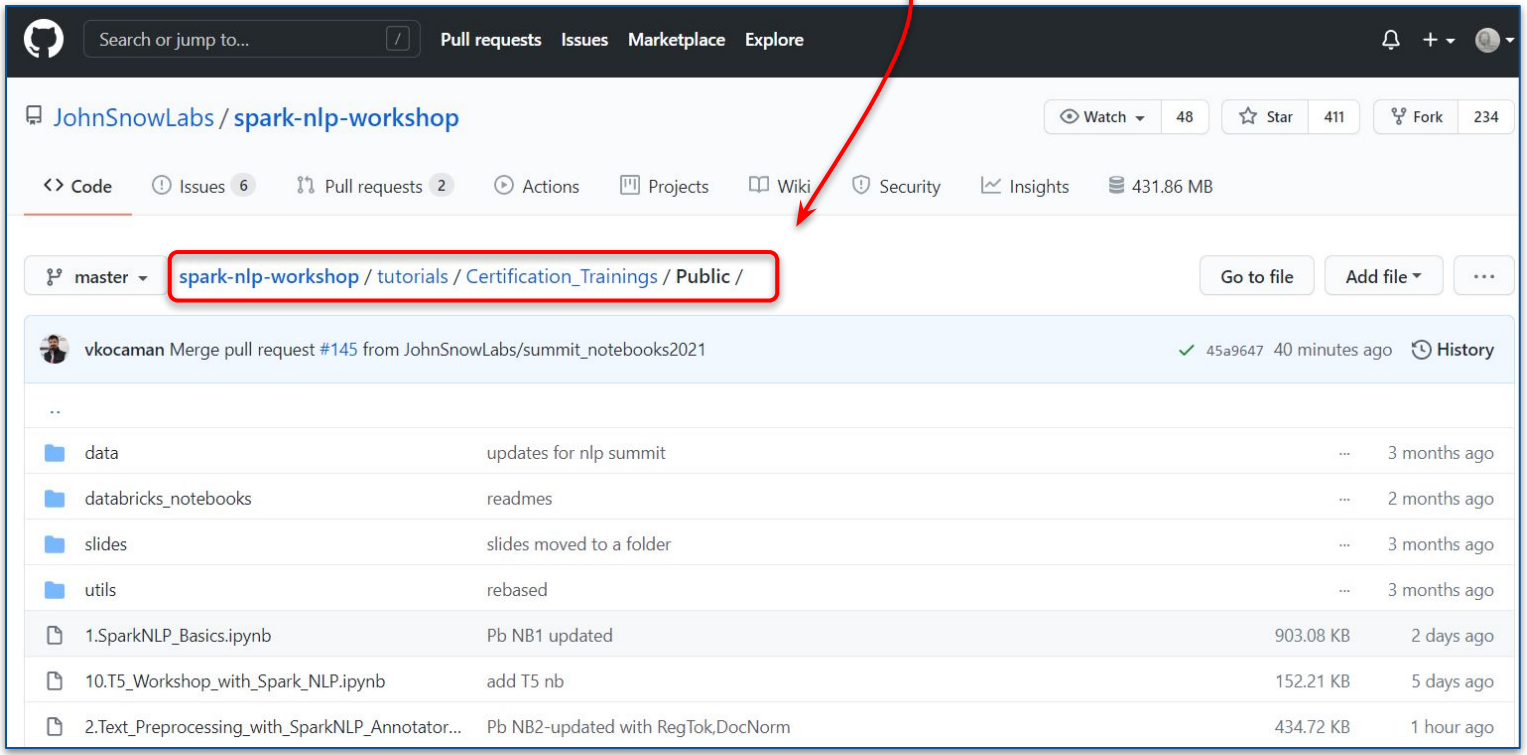


GitHub Repositories

- spark-nlp
- spark-nlp-workshop
- spark-nlp-models
- spark-ocr-workshop
- nlu
- spark-nlp-models
- spark-nlp-display

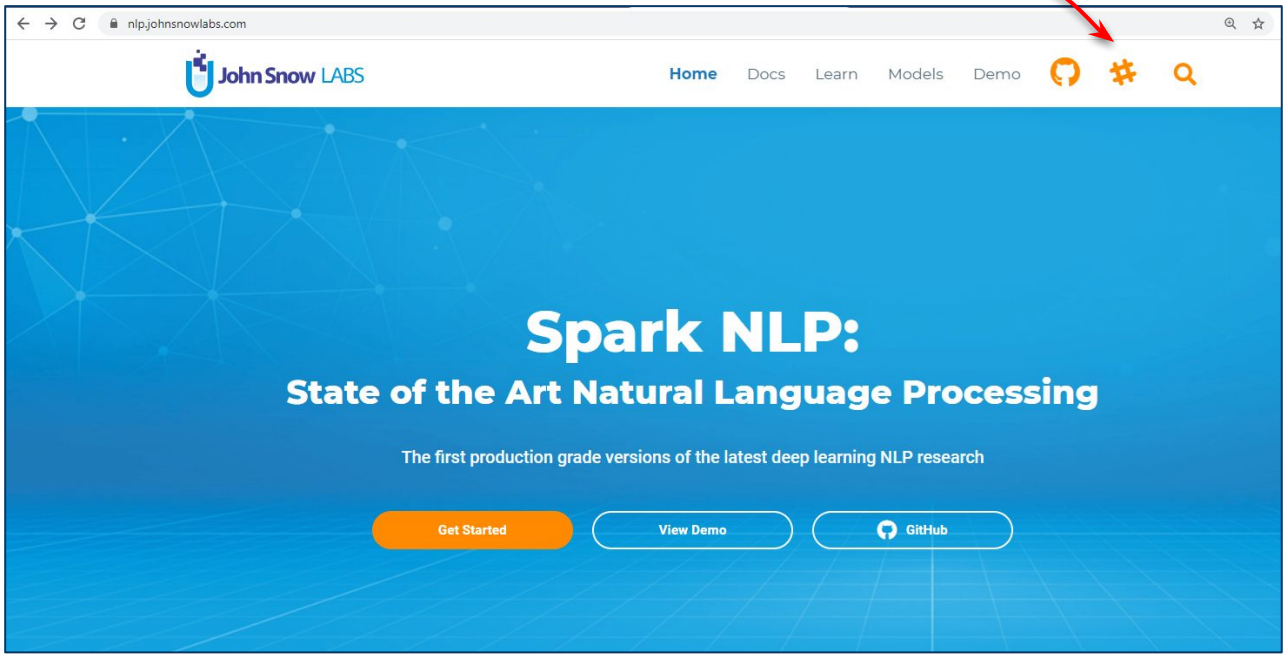


Certification Training



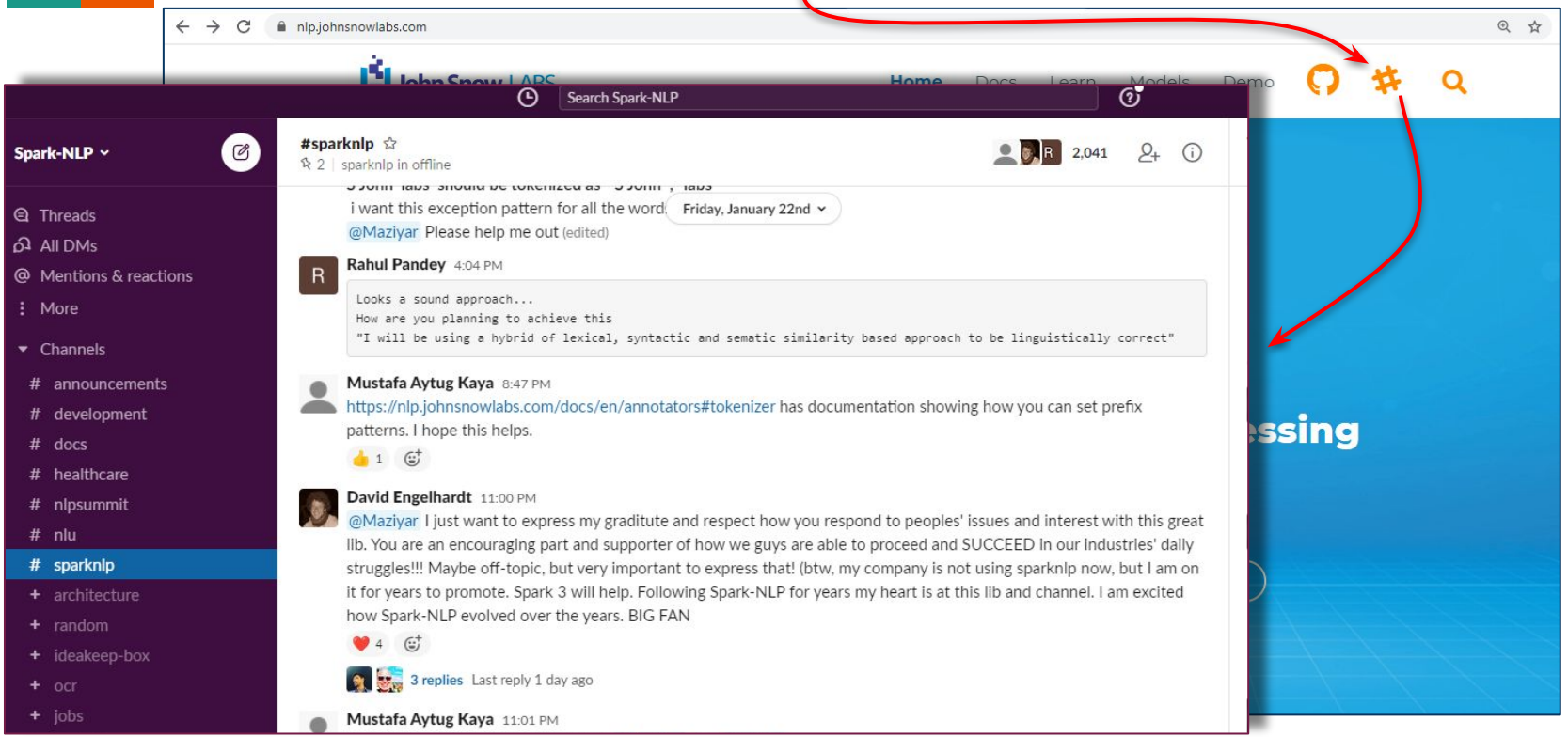
Spark-NLP Slack Channels

- #sparknlp
- #healthcare
- #nlu
- #ocr
- #jobs

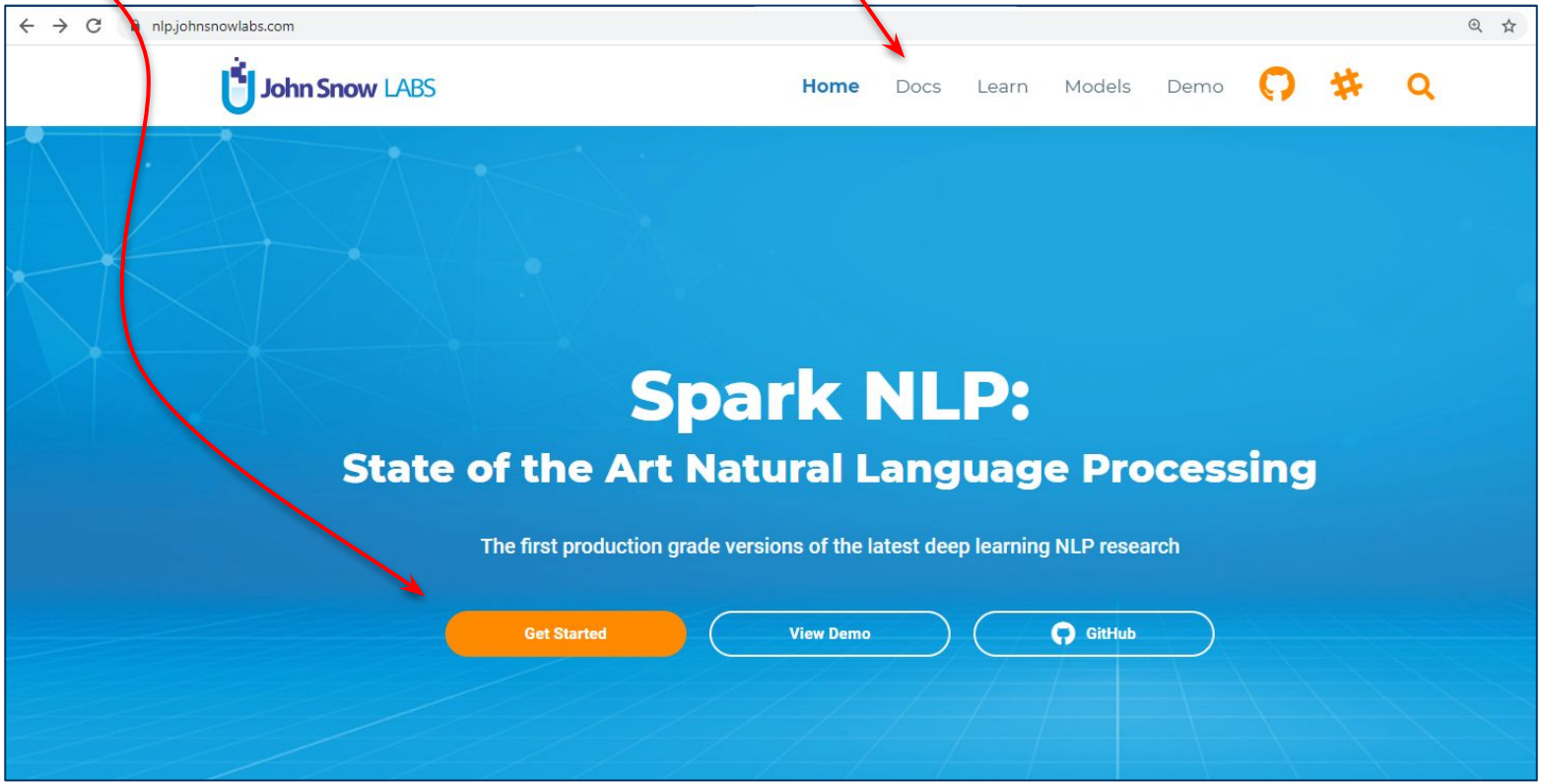


Spark-NLP Slack Channels

`spark-nlp.slack.com`



Docs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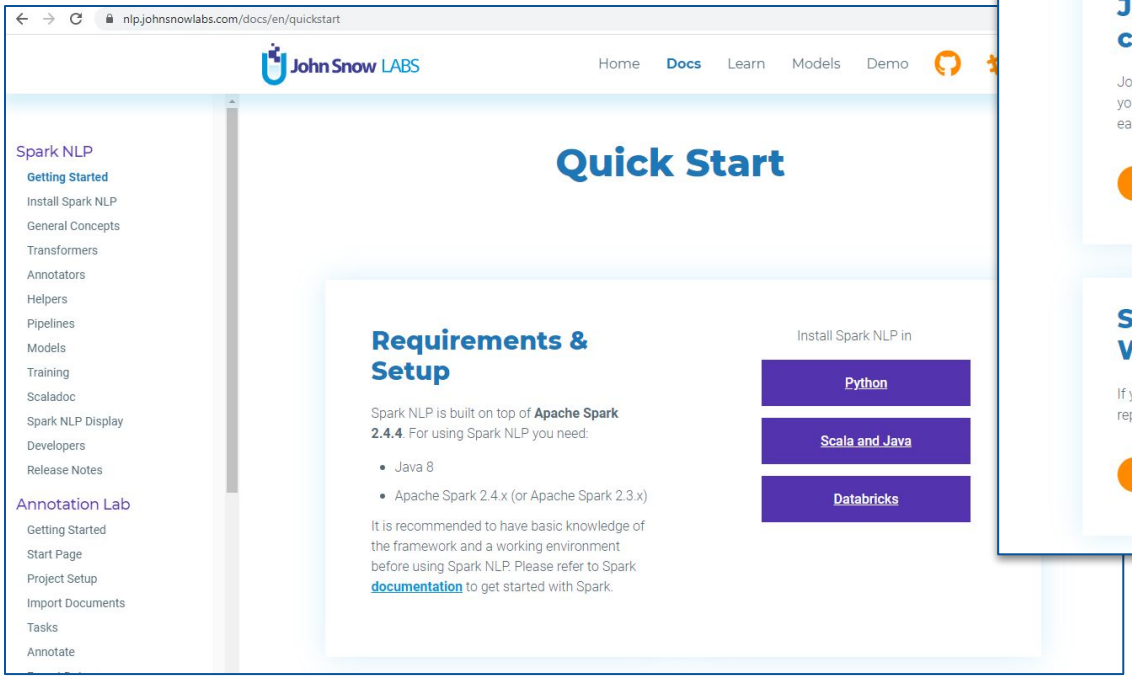
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Start Page
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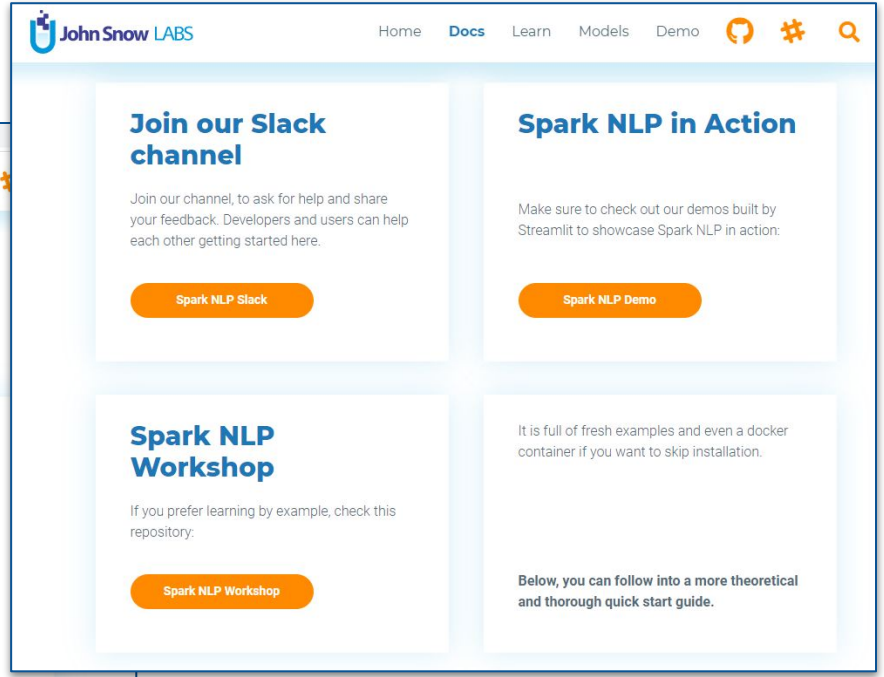
Requirements & Setup
Spark NLP is built on top of Apache Spark 2.4.4. For using Spark NLP you need:
Java 8
Apache Spark 2.4.x (or Apache Spark 2.3.x)
It is recommended to have basic knowledge of the framework and a working environment before using Spark NLP. Please refer to Spark documentation to get started with Spark.
Install Spark NLP in
Python
Scala and Java
Databricks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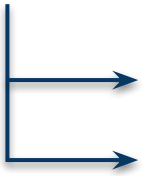
Join our Slack channel
Join our channel, to ask for help and share your feedback. Developers and users can help each other getting started here.
Spark NLP Slack
Spark NLP in Action
Make sure to check out our demos built by Streamlit to showcase Spark NLP in action:
Spark NLP Demo
Spark NLP Workshop
If you prefer learning by example, check this repository:
Spark NLP Workshop
It is full of fresh examples and even a docker container if you want to skip installation.
Below, you can follow into a more theoretical and thorough quick start guide.

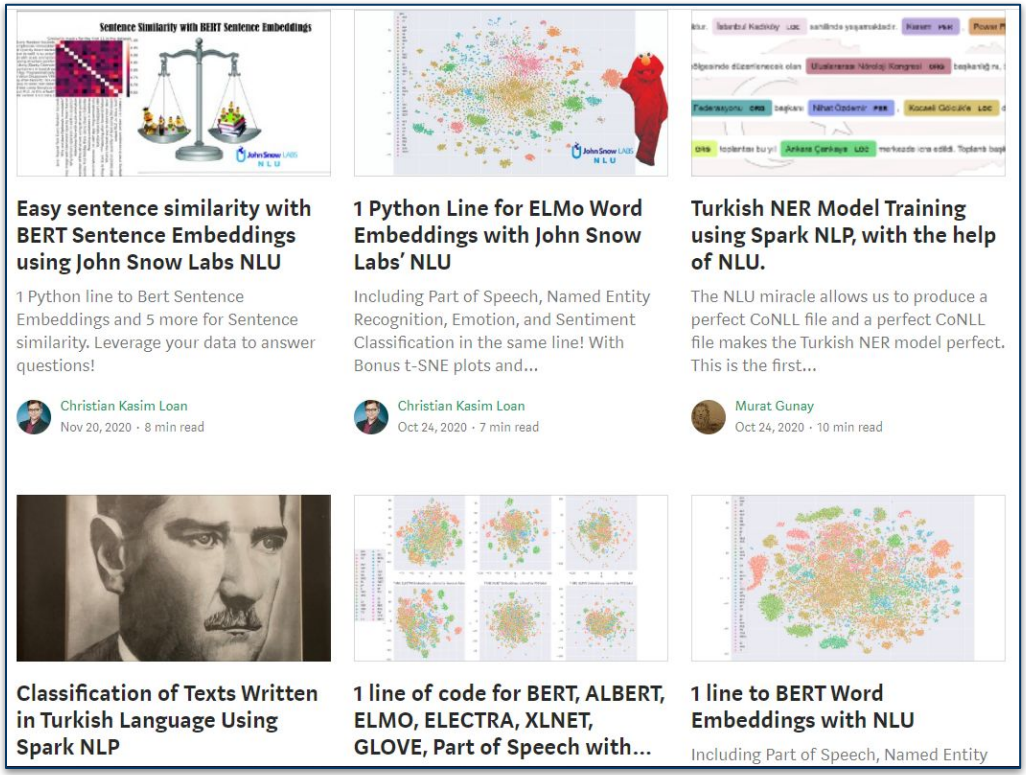
Articles-Blog Posts



Medium-Spark NLP (`https://medium.com/spark-nlp`)

Blog Posts

Medium-Spark NLP



Medium

Blog Posts

an intro article for Spark NLP:

https://towardsdatascience.com/introduction-to-spark-nlp-foundations-and-basic-components-part-i-c83b7629ed59

How to start Spark NLP in 2 weeks:

https://towardsdatascience.com/how-to-get-started-with-sparknlp-in-2-weeks-cb47b2ba994d

https://towardsdatascience.com/how-to-wrap-your-head-around-spark-nlp-a6f6a968b7e8

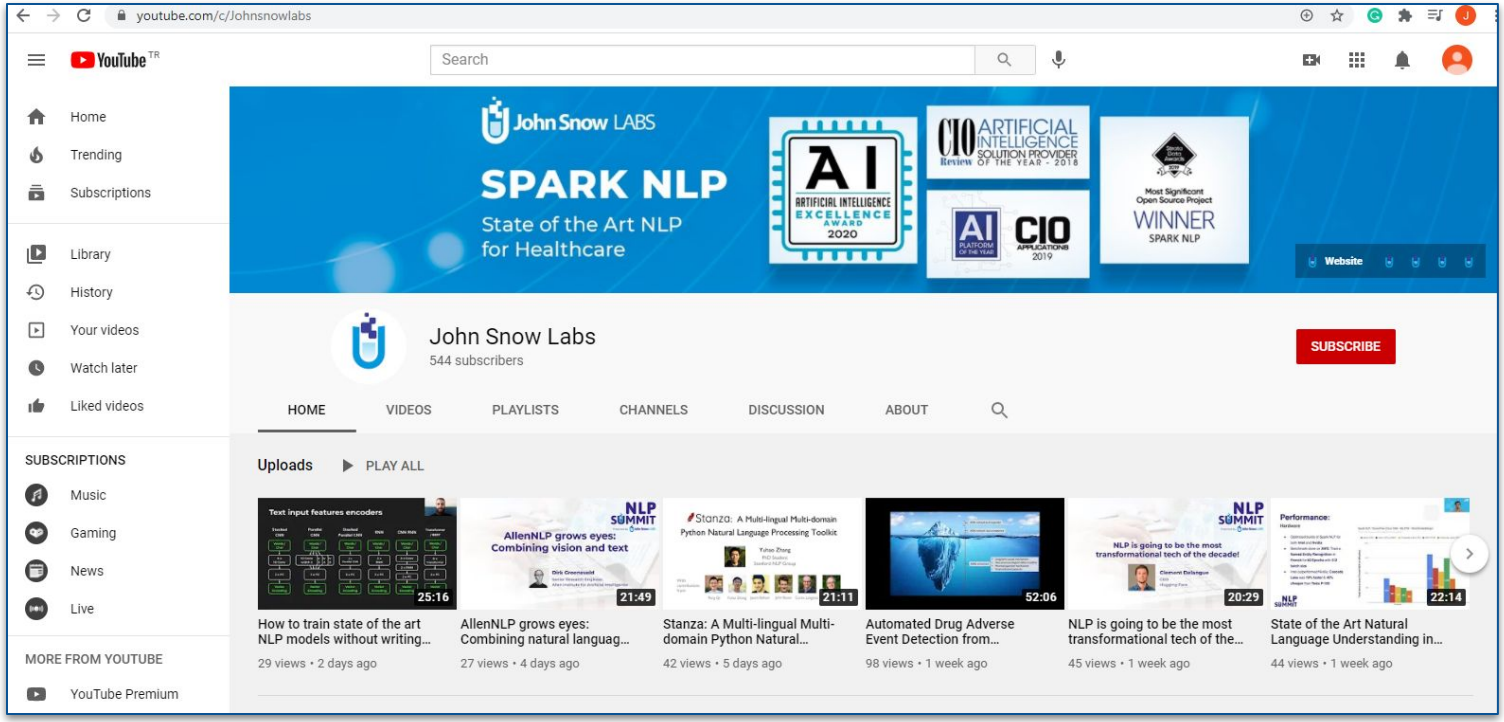
Article for NER and text classification in Spark NLP

https://towardsdatascience.com/named-entity-recognition-ner-with-bert-in-spark-nlp-874df20d1d77

https://medium.com/spark-nlp/named-entity-recognition-for-healthcare-with-sparknlp-nerdl-and-nercrf-a7751b6ad571

https://towardsdatascience.com/text-classification-in-spark-nlp-with-bert-and-universal-sentence-encoders-e644d618ca32

Youtube Channel



```
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```
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 Annotation(chunk, 64, 115, Main Street            OSBORNE, MATTISON  Oroville, {'entity': 'LOCATION', 'sentence': '0', 'chu
nk': '1'}),
 Annotation(chunk, 118, 201, AL  89389                    48423663  (468) 429-7459                    06/14/2080, {'entity':
'LOCATION', 'sentence': '0', 'chunk': '2'}),
 Annotation(chunk, 254, 264, 71-year-old, {'entity': 'AGE', 'sentence': '0', 'chunk': '3'}),
 Annotation(chunk, 1109, 1116, February, {'entity': 'DATE', 'sentence': '0', 'chunk': '4'}),
 Annotation(chunk, 1761, 1772, Willie Knapp, {'entity': 'NAME', 'sentence': '0', 'chunk': '5'}),
 Annotation(chunk, 1856, 1863, 06/17/80, {'entity': 'DATE', 'sentence': '0', 'chunk': '6'}),
 Annotation(chunk, 1870, 1877, 06/17/80, {'entity': 'DATE', 'sentence': '0', 'chunk': '7'}),
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```
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```
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