Day 1: July 17, 2023 – 9:00 to 13:00 PST
Day 2: July 18, 2023 – 9:00 to 13:00 PST

Training Location: Online
Price: $395

Day 1: July 19, 2023 – 9:00 to 13:00 PST
Day 2: July 20, 2023 – 9:00 to 13:00 PST

Training Location: Online
Price: $395

4 days, 16 hrs live training
State-Of-The-Art NLP

Certification exams in 2 weeks

John Snow LABS

Spark NLP for Data Scientists

July 17 & 18, 2023

Meryem Vildan Sarıkaya
meryem@johnsnowlabs.com

Halil Saglamlar
halil@johnsnowlabs.com

David Amore Cecchini
cecchini@johnsnowlabs.com

Gokhan TURER
gokhan@johnsnowlabs.com

Welcome - We have a lot of things ahead of us

Day-1	50 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	- Showcase of the 10000+ pretrained Models for 300+ languages in Spark NLP
		Break
	50 min	- Showcase of the 10000+ pretrained Models for 300+ languages in Spark NLP - Train Named Entity Recognizers (NER)

Welcome - We have a lot of things ahead of us

Day-2	50 min	- Train Text Classifiers - Upload models to the Models Hub
	10 min	Break
	50 min	- Spell Checking - Keyword Extraction with YAKE - Rule-based Entity Recognition with EntityRuler - Graph triplet extraction
	10 min	Break
	50 min	- Token Classification with Transformers - Sequence Classification with Transformers - Image Classification with ViT - Speech to Text with Wav2Vec2
	10 min	Break
	50 min	- Table Question Answering with TAPAS - Question Answering, Summarization and other T5 applications - Multilingual NLP - Train only on English data and predict for 100+ languages

Session 1 (Day 1)

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

Spark NLP
for Data Scientists

John Snow LABS

Resources

CODE:

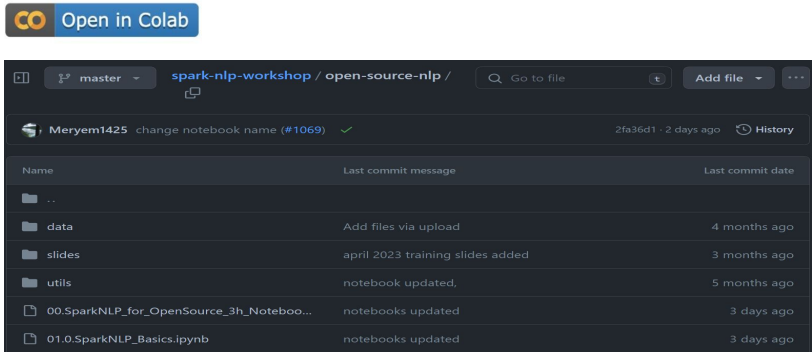
- https://github.com/JohnSnowLabs/spark-nlp-workshop/tree/master/open-source-nlp

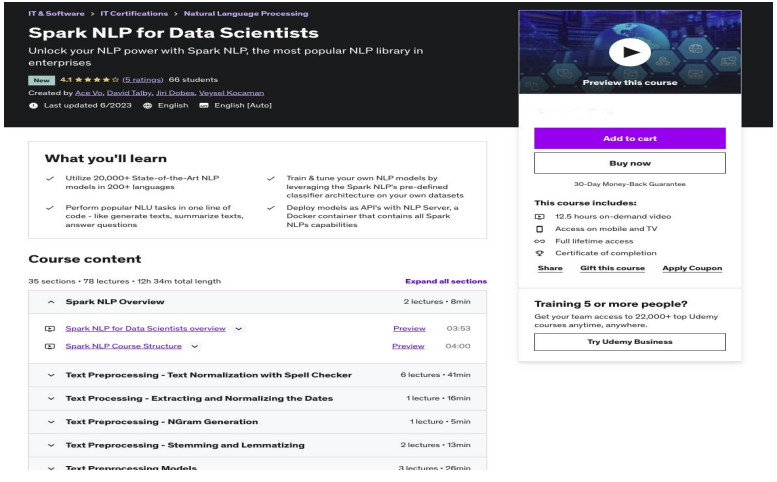
BOOKMARK:

- https://sparknlp.org/
- https://sparknlp.org/docs/en/quickstart
- https://sparknlp.org/api/python/reference/index.html
- Spark-nlp.slack.com

MOOC:

- https://www.udemy.com/course/spark-nlp-for-data-scientists/
- https://github.com/JohnSnowLabs/spark-nlp-workshop/





Introducing Spark NLP

Total downloads

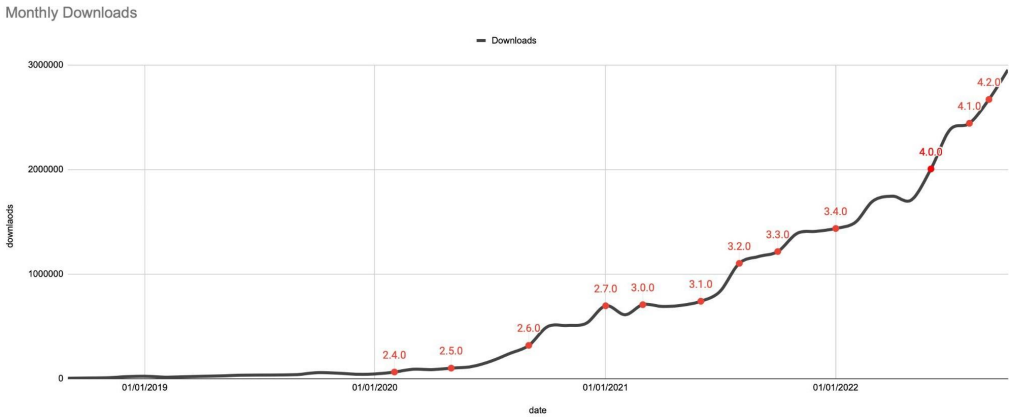
54,315,590

Total downloads - 30 days

2,848,599

Total downloads - 7 days

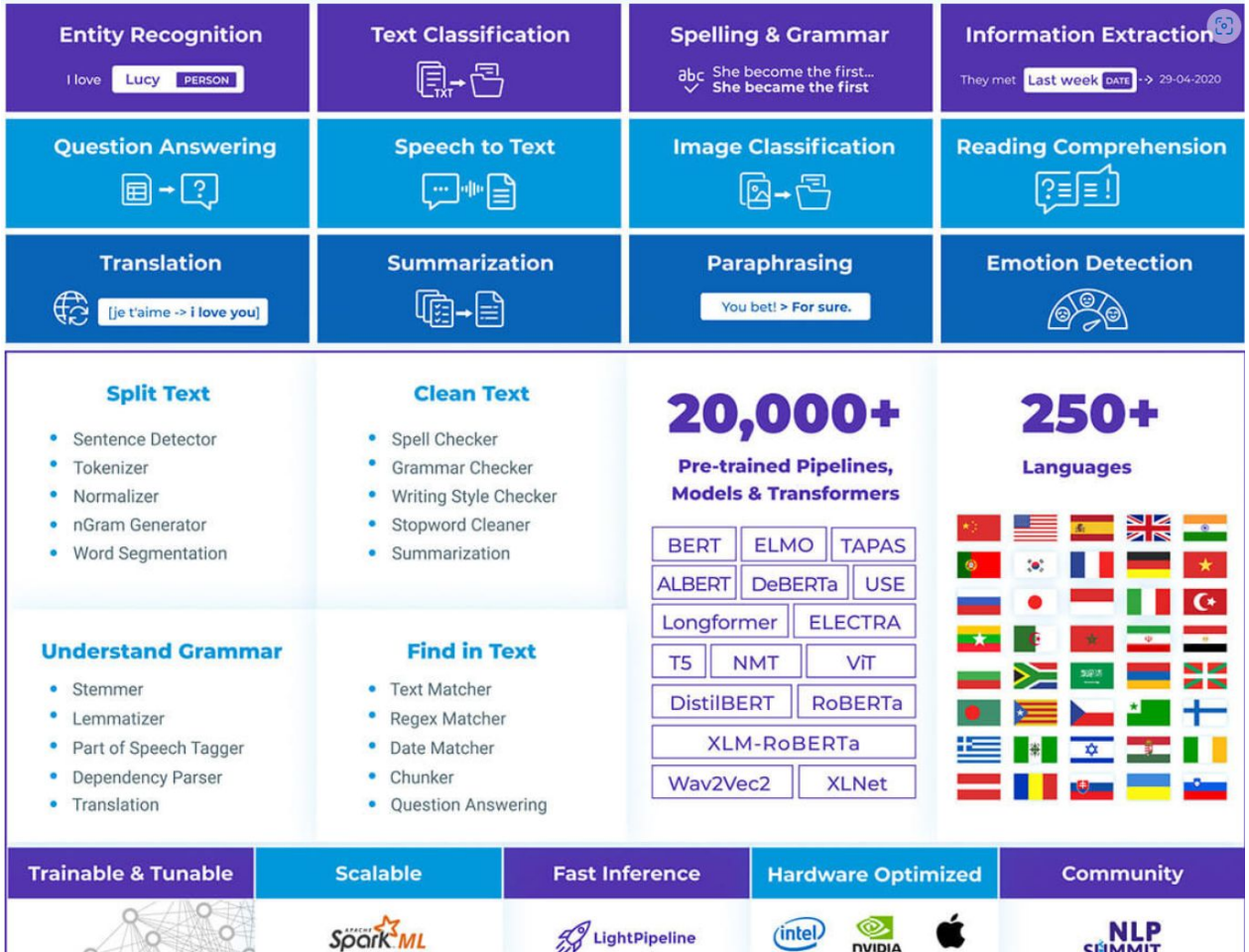
653,272



Spark NLP is an open-source natural language processing library, built on top of **Apache Spark** and **Spark ML**. (first release: July 2017)

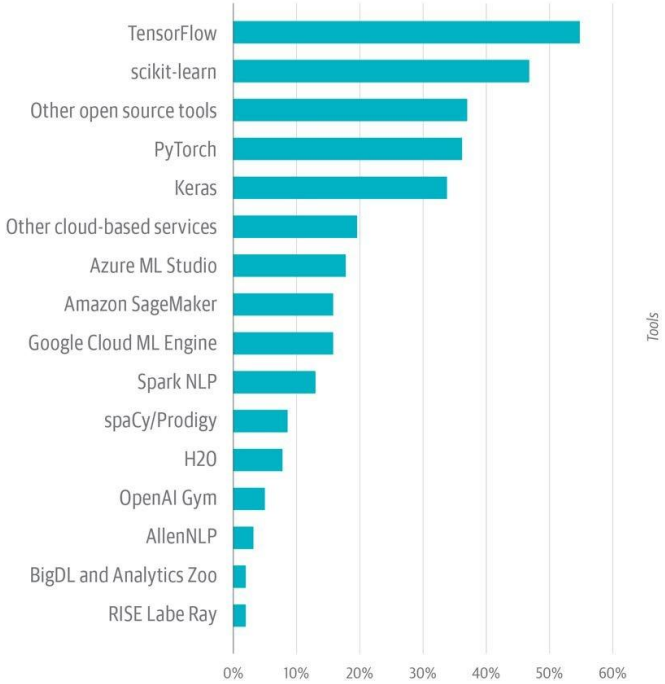
- A single unified solution for all your NLP needs
- Take advantage of transfer learning and implementing the latest and greatest **SOTA** algorithms and models in NLP research
- The most widely used NLP library in industry (5 years in a row)
- The most scalable, accurate and fastest library in NLP history
- 121 total releases, every two weeks for the past years

Spark NLP Modules

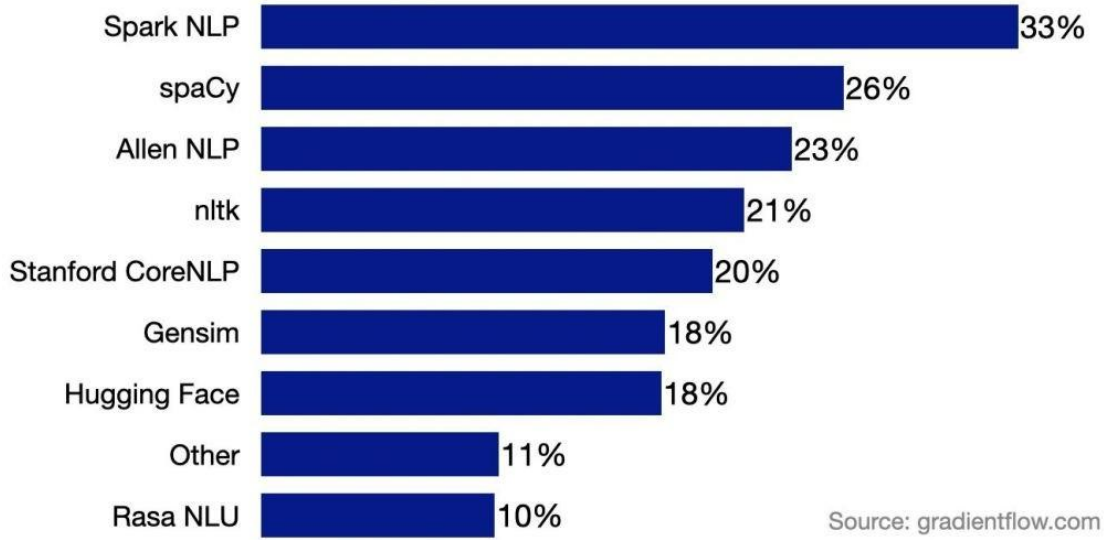


Spark NLP in Industry

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 2021

TRUSTED BY


Microsoft


Google


amazon


intel


IBM


databricks


verizon


indeed


CapitalOne


viacom


McKESSON


MERCK


Roche


selectdata


UiPath
Reboot Work.


ASCO
CANCER·LINQ
DISCOVERY


cnrs


Imperial College
London


Georgia
Tech


STANFORD
UNIVERSITY

Biomedical Named Entity Recognition at Scale

Veysel Kocaman
John Snow Labs Inc.
16192 Coastal Highway
Lewes, DE , USA 19958
veysel@johnsnowlabs.com

***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

Veysel Kocaman, David Talby

John Snow Labs Inc.
16192 Coastal Highway
Lewes, DE , USA 19958
eysel, david}@johnsnowlabs.com

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

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

Abstract

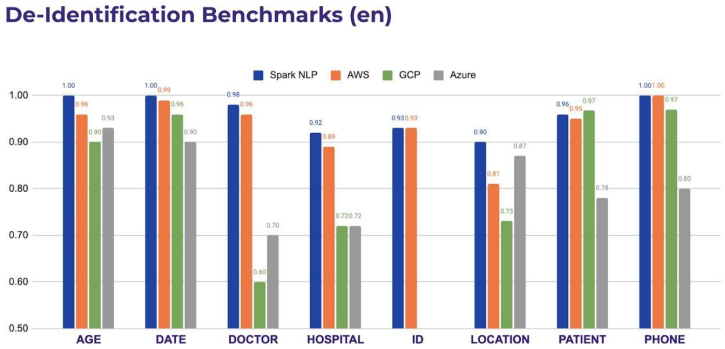
Following the global COVID-19 pandemic, the number of scientific papers studying the virus has grown massively, leading to increased interest in automated literate review. We present a clinical text mining system that improves on previous efforts in three ways. First, it can recognize over 100 different 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.

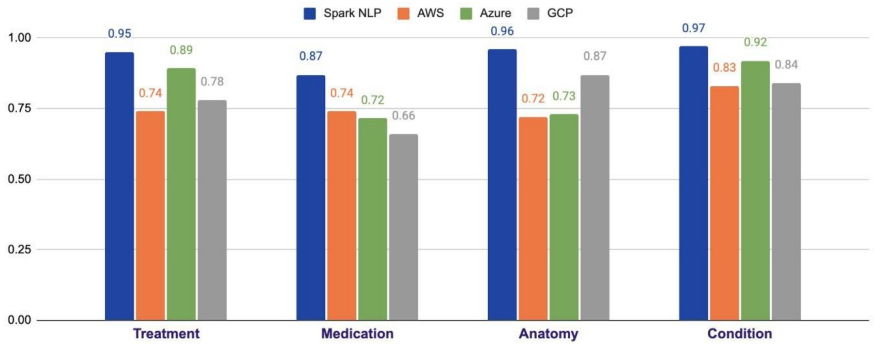
be found in structured fields for which values are inputted electronically (e.g. laboratory test orders or results) (Liede et al. 2015) but most of the time information in these records is unstructured making it largely inaccessible for statistical analysis (Murdoch and Detsky 2013). These records include 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).

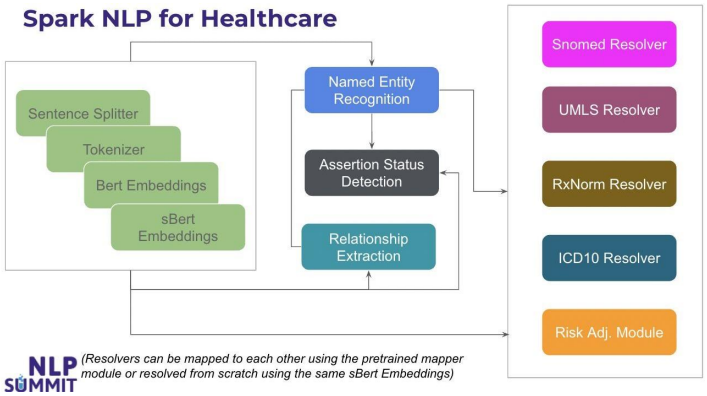
A primary building block in such text mining systems is named entity recognition (NER) - which is regarded as a critical precursor for question answering, topic modelling, information retrieval, etc (Yadav and Bethard 2019). In the medical domain, NER recognizes the first meaningful chunks out of a clinical 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

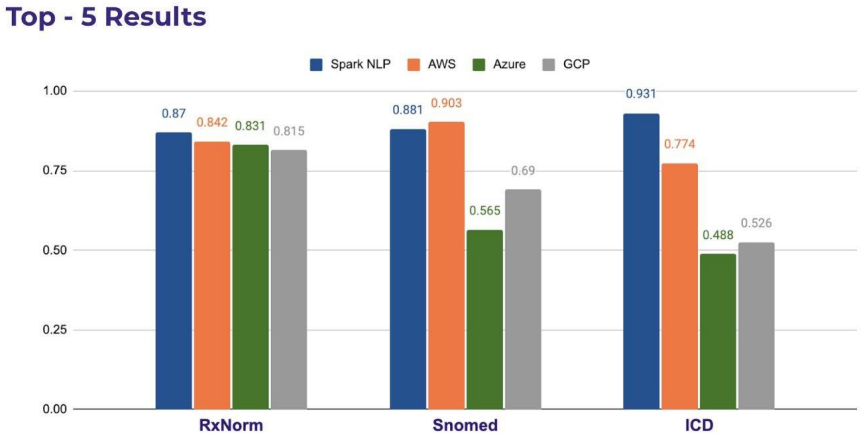
Peer-reviewed papers on
Spark NLP NER

Most Accurate in the Industry









[Spark NLP vs Commercial healthcare NLP Solutions Benchmark]

Introducing Spark NLP

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.

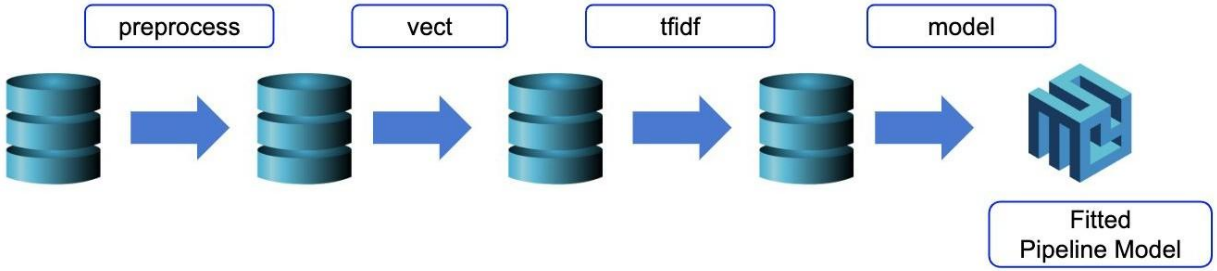
Faster inference

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

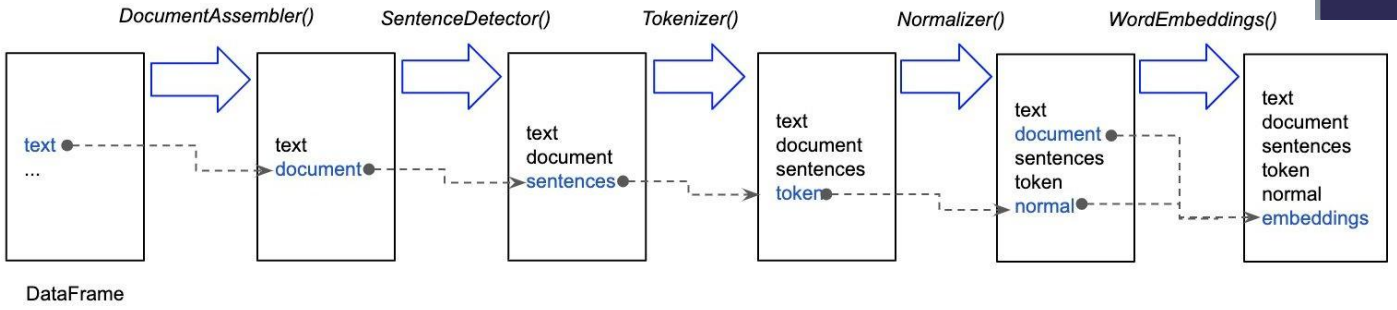
LightPipelines are Spark ML pipelines converted into a single machine but multithreaded task, becoming more than 10x times faster for smaller amounts of data (small is relative, but 50k sentences is roughly a good maximum).

Introducing Spark NLP

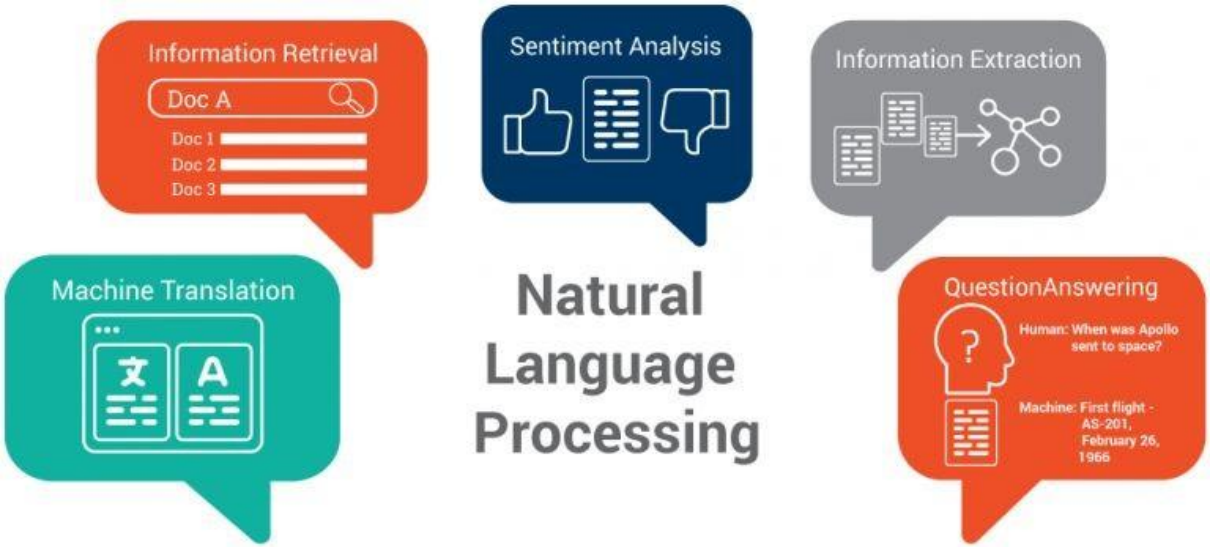
Pipeline of annotators




```
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)
```

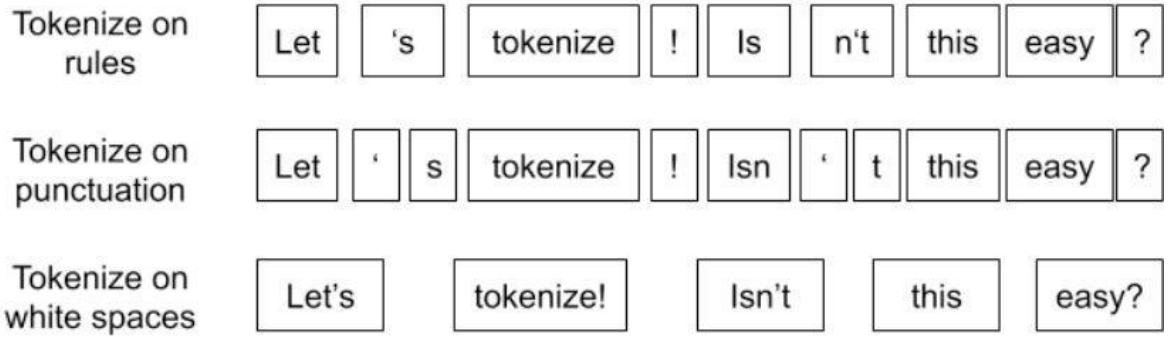


NLP Basics


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

NLP Basics

Tokenization



- First step in NLP pipelines, raw text is broken down into smaller, more manageable pieces. Without tokenization, NLP models would have to process the text as one large unit.
- Many other tokenization methods (character, sub-word, sentence).

Pre-Processing

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.

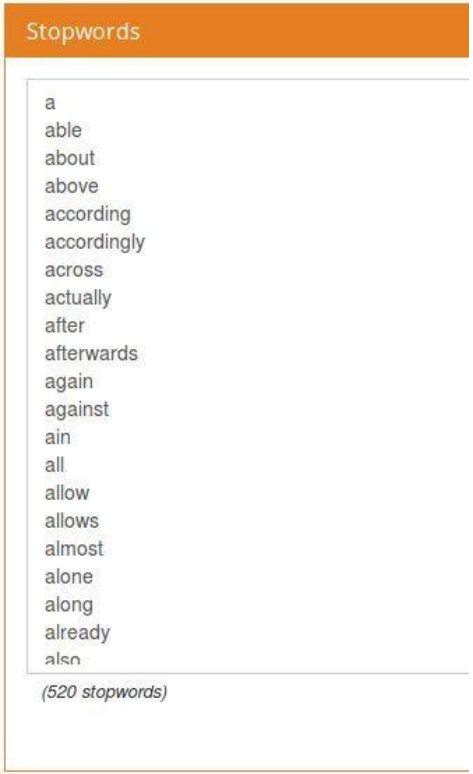
Pre-Processing

NLP Basics

Stopword Removal

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 are considered insignificant in this case.

Pre-Processing

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

Pre-Processing

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

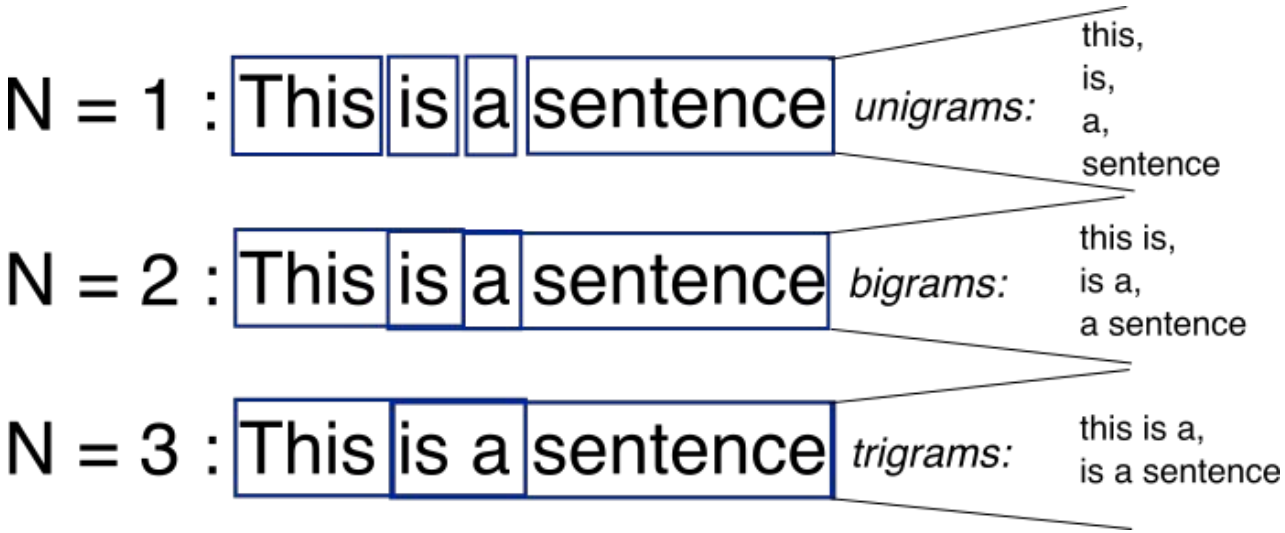
Normalization

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:

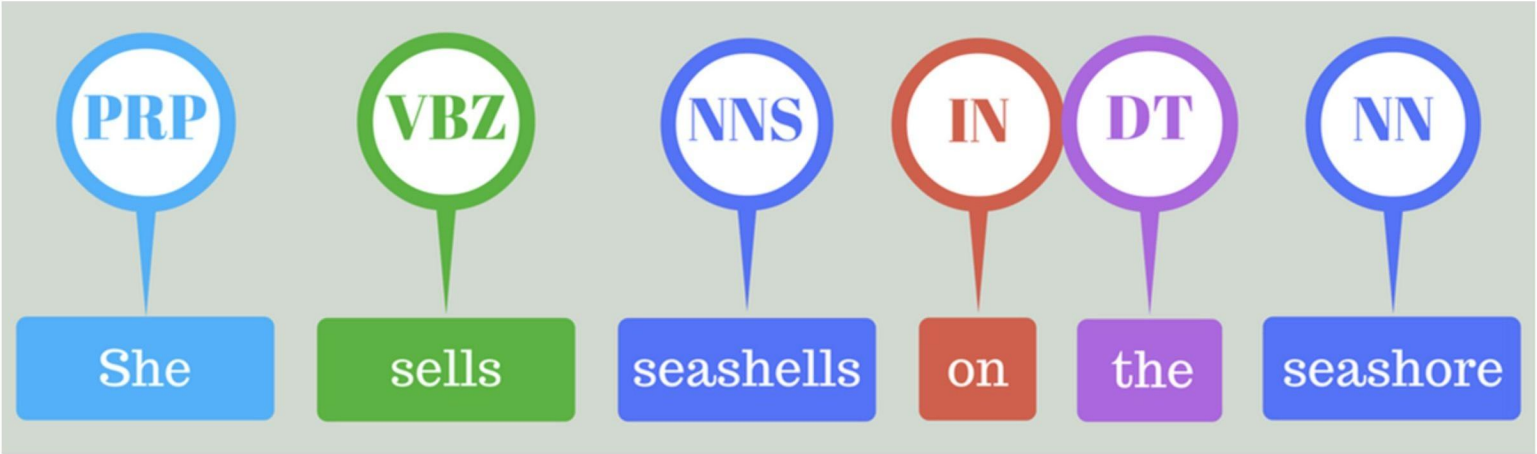
N-gram Tokenization



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

Part Of Speech Tagging

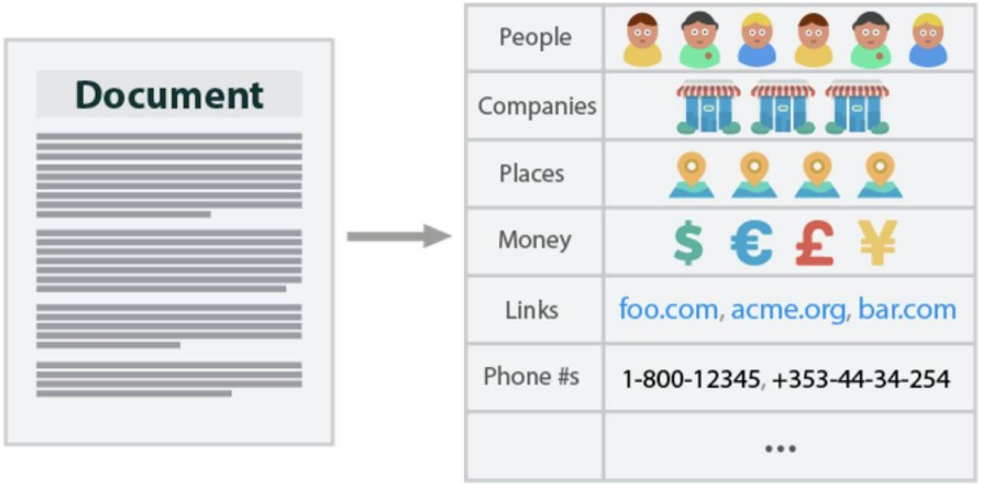
Often useful for recognizing named entities or word relationships.



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.

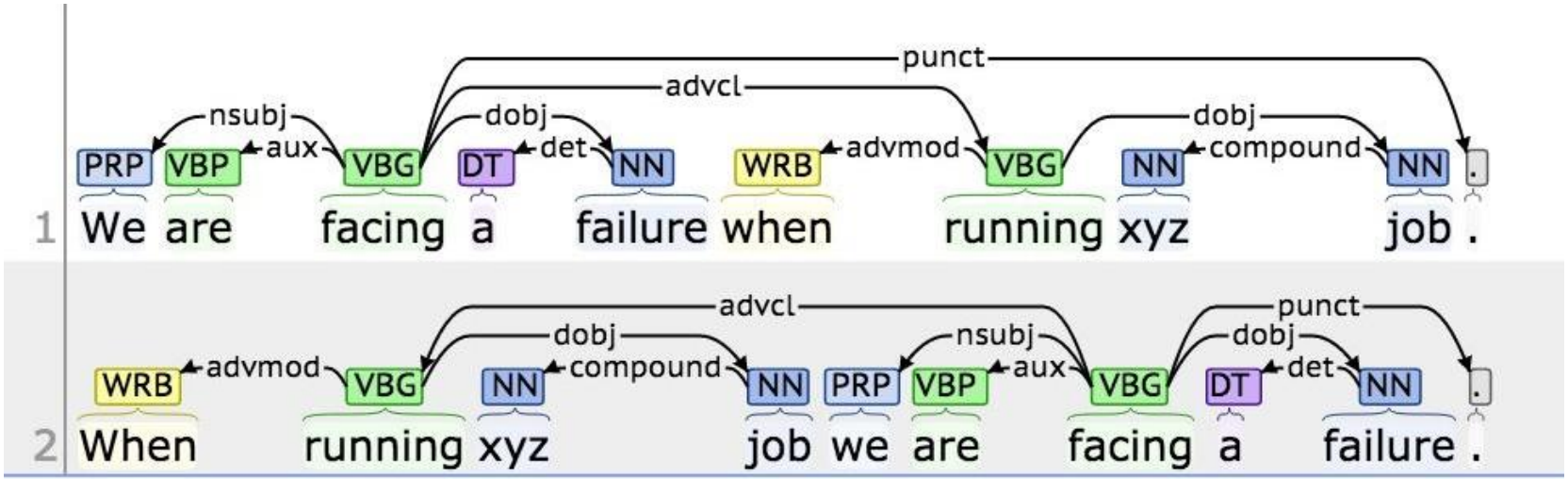


But Google ORG is starting from behind. The company made a late push into hardware, and Apple ORG 's Siri PRODUCT , available on iPhones PRODUCT , and Amazon ORG 's Alexa PRODUCT software, which runs on its Echo PRODUCT and Dot PRODUCT devices, have clear leads in consumer adoption.

Feature-Engineering & Classification

Dependency Parsing

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



Feature-Engineering & Classification

Session 1 (Day 1) - Coding Time

- Notebook 1 - Spark NLP Basics

Session 2 (Day 1)

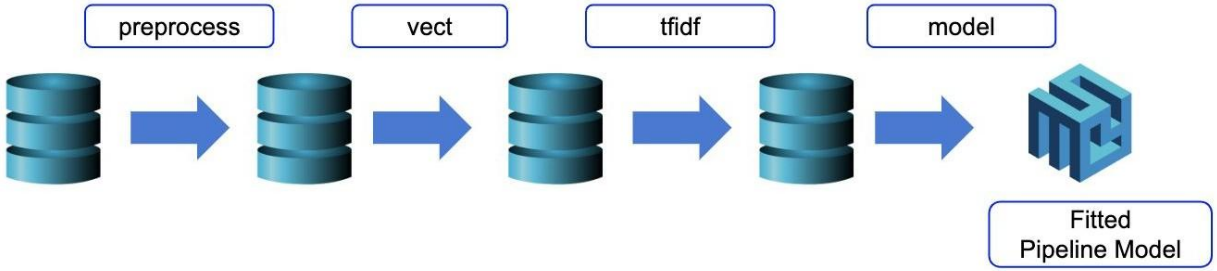
- Text Preprocessing
- Composing Pipelines
- Working with Spark Dataframes

Spark NLP
for Data Scientists

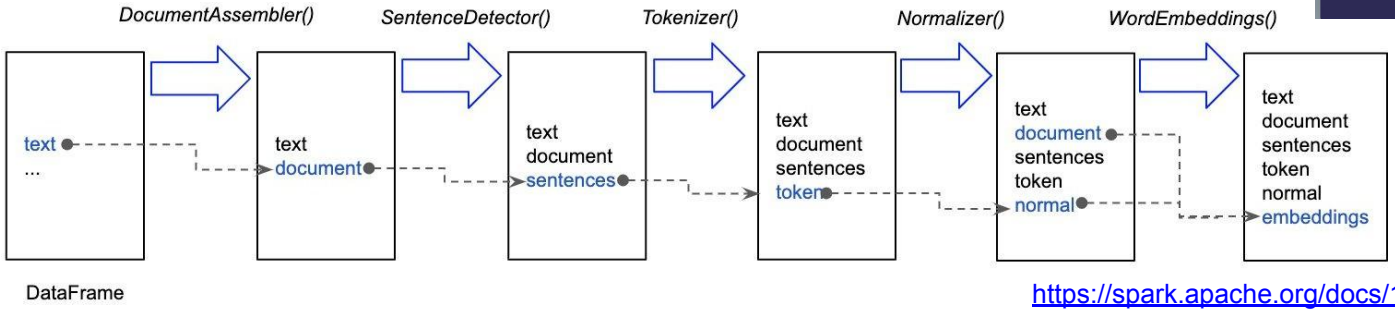
John Snow LABS

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)
```



https://spark.apache.org/docs/1.6.0/ml-guide.html#pipeline-components

Session 2 (Day 1) - Coding Time

- Notebook 2 Text Preprocessing and composing Pipelines

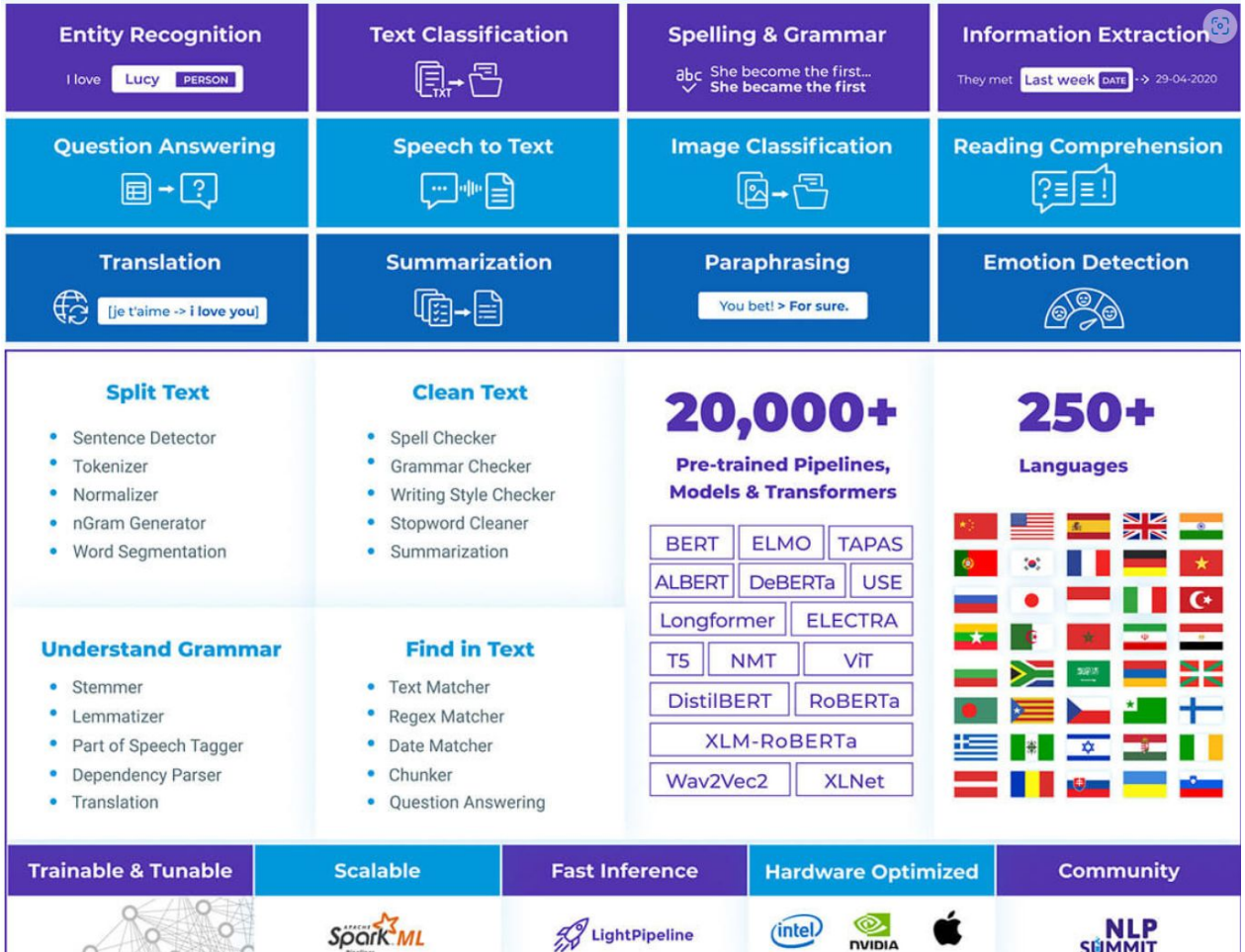
Session 3 (Day 1)

- Usage and overview of the 10000+ pretrained models for 300+ languages

Spark NLP
for Data Scientists

John Snow LABS

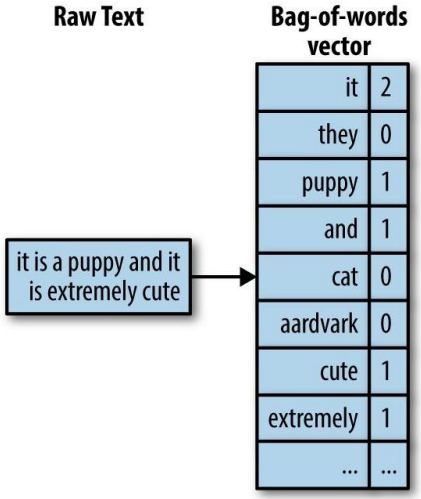
Spark NLP Modules

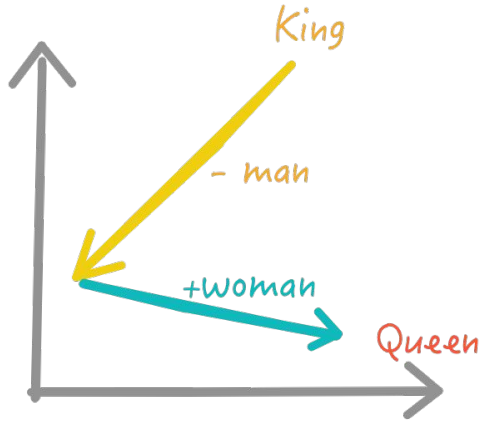


Word & Sentence Embeddings

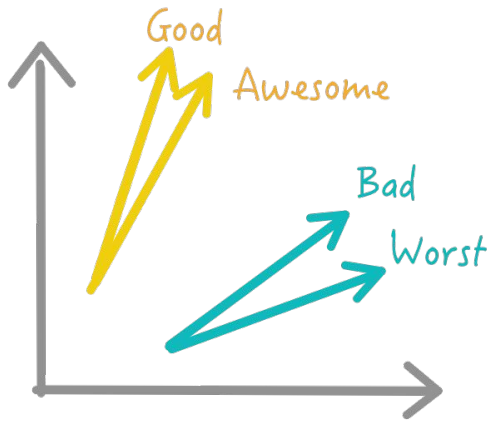
```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   , -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  ,
```

- Neural Networks and most other algorithms don't work well with strings
  - Why not convert a string into a vector with numbers!
  - Semantically similar words vectors should be **close** in the vector space learned by the
  - Dissimilar words are **far** from each other in vector space
  - Usually high dimensional, to give model more space to encode semantics
- Useful for many downstream tasks and commonly used in NLP
- Reduce dimensionality of the input space





a) Learns Analogy



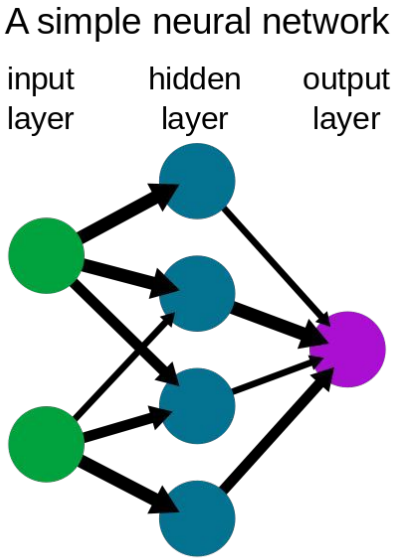
b) Similar Words have same angles

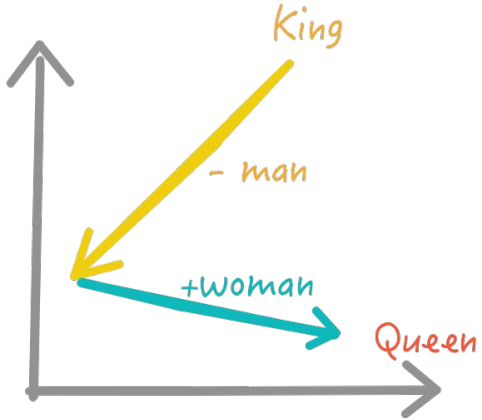
Feature-Engineering

Word & Sentence Embeddings

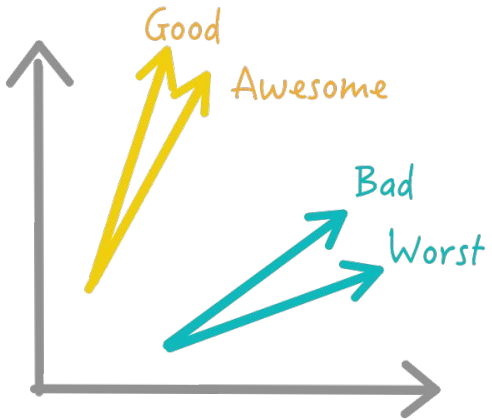
```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   , -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  ,
```

- Deep-Learning-based natural language processing systems 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.





a) Learns Analogy

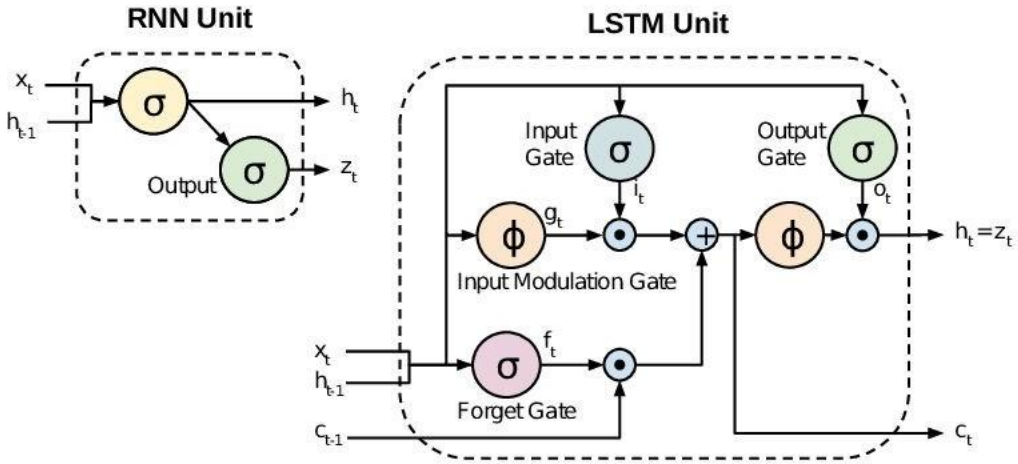


b) Similar Words have same angles

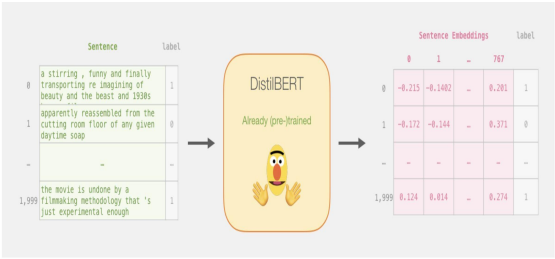
Feature-Engineering

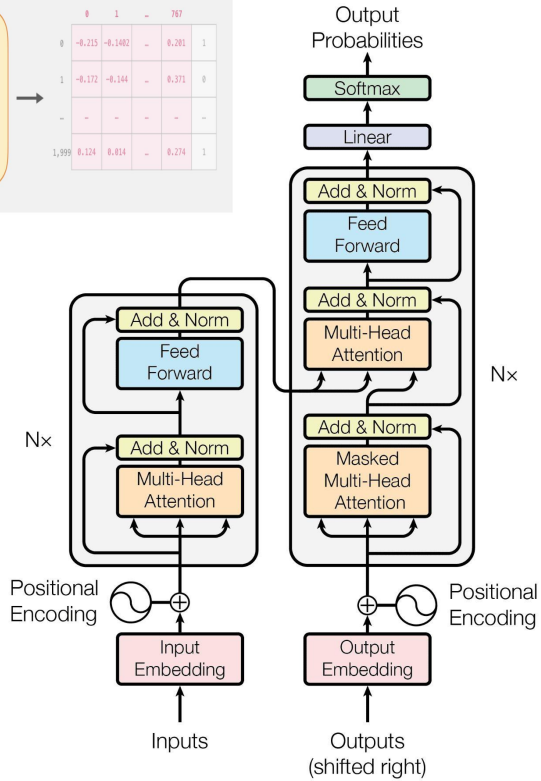
LSTM's and RNN's for Embeddings

- RNN :
  - Slow to train
  - Not well parallelizable
  - Vanishing/Exploding Gradients
- LSTM
  - Fixes vanishing/exploding gradient
  - not scalable
  - No transfer learning



Transformers - Attention is All you Need - **Visualized**
A highlighly parallelizable NN Architecture for Sequential Data





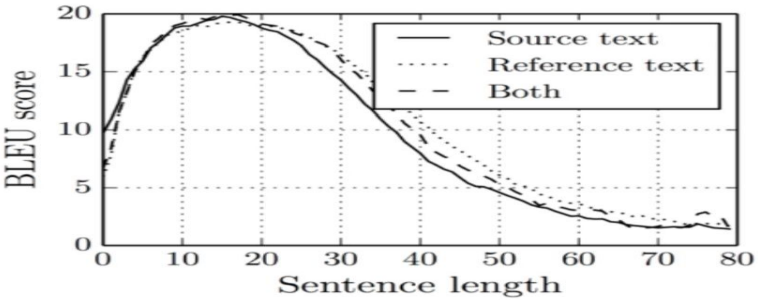
Attention is All You Need

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

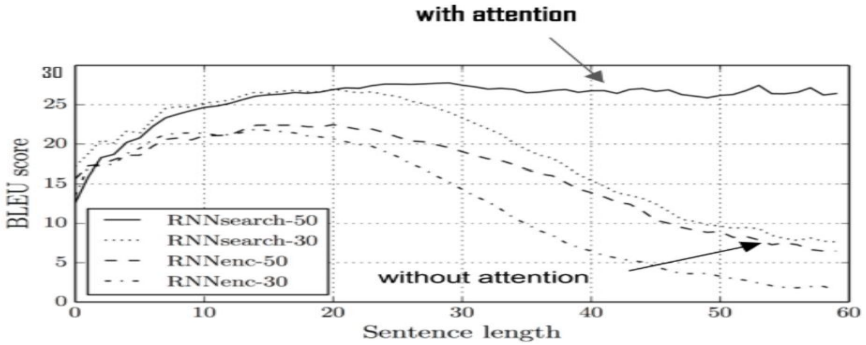
Feature-Engineering

Transformers - Attention is All you Need - Why they rock
A highlighly parallelizable NN Architecture for Sequential Data

NMT with LSTMs



NMT with LSTMs + attention



Bahdanau et al. 2014
Slide: Text generation with attention, GTC 2017, Valentin Malykh (2017)

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Feature-Engineering

The most scalable, accurate and fastest arsenal of NLP transformers in history

John Snow LABS

Apache Spark

Core NLP Transformer Models

CamemBertEmbeddings	GloveEmbeddings	Word2VecEmbeddings	Doc2VecEmbeddings
DeBertaEmbeddings	LongformerEmbeddings	BertEmbeddings	XlmRoBertaEmbeddings
DeBertaForQuestionAnswering	LongformerForTokenClassification	BertForTokenClassification	XlmRoBertaForTokenClassification
GPT2Transformer	LongformerForSequenceClassification	BertForSequenceClassification	XlmRoBertaForSequenceClassification
MarianTransformer	LongformerForQuestionAnswering	BertForQuestionAnswering	XlmRoBertaForQuestionAnswering
T5Transformer	UniversalSentenceEncoder	BertSentenceEmbeddings	XlmRoBertaSentenceEmbeddings
RoBertaEmbeddings	XlnetEmbeddings	DistilBertEmbeddings	AlbertEmbeddings
RoBertaForTokenClassification	XlnetForTokenClassification	DistilBertForTokenClassification	AlbertForTokenClassification
RoBertaForSequenceClassification	XlnetForSequenceClassification	DistilBertForSequenceClassification	AlbertForSequenceClassification
RoBertaForQuestionAnswering	ElmoEmbeddings	DistilBertForQuestionAnswering	AlbertForQuestionAnswering

- Transformer for Sequence to Sequence
- Transformer For Token Classification
- Transformer For Sequence Classification
- Transformer For Question Answering
- Transformer Sentence Embeddings
- Transformer Word Embeddings
- Non Transformer Embeddings

Subflavored NLP Transformer Extensions

SciBertEmbeddings	ElectraForQuestionAnswering	MurilBertForQuestionAnswering	MurilBertEmbeddings	LabseSentenceEmbeddings
IndoBertForQuestionAnswering	ElectraSentenceEmbeddings	MurilBertSentenceEmbeddings	SciBertForQuestionAnswering	SapBertForQuestionAnswering
ElectraEmbeddings	BioBertForQuestionAnswering	CovidBertForQuestionAnswering	MiniLmForQuestionAnswering	MacBertForQuestionAnswering
BioFormerForQuestionAnswering	BioBertSentenceEmbeddings	CovidDistilBertForQuestionAnswering	LinkBertForQuestionAnswering	BioBertEmbeddings

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Christian Kasim Loan
Lead Data Scientist
christian@johnsnowlabs.com

Embeddings in Spark NLP

Part 1

Number	Language	Spark NLP Model Name	Model
0	en	glove_100d	WordEmbeddingsModel
1	xx	glove_6B_300	WordEmbeddingsModel
2	xx	glove_840B_300	WordEmbeddingsModel
3	en	embeddings_clinical	WordEmbeddingsModel
4	en	elmo	ElmoEmbeddings
5	en	embeddings_healthcare	WordEmbeddingsModel
6	en	tfhub_use	UniversalSentenceEncoder
7	en	tfhub_use_lg	UniversalSentenceEncoder
8	en	albert_base_uncased	AlbertEmbeddings
9	en	albert_large_uncased	AlbertEmbeddings
10	en	albert_xlarge_uncased	AlbertEmbeddings
11	en	albert_xxlarge_uncased	AlbertEmbeddings
12	en	xlnet_base_cased	XlnetEmbeddings
13	en	xlnet_large_cased	XlnetEmbeddings
14	es	embeddings_scielo_150d	WordEmbeddingsModel
15	es	embeddings_scielo_300d	WordEmbeddingsModel
16	es	embeddings_scielo_50d	WordEmbeddingsModel
17	es	embeddings_scielowiki_150d	WordEmbeddingsModel
18	es	embeddings_scielowiki_300d	WordEmbeddingsModel
19	es	embeddings_scielowiki_50d	WordEmbeddingsModel
20	es	embeddings_sciwiki_150d	WordEmbeddingsModel
21	es	embeddings_sciwiki_300d	WordEmbeddingsModel
22	es	embeddings_sciwiki_50d	WordEmbeddingsModel
23	en	embeddings_healthcare_100d	WordEmbeddingsModel
24	en	embeddings_biovec	WordEmbeddingsModel
25	en	bert_base_cased	BertEmbeddings

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number	Language	Spark NLP Model Name	Model
26	en	bert_base_uncased	BertEmbeddings
27	en	bert_large_cased	BertEmbeddings
28	en	bert_large_uncased	BertEmbeddings
29	xx	bert_multi_cased	BertEmbeddings
30	en	biobert_clinical_base_cased	BertEmbeddings
31	en	biobert_discharge_base_cased	BertEmbeddings
32	en	biobert_pmc_base_cased	BertEmbeddings
33	en	biobert_pubmed_base_cased	BertEmbeddings
34	en	biobert_pubmed_large_cased	BertEmbeddings
35	en	biobert_pubmed_pmc_base_cased	BertEmbeddings
36	en	sent_biobert_clinical_base_cased	BertSentenceEmbeddings
37	en	sent_bert_base_cased	BertSentenceEmbeddings
38	en	sent_bert_base_uncased	BertSentenceEmbeddings
39	en	sent_bert_large_cased	BertSentenceEmbeddings
40	en	sent_bert_large_uncased	BertSentenceEmbeddings
41	xx	sent_bert_multi_cased	BertSentenceEmbeddings
42	en	sent_biobert_discharge_base_cased	BertSentenceEmbeddings
43	en	sent_biobert_pmc_base_cased	BertSentenceEmbeddings
44	en	sent_biobert_pubmed_base_cased	BertSentenceEmbeddings
45	en	sent_biobert_pubmed_large_cased	BertSentenceEmbeddings
46	en	sent_biobert_pubmed_pmc_base_cased	BertSentenceEmbeddings
47	en	sent_small_bert_L10_128	BertSentenceEmbeddings
48	en	sent_small_bert_L10_256	BertSentenceEmbeddings
49	en	sent_small_bert_L10_512	BertSentenceEmbeddings
50	en	sent_small_bert_L10_768	BertSentenceEmbeddings

Embeddings in Spark NLP

Part 2

Number	Language	Spark NLP Model Name	Model
51	en	sent_small_bert_L12_128	BertSentenceEmbeddings
52	en	sent_small_bert_L12_256	BertSentenceEmbeddings
53	en	sent_small_bert_L12_512	BertSentenceEmbeddings
54	en	sent_small_bert_L12_768	BertSentenceEmbeddings
55	en	sent_small_bert_L2_128	BertSentenceEmbeddings
56	en	sent_small_bert_L2_256	BertSentenceEmbeddings
57	en	sent_small_bert_L2_512	BertSentenceEmbeddings
58	en	sent_small_bert_L2_768	BertSentenceEmbeddings
59	en	sent_small_bert_L4_128	BertSentenceEmbeddings
60	en	sent_small_bert_L4_256	BertSentenceEmbeddings
61	en	sent_small_bert_L4_512	BertSentenceEmbeddings
62	en	sent_small_bert_L4_768	BertSentenceEmbeddings
63	en	sent_small_bert_L6_128	BertSentenceEmbeddings
64	en	sent_small_bert_L6_256	BertSentenceEmbeddings
65	en	sent_small_bert_L6_512	BertSentenceEmbeddings
66	en	sent_small_bert_L6_768	BertSentenceEmbeddings
67	en	sent_small_bert_L8_128	BertSentenceEmbeddings
68	en	sent_small_bert_L8_256	BertSentenceEmbeddings
69	en	sent_small_bert_L8_512	BertSentenceEmbeddings
70	en	sent_small_bert_L8_768	BertSentenceEmbeddings
71	en	small_bert_L10_128	BertEmbeddings
72	en	small_bert_L10_256	BertEmbeddings
73	en	small_bert_L10_512	BertEmbeddings
74	en	small_bert_L10_768	BertEmbeddings
75	en	small_bert_L12_128	BertEmbeddings

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number	Language	Spark NLP Model Name	Model
76	en	small_bert_L12_256	BertEmbeddings
77	en	small_bert_L12_512	BertEmbeddings
78	en	small_bert_L12_768	BertEmbeddings
79	en	small_bert_L2_128	BertEmbeddings
80	en	small_bert_L2_256	BertEmbeddings
81	en	small_bert_L2_512	BertEmbeddings
82	en	small_bert_L2_768	BertEmbeddings
83	en	small_bert_L4_128	BertEmbeddings
84	en	small_bert_L4_256	BertEmbeddings
85	en	small_bert_L4_512	BertEmbeddings
86	en	small_bert_L4_768	BertEmbeddings
87	en	small_bert_L6_128	BertEmbeddings
88	en	small_bert_L6_256	BertEmbeddings
89	en	small_bert_L6_512	BertEmbeddings
90	en	small_bert_L6_768	BertEmbeddings
91	en	small_bert_L8_128	BertEmbeddings
92	en	small_bert_L8_256	BertEmbeddings
93	en	small_bert_L8_512	BertEmbeddings
94	en	small_bert_L8_768	BertEmbeddings
95	en	covidbert_large_uncased	BertEmbeddings
96	en	electra_base_uncased	BertEmbeddings
97	en	electra_large_uncased	BertEmbeddings
98	en	electra_small_uncased	BertEmbeddings
99	en	sent_covidbert_large_uncased	BertSentenceEmbeddings
100	en	sent_electra_base_uncased	BertSentenceEmbeddings

Embeddings in Spark NLP

Part 3

Number	Language	Spark NLP Model Name	Model
101	en	sent_electra_large_uncased	BertSentenceEmbeddings
102	en	sent_electra_small_uncased	BertSentenceEmbeddings
103	fi	bert_finnish_cased	BertEmbeddings
104	fi	bert_finnish_uncased	BertEmbeddings
105	de	w2v_cc_300d	WordEmbeddingsModel
106	en	biobert_clinical_base_cased	BertEmbeddings
107	en	biobert_discharge_base_cased	BertEmbeddings
108	en	biobert_pmc_base_cased	BertEmbeddings
109	en	biobert_pubmed_base_cased	BertEmbeddings
110	en	biobert_pubmed_large_cased	BertEmbeddings
111	en	biobert_pubmed_pmc_base_cased	BertEmbeddings
112	en	sent_biobert_clinical_base_cased	BertSentenceEmbeddings
113	en	sent_biobert_discharge_base_cased	BertSentenceEmbeddings
114	en	sent_biobert_pmc_base_cased	BertSentenceEmbeddings
115	en	sent_biobert_pubmed_base_cased	BertSentenceEmbeddings
116	en	sent_biobert_pubmed_large_cased	BertSentenceEmbeddings
117	en	sent_biobert_pubmed_pmc_base_cased	BertSentenceEmbeddings
118	en	labse	BertSentenceEmbeddings
119	pt	bert_portuguese_base_cased	BertEmbeddings
120	pt	bert_portuguese_large_cased	BertEmbeddings
121	en	sbiobert_base_cased_mli	BertSentenceEmbeddings
122	en	sbluebert_base_uncased_mli	BertSentenceEmbeddings
123	ur	urduvec_140M_300d	WordEmbeddingsModel
124	ar	arabic_w2v_cc_300d	WordEmbeddingsModel
125	fa	persian_w2v_cc_300d	WordEmbeddingsModel

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number	Language	Spark NLP Model Name	Model
126	xx	tfhub_use_multi_lg	UniversalSentenceEncoder
127	xx	tfhub_use_multi	UniversalSentenceEncoder
128	he	hebrew_cc_300d	WordEmbeddingsModel
129	hi	hindi_cc_300d	WordEmbeddingsModel
130	bn	bengali_cc_300d	WordEmbeddingsModel
131	xx	tfhub_use_multi_lg	UniversalSentenceEncoder
132	xx	tfhub_use_multi	UniversalSentenceEncoder
133	en	sbert_jsl_medium_umls_uncased	BertSentenceEmbeddings
134	en	sbert_jsl_medium_uncased	BertSentenceEmbeddings
135	en	sbert_jsl_mini_umls_uncased	BertSentenceEmbeddings
136	en	sbert_jsl_mini_uncased	BertSentenceEmbeddings
137	en	sbert_jsl_tiny_umls_uncased	BertSentenceEmbeddings
138	en	sbert_jsl_tiny_uncased	BertSentenceEmbeddings
139	en	sbiobert_jsl_cased	BertSentenceEmbeddings
140	en	sbiobert_jsl_umls_cased	BertSentenceEmbeddings
141	zh	bert_base_chinese	BertEmbeddings
142	nl	bert_base_dutch_cased	BertEmbeddings
143	de	bert_base_german_cased	BertEmbeddings
144	de	bert_base_german_uncased	BertEmbeddings
145	it	bert_base_italian_cased	BertEmbeddings
146	it	bert_base_italian_uncased	BertEmbeddings
147	xx	bert_base_multilingual_cased	BertEmbeddings
148	xx	bert_base_multilingual_uncased	BertEmbeddings
149	tr	bert_base_turkish_cased	BertEmbeddings
150	tr	bert_base_turkish_uncased	BertEmbeddings

Embeddings in Spark NLP

Part 4

Number	Language	Spark NLP Model Name	Model
151	zh	chinese_bert_wwm	BertEmbeddings
152	en	distilbert_base_cased	DistilBertEmbeddings
153	xx	distilbert_base_multilingual_cased	DistilBertEmbeddings
154	en	distilbert_base_uncased	DistilBertEmbeddings
155	en	distilroberta_base	RoBertaEmbeddings
156	en	roberta_base	RoBertaEmbeddings
157	en	roberta_large	RoBertaEmbeddings
158	xx	twitter_xlm_roberta_base	XlmRoBertaEmbeddings
159	xx	xlm_roberta_base	XlmRoBertaEmbeddings
160	en	albert_base_uncased	AlbertEmbeddings
161	en	albert_large_uncased	AlbertEmbeddings
162	en	albert_xlarge_uncased	AlbertEmbeddings
163	en	albert_xxlarge_uncased	AlbertEmbeddings
164	en	sbert_jsl_medium_umls_uncased	BertSentenceEmbeddings
165	en	sbert_jsl_medium_uncased	BertSentenceEmbeddings
166	en	sbert_jsl_mini_umls_uncased	BertSentenceEmbeddings
167	en	sbert_jsl_mini_uncased	BertSentenceEmbeddings
168	en	sbert_jsl_tiny_umls_uncased	BertSentenceEmbeddings
169	en	sbert_jsl_tiny_uncased	BertSentenceEmbeddings
170	en	sbiobert_jsl_cased	BertSentenceEmbeddings
171	en	sbiobert_jsl_umls_cased	BertSentenceEmbeddings
172	zh	chinese_xlnet_base	XlnetEmbeddings
173	en	xlnet_base_cased	XlnetEmbeddings
174	en	xlnet_large_cased	XlnetEmbeddings
175	xx	xlm_roberta_xtreme_base	XlmRoBertaEmbeddings

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number	Language	Spark NLP Model Name	Model
176	en	sent_bert_use_cmlm_en_base	BertSentenceEmbeddings
177	en	sent_bert_use_cmlm_en_large	BertSentenceEmbeddings
178	xx	sent_bert_use_cmlm_multi_base_br	BertSentenceEmbeddings
179	xx	sent_bert_use_cmlm_multi_base	BertSentenceEmbeddings
180	en	longformer_base_4096	LongformerEmbeddings
181	en	longformer_large_4096	LongformerEmbeddings
182	xx	bert_muril	BertEmbeddings
183	en	bert_pubmed	BertEmbeddings
184	en	bert_pubmed_squad2	BertEmbeddings
185	en	bert_wiki_books	BertEmbeddings
186	en	bert_wiki_books_mnli	BertEmbeddings
187	en	bert_wiki_books_qnli	BertEmbeddings
188	en	bert_wiki_books_qqp	BertEmbeddings
189	en	bert_wiki_books_squad2	BertEmbeddings
190	en	bert_wiki_books_sst2	BertEmbeddings
191	te	sentence_detector_dl	SentenceDetectorDLModel
192	en	sent_bert_pubmed	BertSentenceEmbeddings
193	en	sent_bert_pubmed_squad2	BertSentenceEmbeddings
194	en	sent_bert_wiki_books	BertSentenceEmbeddings
195	en	sent_bert_wiki_books_mnli	BertSentenceEmbeddings
196	en	sent_bert_wiki_books_qnli	BertSentenceEmbeddings
197	en	sent_bert_wiki_books_qqp	BertSentenceEmbeddings
198	en	sent_bert_wiki_books_squad2	BertSentenceEmbeddings
199	en	sent_bert_wiki_books_sst2	BertSentenceEmbeddings
200	xx	sent_bert_muril	BertSentenceEmbeddings

Embeddings in Spark NLP

Part 5

Number	Language	Spark NLP Model Name	Model
201	xx	sent_xlm_roberta_base	XlmRoBertaForTokenClassification
202	es	sent_bert_base_cased	BertSentenceEmbeddings
203	nl	sent_bert_base_cased	BertSentenceEmbeddings
204	sv	sent_bert_base_cased	BertSentenceEmbeddings
205	el	sent_bert_base_uncased	BertSentenceEmbeddings
206	es	sent_bert_base_uncased	BertSentenceEmbeddings
207	en	sent_bert_base_uncased_legal	BertSentenceEmbeddings
208	es	bert_base_cased	BertEmbeddings
209	nl	bert_base_cased	BertEmbeddings
210	sv	bert_base_cased	BertEmbeddings
211	el	bert_base_uncased	BertEmbeddings
212	es	bert_base_uncased	BertEmbeddings
213	en	bert_base_uncased_legal	BertEmbeddings
214	ja	japanese_cc_300d	WordEmbeddingsModel
215	ro	bert_base_cased	BertEmbeddings
216	de	sent_bert_base_cased	BertSentenceEmbeddings
217	am	xlm_roberta_base_finetuned_amharic	XlmRoBertaEmbeddings
218	ha	xlm_roberta_base_finetuned_hausa	XlmRoBertaEmbeddings
219	ig	xlm_roberta_base_finetuned_igbo	XlmRoBertaEmbeddings
220	rw	xlm_roberta_base_finetuned_kinyarwanda	XlmRoBertaEmbeddings
221	lg	xlm_roberta_base_finetuned_luganda	XlmRoBertaEmbeddings
222	xx	xlm_roberta_large	XlmRoBertaEmbeddings
223	am	sent_xlm_roberta_base_finetuned_amharic	XlmRoBertaSentenceEmbeddings
224	ha	sent_xlm_roberta_base_finetuned_hausa	XlmRoBertaSentenceEmbeddings
225	ig	sent_xlm_roberta_base_finetuned_igbo	XlmRoBertaSentenceEmbeddings
226	rw	sent_xlm_roberta_base_finetuned_kinyarwanda	XlmRoBertaSentenceEmbeddings
227	lg	sent_xlm_roberta_base_finetuned_luganda	XlmRoBertaSentenceEmbeddings
228	pcm	sent_xlm_roberta_base_finetuned_naija	XlmRoBertaSentenceEmbeddings
229	sw	sent_xlm_roberta_base_finetuned_swahili	XlmRoBertaSentenceEmbeddings
230	wo	sent_xlm_roberta_base_finetuned_wolof	XlmRoBertaSentenceEmbeddings
231	yo	sent_xlm_roberta_base_finetuned_yoruba	XlmRoBertaSentenceEmbeddings
232	lou	xlm_roberta_base_finetuned_luo	XlmRoBertaEmbeddings
233	pcm	xlm_roberta_base_finetuned_naija	XlmRoBertaEmbeddings
234	sw	xlm_roberta_base_finetuned_swahili	XlmRoBertaEmbeddings
235	wo	xlm_roberta_base_finetuned_wolof	XlmRoBertaEmbeddings
236	yo	xlm_roberta_base_finetuned_yoruba	XlmRoBertaEmbeddings
237	es	roberta_base_biomedical	RoBertaEmbeddings
238	en	doc2vec_gigaword_300	Doc2VecModel
239	en	doc2vec_gigaword_wiki_300	Doc2VecModel
240	te	distilbert_uncased	DistilBertEmbeddings
241	en	sbert_jsl_medium_rxnorm_uncased	BertSentenceEmbeddings
242	fi	bert_base_finnish_cased	BertSentenceEmbeddings
243	fi	bert_base_finnish_uncased	BertSentenceEmbeddings
244	en	sbert_jsl_medium_rxnorm_uncased	BertSentenceEmbeddings
245	en	word2vec_gigaword_300	Word2VecModel
246	en	word2vec_gigaword_wiki_300	Word2VecModel
247	en	electra_medal_acronym	BertEmbeddings
248	vi	distilbert_base_cased	DistilBertEmbeddings

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Transformer **Sequence** Classifiers in Spark NLP

Number	Language	Spark NLP Model Name	Model
0	en	bert_base_sequence_classifier_dbpedia_14	BertForSequenceClassification
1	en	bert_base_sequence_classifier_imdb	BertForSequenceClassification
2	en	bert_large_sequence_classifier_imdb	BertForSequenceClassification
3	fr	bert_multilingual_sequence_classifier_allocine	BertForSequenceClassification
4	en	bert_base_sequence_classifier_ag_news	BertForSequenceClassification
5	es	bert_sequence_classifier_beto_emotion_analysis	BertForSequenceClassification
6	es	bert_sequence_classifier_beto_sentiment_analysis	BertForSequenceClassification
7	en	bert_sequence_classifier_dehatebert_mono	BertForSequenceClassification
8	en	bert_sequence_classifier_finbert	BertForSequenceClassification
9	ja	bert_sequence_classifier_japanese_sentiment	BertForSequenceClassification
10	xx	bert_sequence_classifier_multilingual_sentiment	BertForSequenceClassification
11	ru	bert_sequence_classifier_rubert_sentiment	BertForSequenceClassification
12	de	bert_sequence_classifier_sentiment	BertForSequenceClassification
13	tr	bert_sequence_classifier_turkish_sentiment	BertForSequenceClassification
14	en	bert_sequence_classifier_question_statement	BertForSequenceClassification
15	en	bert_sequence_classifier_question_statement_cl...	BertForSequenceClassification
16	en	bert_sequence_classifier_antisemitism	BertForSequenceClassification
17	en	bert_sequence_classifier_hatexplain	BertForSequenceClassification
18	en	bert_sequence_classifier_trec_coarse	BertForSequenceClassification
19	en	bert_sequence_classifier_age_news	BertForSequenceClassification
20	en	bert_sequence_classifier_banking77	BertForSequenceClassification
21	en	bert_sequence_classifier_sms_spam	BertForSequenceClassification
22	en	bert_sequence_classifier_song_lyrics	BertForSequenceClassification
23	en	distilbert_base_sequence_classifier_ag_news	DistilBertForSequenceClassification
24	en	distilbert_base_sequence_classifier_amazon_pol...	DistilBertForSequenceClassification
25	en	distilbert_base_sequence_classifier_imdb	DistilBertForSequenceClassification
26	ur	distilbert_base_sequence_classifier_imdb	DistilBertForSequenceClassification
27	fr	distilbert_multilingual_sequence_classifier_al...	DistilBertForSequenceClassification
28	en	distilbert_sequence_classifier_banking77	DistilBertForSequenceClassification
29	en	distilbert_sequence_classifier_emotion	DistilBertForSequenceClassification
30	en	distilbert_sequence_classifier_industry	DistilBertForSequenceClassification
31	en	distilbert_sequence_classifier_policy	DistilBertForSequenceClassification
32	en	distilbert_sequence_classifier_sst2	DistilBertForSequenceClassification
33	en	albert_base_sequence_classifier_ag_news	AlbertForSequenceClassification
34	en	albert_base_sequence_classifier_imdb	AlbertForSequenceClassification
35	en	longformer_base_sequence_classifier_ag_news	LongformerForSequenceClassification
36	en	longformer_base_sequence_classifier_imdb	LongformerForSequenceClassification
37	en	roberta_base_sequence_classifier_ag_news	RoBertaForSequenceClassification
38	en	roberta_base_sequence_classifier_imdb	RoBertaForSequenceClassification
39	en	xlm_roberta_base_sequence_classifier_ag_news	XlmRoBertaForSequenceClassification
40	fr	xlm_roberta_base_sequence_classifier_allocine	XlmRoBertaForSequenceClassification
41	en	xlm_roberta_base_sequence_classifier_imdb	XlmRoBertaForSequenceClassification
42	en	xlnet_base_sequence_classifier_ag_news	XlnetForSequenceClassification
43	en	xlnet_base_sequence_classifier_imdb	XlnetForSequenceClassification

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Transformer **Token** Classifiers in Spark NLP Part 1

Number	Language	Spark NLP Model Name	Model
0	en	bert_base_token_classifier_conll03	BertForTokenClassification
1	en	bert_base_token_classifier_ontonote	BertForTokenClassification
2	en	bert_large_token_classifier_conll03	BertForTokenClassification
3	en	bert_large_token_classifier_ontonote	BertForTokenClassification
4	fa	bert_token_classifier_parsbert_armanner	BertForTokenClassification
5	fa	bert_token_classifier_parsbert_ner	BertForTokenClassification
6	fa	bert_token_classifier_parsbert_peymaner	BertForTokenClassification
7	es	bert_token_classifier_spanish_ner	BertForTokenClassification
8	sv	bert_token_classifier_swedish_ner	BertForTokenClassification
9	tr	bert_token_classifier_turkish_ner	BertForTokenClassification
10	en	distilbert_base_token_classifier_conll03	DistilBertForTokenClassification
11	en	distilbert_base_token_classifier_ontonotes	DistilBertForTokenClassification
12	fa	distilbert_token_classifier_persian_ner	DistilBertForTokenClassification
13	en	bert_base_token_classifier_few_nerd	BertForTokenClassification
14	en	distilbert_base_token_classifier_few_nerd	DistilBertForTokenClassification
15	en	bert_token_classifier_ner_clinical	MedicalBertForTokenClassifier
16	en	bert_token_classifier_ner_jsl	MedicalBertForTokenClassifier
17	en	bert_token_classifier_ner_btc	BertForTokenClassification
18	ja	bert_token_classifier_ner_ud_gsd	BertForTokenClassification
19	en	bert_token_classifier_ner_deid	MedicalBertForTokenClassifier
20	en	bert_token_classifier_ner_jsl	MedicalBertForTokenClassifier
21	en	bert_token_classifier_ner_drugs	MedicalBertForTokenClassifier
22	en	bert_token_classifier_ner_jsl_slim	MedicalBertForTokenClassifier
23	en	albert_base_token_classifier_conll03	AlbertForTokenClassification
24	en	albert_large_token_classifier_conll03	AlbertForTokenClassification
26	en	distilroberta_base_token_classifier_ontonotes	RoBertaForTokenClassification
27	en	roberta_base_token_classifier_conll03	RoBertaForTokenClassification
28	en	roberta_base_token_classifier_ontonotes	RoBertaForTokenClassification
29	en	roberta_large_token_classifier_conll03	RoBertaForTokenClassification
30	en	roberta_large_token_classifier_ontonotes	RoBertaForTokenClassification
31	fa	roberta_token_classifier_zwnj_base_ner	RoBertaForTokenClassification
32	xx	xlm_roberta_token_classifier_ner_40_lang	XlmRoBertaForTokenClassification
33	en	xlnet_base_token_classifier_conll03	XlnetForTokenClassification
34	en	xlnet_large_token_classifier_conll03	XlnetForTokenClassification
35	en	bert_token_classifier_ner_ade	MedicalBertForTokenClassifier
36	en	bert_token_classifier_ner_anatomy	MedicalBertForTokenClassifier
37	en	bert_token_classifier_ner_bacteria	MedicalBertForTokenClassifier
38	en	xlm_roberta_base_token_classifier_conll03	XlmRoBertaForTokenClassification
39	en	xlm_roberta_base_token_classifier_ontonotes	XlmRoBertaForTokenClassification
40	en	longformer_base_token_classifier_conll03	LongformerForTokenClassification
41	en	longformer_large_token_classifier_conll03	LongformerForTokenClassification
42	en	bert_token_classifier_ner_chemicals	MedicalBertForTokenClassifier
43	en	bert_token_classifier_ner_chemprot	MedicalBertForTokenClassifier
44	en	bert_token_classifier_ner_bionlp	MedicalBertForTokenClassifier
45	en	bert_token_classifier_ner_cellular	MedicalBertForTokenClassifier
46	tr	xlm_roberta_base_token_classifier_ner	XlmRoBertaForTokenClassification
47	id	xlm_roberta_large_token_classification_ner	XlmRoBertaForTokenClassification
48	is	roberta_token_classifier_icelandic_ner	RoBertaForTokenClassification
49	xx	xlm_roberta_large_token_classifier_masakhaner	XlmRoBertaForTokenClassification
50	zh	bert_token_classifier_chinese_ner	BertForTokenClassification

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Transformer **Question** Answering in Spark NLP Part 1

Number	Language	Spark NLP Model Name	Model
0	en	google_t5_small_ssm_nq	T5Transformer
1	en	google_t5_small_ssm_nq	T5Transformer
2	en	bert_base_cased_qa_squad2	BertForQuestionAnswering
3	en	bert_qa_Bertv1_fine	BertForQuestionAnswering
4	en	bert_qa_COVID_BERTa	BertForQuestionAnswering
5	en	bert_qa_COVID_BERTb	BertForQuestionAnswering
6	en	bert_qa_COVID_BERTc	BertForQuestionAnswering
7	de	bert_qa_GBERTQnA	BertForQuestionAnswering
8	en	bert_qa_HomayounSadri_bert_base_uncased_finetu...	BertForQuestionAnswering
9	id	bert_qa_Indobert_QA	BertForQuestionAnswering
10	en	bert_qa_Klue_CommonSense_model	BertForQuestionAnswering
11	en	bert_qa_MTL_bert_base_uncased_ww_squad	BertForQuestionAnswering
12	en	bert_qa_ManuERT_for_xqua	BertForQuestionAnswering
13	en	bert_qa_MiniLM_L12_H384_uncased_finetuned_squad	BertForQuestionAnswering
14	en	bert_qa_Multi_ling_BERT	BertForQuestionAnswering
15	xx	bert_qa_Part_1_mBERT_Model_E1	BertForQuestionAnswering
16	en	bert_qa_Part_1_mBERT_Model_E2	BertForQuestionAnswering
17	en	bert_qa_Part_2_BERT_Multilingual_Dutch_Model_E1	BertForQuestionAnswering
18	en	bert_qa_Part_2_mBERT_Model_E2	BertForQuestionAnswering
19	en	bert_qa_Paul_Vinh_bert_base_multilingual_cased...	BertForQuestionAnswering
20	en	bert_qa_PruebaBert	BertForQuestionAnswering
21	en	bert_qa_SciBERT_SQuAD_QuAC	BertForQuestionAnswering
22	en	bert_qa_Seongkyu_bert_base_cased_finetuned_squad	BertForQuestionAnswering
23	en	bert_qa_Shushant_BiomedNLP_PubMedBERT_base_unc...	BertForQuestionAnswering
24	en	bert_qa_Spanbert_emotion_extraction	BertForQuestionAnswering
25	en	bert_qa_SreyanG_NVIDIA_bert_base_cased_finetun...	BertForQuestionAnswering
26	en	bert_qa_SreyanG_NVIDIA_bert_base_uncased_finet...	BertForQuestionAnswering
27	en	bert_qa_SupriyaArun_bert_base_uncased_finetune...	BertForQuestionAnswering
28	en	bert_qa_Tianle_bert_base_uncased_finetuned_squad	BertForQuestionAnswering
29	en	bert_qa_Trial_3_Results	BertForQuestionAnswering
30	ko	bert_qa_ainize_klue_bert_base_mrc	BertForQuestionAnswering
31	en	bert_qa_andresestevez_bert_base_cased_finetune...	BertForQuestionAnswering
32	en	bert_qa_araSpeedest	BertForQuestionAnswering
33	ar	bert_qa_arap_qa_bert	BertForQuestionAnswering
34	ar	bert_qa_arap_qa_bert_large_v2	BertForQuestionAnswering
35	ar	bert_qa_arap_qa_bert_v2	BertForQuestionAnswering
36	en	bert_qa_augmented_Squad_Translated	BertForQuestionAnswering
37	en	bert_qa_augmented	BertForQuestionAnswering
38	en	bert_qa_batterybert_cased_squad_v1	BertForQuestionAnswering
39	en	bert_qa_batterybert_uncased_squad_v1	BertForQuestionAnswering
40	en	bert_qa_batterydata_bert_base_uncased_squad_v1	BertForQuestionAnswering
41	en	bert_qa_batteryonlybert_cased_squad_v1	BertForQuestionAnswering
42	en	bert_qa_batteryonlybert_uncased_squad_v1	BertForQuestionAnswering
43	en	bert_qa_batteryscibert_cased_squad_v1	BertForQuestionAnswering
44	en	bert_qa_batteryscibert_uncased_squad_v1	BertForQuestionAnswering
45	en	bert_qa_bdickson_bert_base_uncased_finetuned_s...	BertForQuestionAnswering
46	en	bert_qa_bert_FT_new_newsqa	BertForQuestionAnswering
47	en	bert_qa_bert_FT_newsqa	BertForQuestionAnswering
48	en	bert_qa_bert_all	BertForQuestionAnswering
49	en	bert_qa_bert_all_squad_all_translated	BertForQuestionAnswering

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Transformer **Question** Answering in Spark NLP Part 2

Number	Language	Spark NLP Model Name	Model
51	en	bert_qa_bert_all_squad_que_translated	BertForQuestionAnswering
52	en	bert_qa_bert_all_translated	BertForQuestionAnswering
53	en	bert_qa_bert_base_1024_full_trivia_copied_embe...	BertForQuestionAnswering
54	en	bert_qa_bert_base_2048_full_trivia_copied_embe...	BertForQuestionAnswering
55	en	bert_qa_bert_base_4096_full_trivia_copied_embe...	BertForQuestionAnswering
56	en	bert_qa_bert_base_512_full_trivia	BertForQuestionAnswering
57	en	bert_qa_bert_base_cased_IUChatbot_ontologyDts	BertForQuestionAnswering
58	en	bert_qa_bert_base_cased_chaii	BertForQuestionAnswering
59	en	bert_qa_bert_base_cased_finetuned_squad_test	BertForQuestionAnswering
60	pt	bert_qa_bert_base_cased_squad_v1.1_portuguese	BertForQuestionAnswering
61	en	bert_qa_bert_base_cased_squad_v1	BertForQuestionAnswering
62	zh	bert_qa_bert_base_chinese_finetuned_squad_colab	BertForQuestionAnswering
63	fa	bert_qa_bert_base_fa_qa	BertForQuestionAnswering
64	en	bert_qa_bert_base_faquad	BertForQuestionAnswering
65	en	bert_qa_bert_base_finetuned_squad2	BertForQuestionAnswering
66	th	bert_qa_bert_base_multilingual_cased_finetune_qa	BertForQuestionAnswering
67	en	bert_qa_bert_base_multilingual_cased_finetuned...	BertForQuestionAnswering
68	nl	bert_qa_bert_base_multilingual_cased_finetuned...	BertForQuestionAnswering
69	en	bert_qa_bert_base_multilingual_cased_finetuned...	BertForQuestionAnswering
70	pl	bert_qa_bert_base_multilingual_cased_finetuned...	BertForQuestionAnswering
71	pl	bert_qa_bert_base_multilingual_cased_finetuned...	BertForQuestionAnswering
72	en	bert_qa_bert_base_multilingual_cased_finetuned...	BertForQuestionAnswering
73	en	bert_qa_bert_base_multilingual_cased_korquad	BertForQuestionAnswering
74	en	bert_qa_bert_base_multilingual_cased_korquad_v1	BertForQuestionAnswering
75	en	bert_qa_bert_base_multilingual_uncased_finetun...	BertForQuestionAnswering
76	en	bert_qa_bert_base_multilingual_xquad	BertForQuestionAnswering
77	si	bert_qa_bert_base_sinhala_qa	BertForQuestionAnswering
78	en	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
79	en	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
80	en	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
81	es	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
82	es	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
83	es	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
84	es	bert_qa_bert_base_spanish_wwm_cased_finetuned_...	BertForQuestionAnswering
85	en	bert_qa_bert_base_spanish_wwm_uncased_finetune...	BertForQuestionAnswering
86	en	bert_qa_bert_base_spanish_wwm_uncased_finetune...	BertForQuestionAnswering
87	en	bert_qa_bert_base_spanish_wwm_uncased_finetune...	BertForQuestionAnswering
88	en	bert_qa_bert_base_squadv1	BertForQuestionAnswering
89	en	bert_qa_bert_base_swedish_cased_squad_experime...	BertForQuestionAnswering
90	sv	bert_qa_bert_base_swedish_squad2	BertForQuestionAnswering
91	en	bert_qa_bert_base_turkish_cased_finetuned_lr_2...	BertForQuestionAnswering
92	tr	bert_qa_bert_base_turkish_squad	BertForQuestionAnswering
93	en	bert_qa_bert_base_uncased_coqa	BertForQuestionAnswering
94	en	bert_qa_bert_base_uncased_few_shot_k_1024_fine...	BertForQuestionAnswering
95	en	bert_qa_bert_base_uncased_few_shot_k_128_finet...	BertForQuestionAnswering
96	en	bert_qa_bert_base_uncased_few_shot_k_16_finetu...	BertForQuestionAnswering
97	en	bert_qa_bert_base_uncased_few_shot_k_256_finet...	BertForQuestionAnswering
98	en	bert_qa_bert_base_uncased_few_shot_k_32_finetu...	BertForQuestionAnswering
99	en	bert_qa_bert_base_uncased_few_shot_k_512_finet...	BertForQuestionAnswering

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number			
100	en	bert_qa_bert_base_uncased_few_shot_k_64_finetu...	BertForQuestionAnswering
101	en	bert_qa_bert_base_uncased_finetuned_docvqa	BertForQuestionAnswering
102	en	bert_qa_bert_base_uncased_finetuned_duorc_bert	BertForQuestionAnswering
103	en	bert_qa_bert_base_uncased_finetuned_infovqa	BertForQuestionAnswering
104	en	bert_qa_bert_base_uncased_finetuned_newsqa	BertForQuestionAnswering
105	en	bert_qa_bert_base_uncased_finetuned_squad_froz...	BertForQuestionAnswering
106	en	bert_qa_bert_base_uncased_finetuned_squad_v1	BertForQuestionAnswering
107	en	bert_qa_bert_base_uncased_finetuned_squad_v2	BertForQuestionAnswering
108	en	bert_qa_bert_base_uncased_finetuned_vi_infovqa	BertForQuestionAnswering
109	en	bert_qa_bert_base_uncased_fiqa_flm_sq_flit	BertForQuestionAnswering
110	en	bert_qa_bert_base_uncased_qa_squad2	BertForQuestionAnswering
111	en	bert_qa_bert_base_uncased_squad1.1_block_spars...	BertForQuestionAnswering
112	en	bert_qa_bert_base_uncased_squad1.1_block_spars...	BertForQuestionAnswering
113	en	bert_qa_bert_base_uncased_squad1.1_block_spars...	BertForQuestionAnswering
114	en	bert_qa_bert_base_uncased_squad1.1_block_spars...	BertForQuestionAnswering
115	en	bert_qa_bert_base_uncased_squad1.1_pruned_x3.2_v2	BertForQuestionAnswering
116	en	bert_qa_bert_base_uncased_squad2_covid_qa_deepset	BertForQuestionAnswering
117	en	bert_qa_bert_base_uncased_squad_L3	BertForQuestionAnswering
118	en	bert_qa_bert_base_uncased_squad_L6	BertForQuestionAnswering
119	en	bert_qa_bert_base_uncased_squad_v1_sparse0.25	BertForQuestionAnswering
120	en	bert_qa_bert_base_uncased_squadv1.1_sparse_80_...	BertForQuestionAnswering
121	en	bert_qa_bert_base_uncased_squadv1_x1.16_f88.1_...	BertForQuestionAnswering
122	en	bert_qa_bert_base_uncased_squadv1_x1.84_f88.7_...	BertForQuestionAnswering
123	en	bert_qa_bert_base_uncased_squadv1_x1.96_f88.3_...	BertForQuestionAnswering
124	en	bert_qa_bert_base_uncased_squadv1_x2.01_f89.2_...	BertForQuestionAnswering
125	en	bert_qa_bert_base_uncased_squadv1_x2.32_f86.6_...	BertForQuestionAnswering

Transformer **Question** Answering in Spark NLP Part 3

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number	Language	Spark NLP Model Name	Model
126	en	bert_qa_bert_base_uncased_squadv1_x2.44_f87.7_...	BertForQuestionAnswering
127	zh	bert_qa_bert_chinese_finetuned	BertForQuestionAnswering
128	en	bert_qa_bert	BertForQuestionAnswering
129	en	bert_qa_bert_fa_QA_v1	BertForQuestionAnswering
130	en	bert_qa_bert_large_faquad	BertForQuestionAnswering
131	en	bert_qa_bert_large_uncased_wwm_squadv2_x2.63_f...	BertForQuestionAnswering
132	en	bert_qa_bert_medium_finetuned_squad	BertForQuestionAnswering
133	en	bert_qa_bert_medium_finetuned_squadv2	BertForQuestionAnswering
134	en	bert_qa_bert_medium_pretrained_finetuned_squad	BertForQuestionAnswering
135	en	bert_qa_bert_medium_squad2_distilled	BertForQuestionAnswering
136	en	bert_qa_bert_medium_wrslb_finetuned_squadv1	BertForQuestionAnswering
137	en	bert_qa_bert_mini_5_finetuned_squadv2	BertForQuestionAnswering
138	en	bert_qa_bert_mini_finetuned_squadv2	BertForQuestionAnswering
139	en	bert_qa_bert_mini_wrslb_finetuned_squadv1	BertForQuestionAnswering
140	en	bert_qa_bert_multi_cased_finedtuned_xquad_chaii	BertForQuestionAnswering
141	en	bert_qa_bert_multi_cased_finetuned_chaii	BertForQuestionAnswering
142	en	bert_qa_bert_multi_cased_finetuned_xquadv1_fin...	BertForQuestionAnswering
143	xx	bert_qa_bert_multi_cased_finetuned_xquadv1	BertForQuestionAnswering
144	de	bert_qa_bert_multi_english_german_squad2	BertForQuestionAnswering
145	en	bert_qa_bert_multi_uncased_finetuned_chaii	BertForQuestionAnswering
146	xx	bert_qa_bert_multi_uncased_finetuned_xquadv1	BertForQuestionAnswering
147	en	bert_qa_bert_qasper	BertForQuestionAnswering
148	en	bert_qa_bert_reader_squad2	BertForQuestionAnswering
149	en	bert_qa_bert_set_date_1_lr_2e_5_bs_32_ep_4	BertForQuestionAnswering

Number	Language	Spark NLP Model Name	Model
150	en	bert_qa_bert_small_2_finetuned_squadv2	BertForQuestionAnswering
151	en	bert_qa_bert_small_cord19_squad2	BertForQuestionAnswering
152	en	bert_qa_bert_small_cord19qa	BertForQuestionAnswering
153	en	bert_qa_bert_small_finetuned_squad	BertForQuestionAnswering
154	en	bert_qa_bert_small_finetuned_squadv2	BertForQuestionAnswering
155	en	bert_qa_bert_small_pretrained_finetuned_squad	BertForQuestionAnswering
156	en	bert_qa_bert_small_wrslb_finetuned_squadv1	BertForQuestionAnswering
157	en	bert_qa_bert_tiny_2_finetuned_squadv2	BertForQuestionAnswering
158	en	bert_qa_bert_tiny_3_finetuned_squadv2	BertForQuestionAnswering
159	en	bert_qa_bert_tiny_4_finetuned_squadv2	BertForQuestionAnswering
160	en	bert_qa_bert_tiny_5_finetuned_squadv2	BertForQuestionAnswering
161	en	bert_qa_bert_tiny_finetuned_squad	BertForQuestionAnswering
162	en	bert_qa_bert_tiny_finetuned_squadv2	BertForQuestionAnswering
163	tr	bert_qa_bert_turkish_question_answering	BertForQuestionAnswering
164	en	bert_qa_bert_uncased_L_10_H_512_A_8_cord19_200...	BertForQuestionAnswering
165	en	bert_qa_bert_uncased_L_10_H_512_A_8_cord19_200...	BertForQuestionAnswering
166	en	bert_qa_bert_uncased_L_10_H_512_A_8_squad2_cov...	BertForQuestionAnswering
167	en	bert_qa_bert_uncased_L_10_H_512_A_8_squad2	BertForQuestionAnswering
168	en	bert_qa_bert_uncased_L_2_H_512_A_8_cord19_2006...	BertForQuestionAnswering
169	en	bert_qa_bert_uncased_L_2_H_512_A_8_squad2_covi...	BertForQuestionAnswering
170	en	bert_qa_bert_uncased_L_2_H_512_A_8_squad2	BertForQuestionAnswering
171	en	bert_qa_bert_uncased_L_4_H_256_A_4_cord19_2006...	BertForQuestionAnswering
172	en	bert_qa_bert_uncased_L_4_H_256_A_4_cord19_2006...	BertForQuestionAnswering
173	en	bert_qa_bert_uncased_L_4_H_256_A_4_squad2_covi...	BertForQuestionAnswering
174	en	bert_qa_bert_uncased_L_4_H_256_A_4_squad2	BertForQuestionAnswering

Transformer **Question** Answering in Spark NLP Part 4

Search them all in the Modelshub
https://nlp.johnsnowlabs.com/models

Number	Language	Spark NLP Model Name	Model
175	en	bert_qa_bert_uncased_L_4_H_512_A_8_cord19_2006...	BertForQuestionAnswering
176	en	bert_qa_bert_uncased_L_4_H_512_A_8_cord19_2006...	BertForQuestionAnswering
177	en	bert_qa_bert_uncased_L_4_H_512_A_8_squad2_covi...	BertForQuestionAnswering
178	en	bert_qa_bert_uncased_L_4_H_512_A_8_squad2	BertForQuestionAnswering
179	en	bert_qa_bert_uncased_L_4_H_768_A_12_cord19_200...	BertForQuestionAnswering
180	en	bert_qa_bert_uncased_L_4_H_768_A_12_cord19_200...	BertForQuestionAnswering
181	en	bert_qa_bert_uncased_L_4_H_768_A_12_squad2_cov...	BertForQuestionAnswering
182	en	bert_qa_bert_uncased_L_4_H_768_A_12_squad2	BertForQuestionAnswering
183	en	bert_qa_bert_uncased_L_6_H_128_A_2_squad2_covi...	BertForQuestionAnswering
184	en	bert_qa_bert_uncased_L_6_H_128_A_2_squad2	BertForQuestionAnswering
185	en	bert_qa_bertimbau_squad1.1	BertForQuestionAnswering
186	en	bert_qa_bertserini_bert_base_squad	BertForQuestionAnswering
187	en	bert_qa_bertserini_bert_large_squad	BertForQuestionAnswering
188	ko	bert_qa_bespin_global_klue_bert_base_mrc	BertForQuestionAnswering
189	es	bert_qa_beto_base_spanish_sqac	BertForQuestionAnswering
190	pt	bert_qa_bioBERTpt_squad_v1.1_portuguese	BertForQuestionAnswering
191	en	bert_qa_biobert_base_cased_v1.1_squad	BertForQuestionAnswering
192	en	bert_qa_biobert_base_cased_v1.1_squad_finetune...	BertForQuestionAnswering
193	en	bert_qa_biobert_base_cased_v1.1_squad_finetune...	BertForQuestionAnswering
194	en	bert_qa_biobert_base_cased_v1.1_squad_finetune...	BertForQuestionAnswering
195	en	bert_qa_biobert_bioasq	BertForQuestionAnswering
196	en	bert_qa_biobert_squad2_cased	BertForQuestionAnswering
197	en	bert_qa_biobert_squad2_cased_finetuned_squad	BertForQuestionAnswering
198	en	bert_qa_biobert_v1.1_pubmed_finetuned_squad	BertForQuestionAnswering
199	en	bert_qa_biobert_v1.1_pubmed_squad_v2	BertForQuestionAnswering
200	en	bert_qa_bioformer_cased_v1.0_squad1	BertForQuestionAnswering

Transformers & Embeddings

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. It is an Auto Encoder Language Model.

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. It is an Autoregressive Language Model.

Albert is 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 pre training method BERT. Researchers introduced two parameter-reduction techniques in ALBERT to lower memory consumption and increase training speed and the Next Sentence Prediction task is replace by Sentence Order Prediction

USE (Universal Sentence Encoder) is a Transformer-based model for encoding sentences into embedding vectors that specifically target transfer learning to other NLP tasks and outperforms previous word-embedding models on various NLP tasks

Transformers & Embeddings

DistilBert is a compressed version of BERT, which leverages knowledge distillation during the pre-training phase and shows that it is possible to reduce the size of a BERT model by 40%, while retaining 97% of its language understanding capabilities and being 60% faster. It introduces a triple loss combining language modeling, distillation and cosine-distance losses. The smaller, faster and lighter model is cheaper to pre-train and we demonstrate its capabilities for on-device computations in a proof-of-concept experiment and a comparative

on-device

RoBerta is a optimized version of BERT, which has improved hyperparameters and training data size. The findings show that the original BERT was significantly undertrained and with (1) Longer training, bigger batches, (2) removing next sentence prediction objective, (3) training on longer sequences and (4) dynamically changing the masking pattern applied to the training data every previous BERT can be outperformed and new state of the art can be achieved

XlmRoBerta is a multilingual BERT model which significantly outperforms multilingual BERT on a variety of cross-lingual benchmark and large accuracy gains on various multi-lingual benchmarks for 88 languages that appear in the Wiki-100 corpus

Longformer is a Transformer-based model which improves on processing long sequences by introduces a windowed attention mechanism and a linearly scaling self-attention mechanism which scales linearly with sequence length and easily processes documents with thousands or more tokens.

NLP Transformers & Embeddings

- BERT : https://arxiv.org/abs/1810.04805
- XLNet : https://arxiv.org/abs/1906.08237
- Albert : https://arxiv.org/abs/1909.11942
- Elmo : https://arxiv.org/abs/1802.05365
- USE : https://arxiv.org/abs/1803.11175
- DistilBert : https://arxiv.org/abs/1910.01108
- RoBerta : https://arxiv.org/abs/1907.11692
- DeBerta : https://arxiv.org/abs/2006.03654
- XlmRoberta : https://arxiv.org/abs/1911.02116
- Longformer : https://arxiv.org/abs/2004.05150
- Electra : https://arxiv.org/abs/2003.10555
- T5 : https://arxiv.org/abs/1910.10683
- Marian: https://arxiv.org/abs/1804.00344
- GPT2: https://openai.com/blog/better-language-models/
- SpanBERT https://arxiv.org/abs/1907.10529
- CamemBERT https://camembert-model.fr/
- SciBert https://www.aclweb.org/anthology/D19-1371/
- MiniLm https://arxiv.org/abs/2002.10957
- CovidBERT https://arxiv.org/abs/2005.07503
- BioBERT https://arxiv.org/abs/1901.08746
- indoBERT https://arxiv.org/abs/2011.00677
- MuRIL https://arxiv.org/abs/2103.10730
- sapBERT https://github.com/cambridgeltl/sapbert
- BioFormer https://github.com/WGLab/Bioformer
- LinkBERT https://arxiv.org/abs/2203.15827
- MacBERT https://aclanthology.org/2020.findings-emnlp.58
- DOC2Vec : https://arxiv.org/abs/1301.3781
- Word2Vec: https://arxiv.org/abs/1301.3781

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)
```

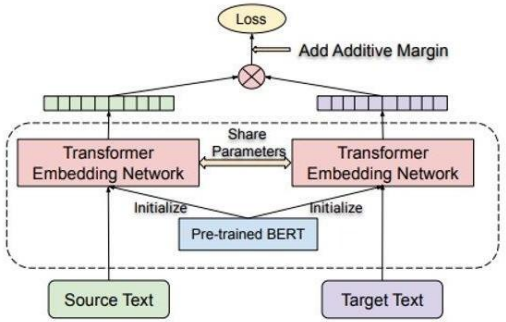


Figure 1: Dual encoder model with BERT based encoding modules.

Microsoft

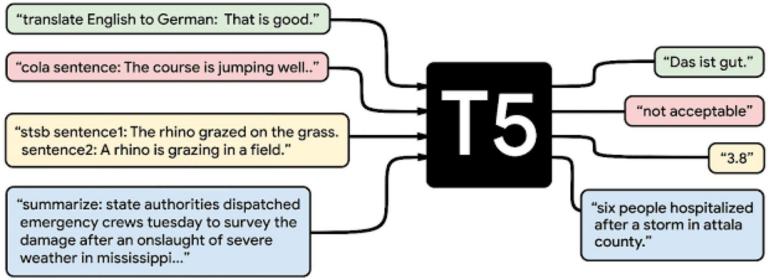
Translate between **200+ Languages**

[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')`
```




```
# 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 Transformer Models via Huggingface or TfHub and scale with Spark NLP

TensorFlow Hub

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

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
CamemBertEmbeddings	HuggingFace in Spark NLP - CamemBERT	Open in Colab
RoBertaEmbeddings	HuggingFace in Spark NLP - RoBERTa	Open in Colab
DeBertaEmbeddings	HuggingFace in Spark NLP - DeBERTa	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
BertForSequenceClassification	HuggingFace in Spark NLP - BertForSequenceClassification	Open in Colab
DistilBertForSequenceClassification	HuggingFace in Spark NLP - DistilBertForSequenceClassification	Open in Colab
AlbertForSequenceClassification	HuggingFace in Spark NLP - AlbertForSequenceClassification	Open in Colab
RoBertaForSequenceClassification	HuggingFace in Spark NLP - RoBertaForSequenceClassification	Open in Colab
XlmRoBertaForSequenceClassification	HuggingFace in Spark NLP - XlmRoBertaForSequenceClassification	Open in Colab
XlnetForSequenceClassification	HuggingFace in Spark NLP - XlnetForSequenceClassification	Open in Colab
LongformerForSequenceClassification	HuggingFace in Spark NLP - LongformerForSequenceClassification	Open in Colab
AlbertForQuestionAnswering	HuggingFace in Spark NLP - AlbertForQuestionAnswering	Open in Colab
BertForQuestionAnswering	HuggingFace in Spark NLP - BertForQuestionAnswering	Open in Colab
DeBertaForQuestionAnswering	HuggingFace in Spark NLP - DeBertaForQuestionAnswering	Open in Colab
DistilBertForQuestionAnswering	HuggingFace in Spark NLP - DistilBertForQuestionAnswering	Open in Colab
LongformerForQuestionAnswering	HuggingFace in Spark NLP - LongformerForQuestionAnswering	Open in Colab
RoBertaForQuestionAnswering	HuggingFace in Spark NLP - RoBertaForQuestionAnswering	Open in Colab
XlmRobertaForQuestionAnswering	HuggingFace in Spark NLP - XlmRobertaForQuestionAnswering	Open in Colab

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

Session 3 (Day 1) - Coding Time

- Notebook 3 Spark NLP pretrained models

Spark NLP
for Data Scientists

John Snow LABS

Session 4 (Day 1)

- (cont.) Usage and overview of the 10000+ pretrained models for 300+ languages
- Training Named Entity Recognition (NER) models

Spark NLP
for Data Scientists

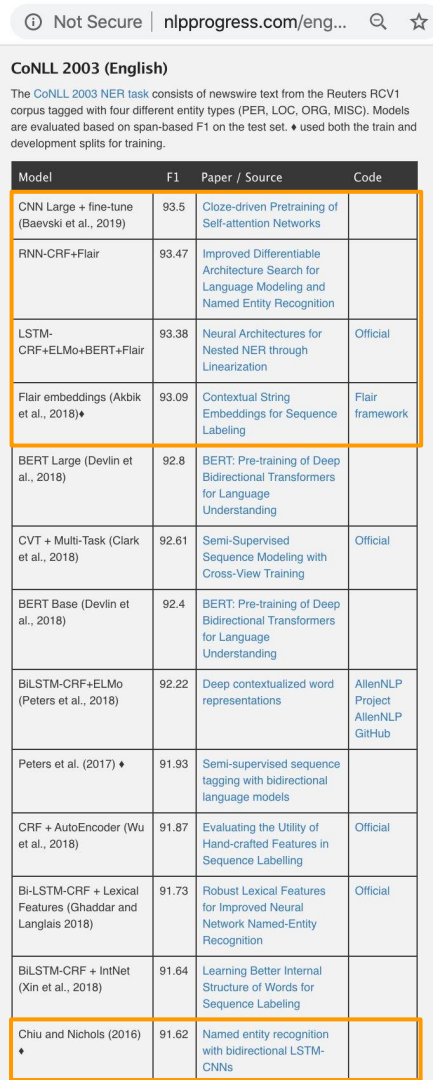
John Snow LABS

Session 4 (Day 1) - Coding Time

- Notebook 3 Spark NLP pretrained models

Spark NLP
for Data Scientists

John Snow LABS



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

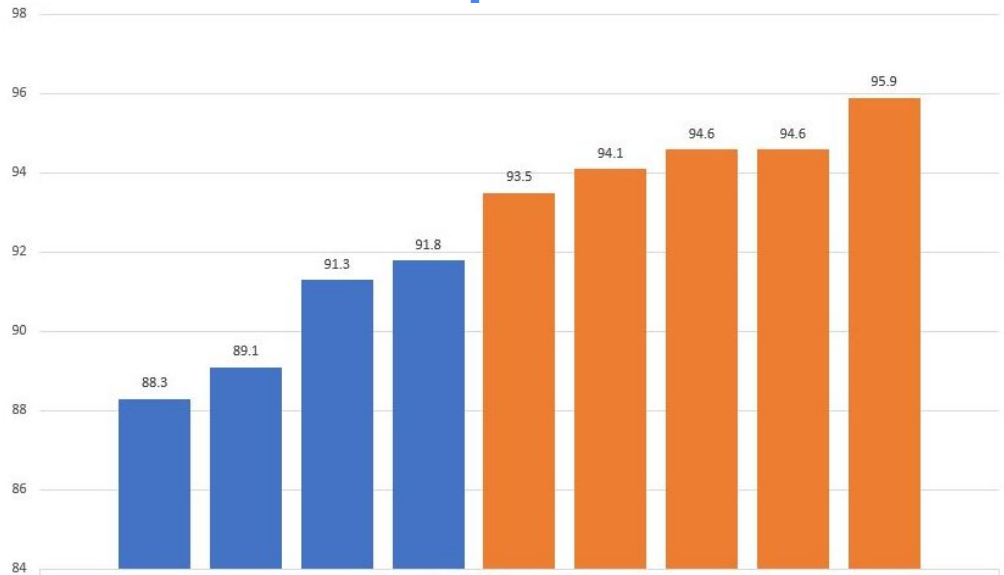
93.3 %
Test Set

Bert

NerDLApproach

John Snow LABS

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

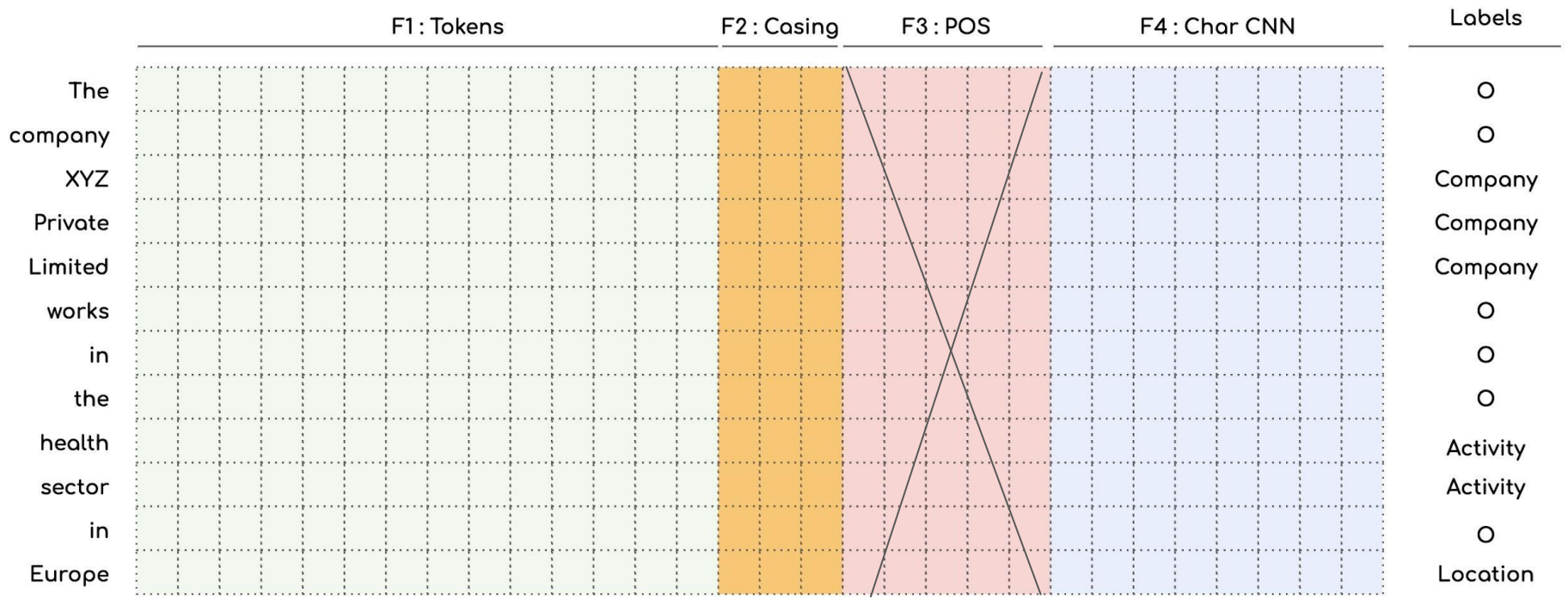
Feature-engineered machine learning systems	Dict	SP	DU	EN	GE
Carreras et al. (2002) binary AdaBoost classifiers	Yes	81.39	77.05	-	-
Malouf (2002) - Maximum Entropy (ME) + features	Yes	73.66	68.08	-	-
Li et al. (2005) SVM with class weights	Yes	-	-	88.3	-
Passos et al. (2014) CRF	Yes	-	-	90.90	-
Ando 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)

John Snow LABS

NER-DL in Spark NLP

Char-CNN-BiLSTM



NER-DL in Spark NLP

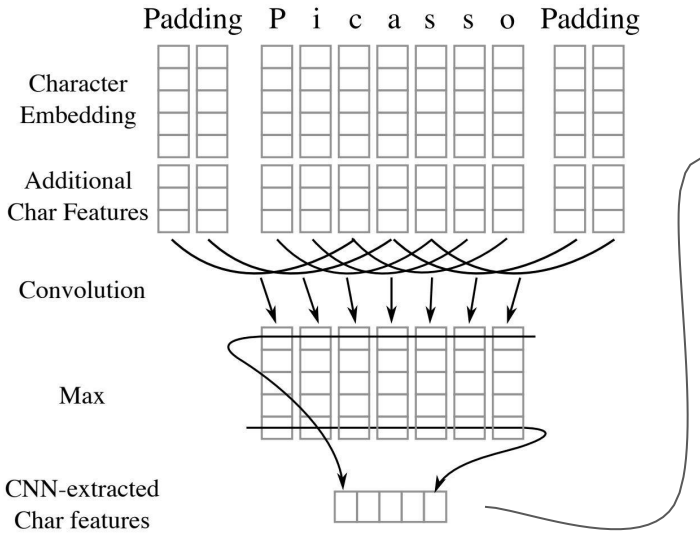


Figure 2: The convolutional neural network extracts character features from each word. The character embedding and (optionally) the character type feature vector are computed through lookup tables. Then, they are concatenated and passed into the CNN.

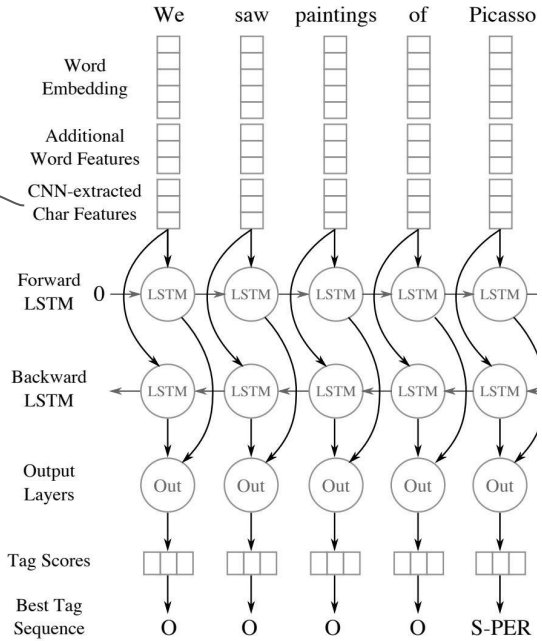


Figure 1: The (unrolled) BLSTM for tagging named entities. Multiple tables look up word-level feature vectors. The CNN (Figure 2) extracts a fixed length feature vector from character-level features. For each word, these vectors are concatenated and fed to the BLSTM network and then to the output layers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

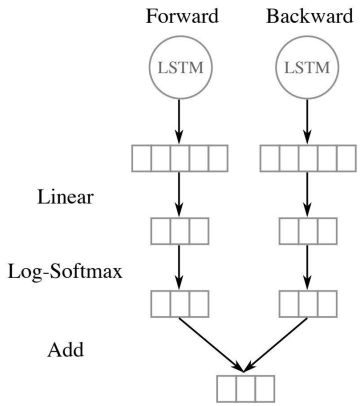


Figure 3: The output layers ("Out" in Figure 1) decode output into a score for each tag category.

Char-CNN-BiLSTM

John Snow LABS

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.

BIO schema

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

John Smith ⇒ PERSON
New York ⇒ LOCATION

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

John Snow LABS

Session 4 (Day 1) - Coding Time

- Notebook 4: NERDL Training

Spark NLP
for Data Scientists

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/open-source-nlp/04.0.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
```

John Snow LABS

End of Day 1 - see you tomorrow!
Same time, same place :)

Spark NLP
for Data Scientists

John Snow LABS

Welcome to Day-2 - We have a lot of things ahead of us

Day-2	50 min	- Train Text Classifiers - Upload models to the Models Hub
	10 min	Break
	50 min	- Spell Checking - Keyword Extraction with YAKE - Rule-based Entity Recognition with EntityRuler - Graph triplet extraction
	10 min	Break
	50 min	- Token Classification with Transformers - Sequence Classification with Transformers - Image Classification with ViT - Speech to Text with Wav2Vec2
	10 min	Break
	50 min	- Table Question Answering with TAPAS - Question Answering, Summarization and other T5 applications - Multilingual NLP - Train only on English data and predict for 100+ languages

Session 1 (Day 2)

- Training a Deep Learning Text Classifier
- Upload/Download your own model via John Snow Labs Models Hub

Spark NLP
for Data Scientists

John Snow LABS

SentimentDL, ClassifierDL, and MultiClassifierDL

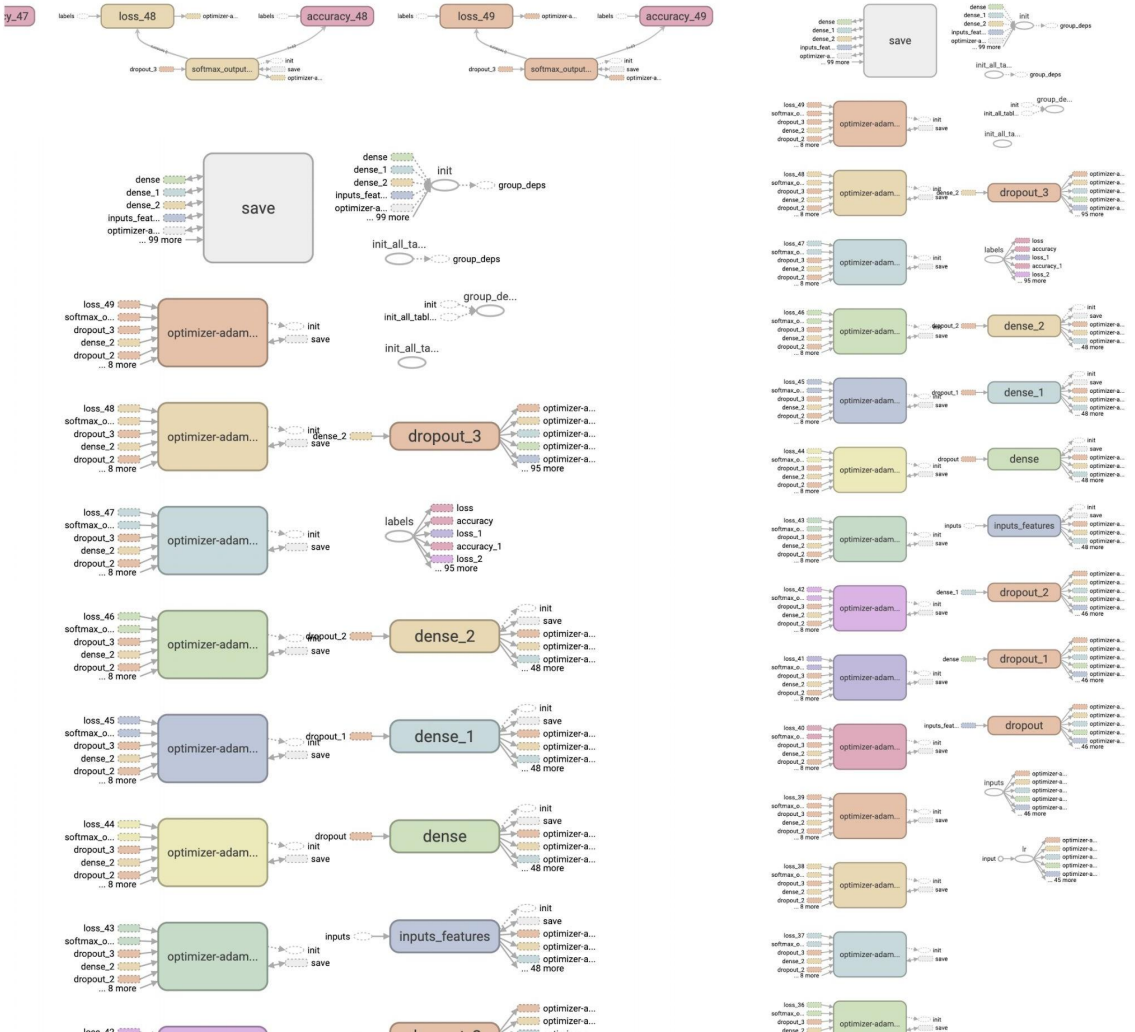
- BERT
- Small BERT
- BioBERT
- CovidBERT
- LaBSE
- ALBERT
- ELECTRA
- XLNet
- ELMO
- Universal Sentence Encoder
- GloVe

- 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!

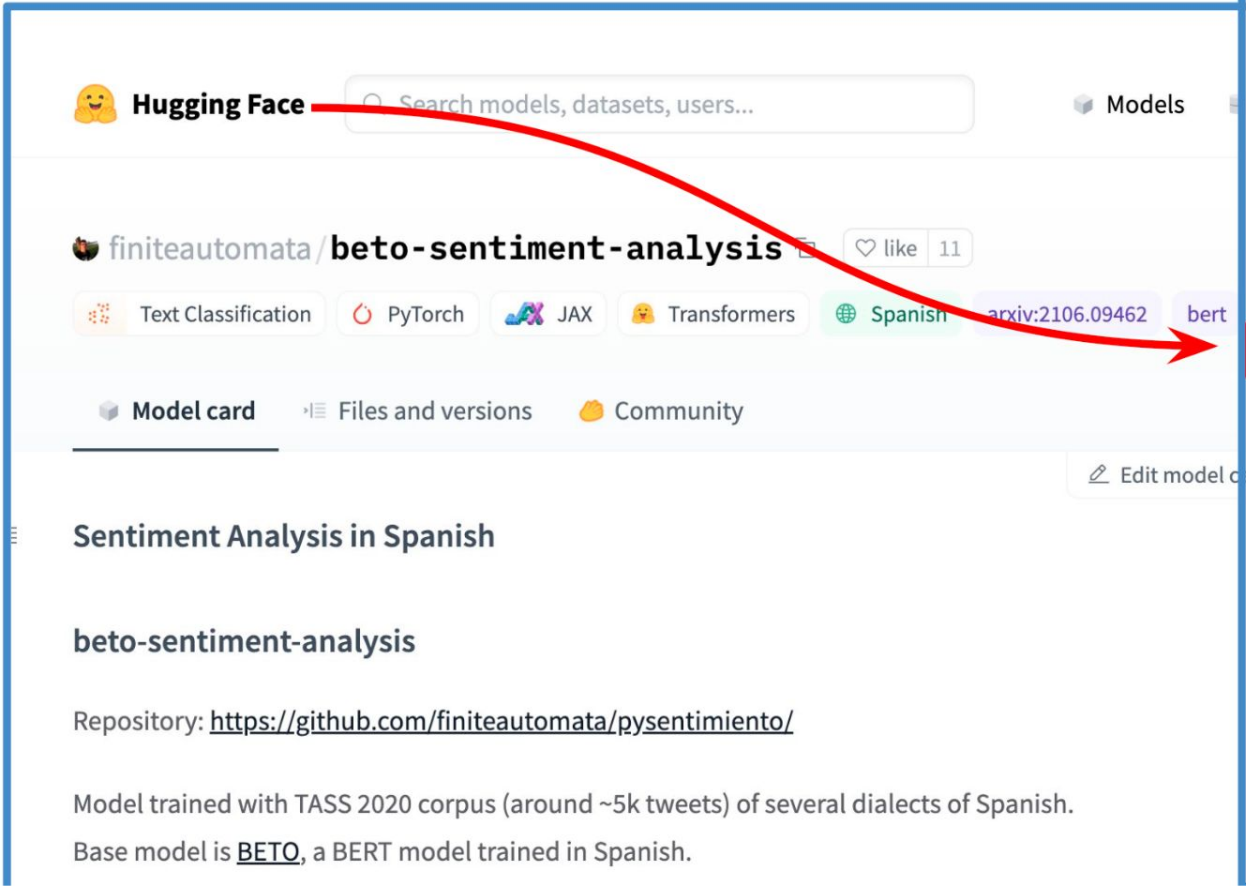
- 100 dimensions
- 200 dimensions
- 128 dimensions
- 256 dimensions
- 300 dimensions
- 512 dimensions
- 768 dimensions
- 1024

- 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



Import a model from HuggingFace 🤗 into Spark NLP 🚀



Example Notebooks

HuggingFace to Spark NLP

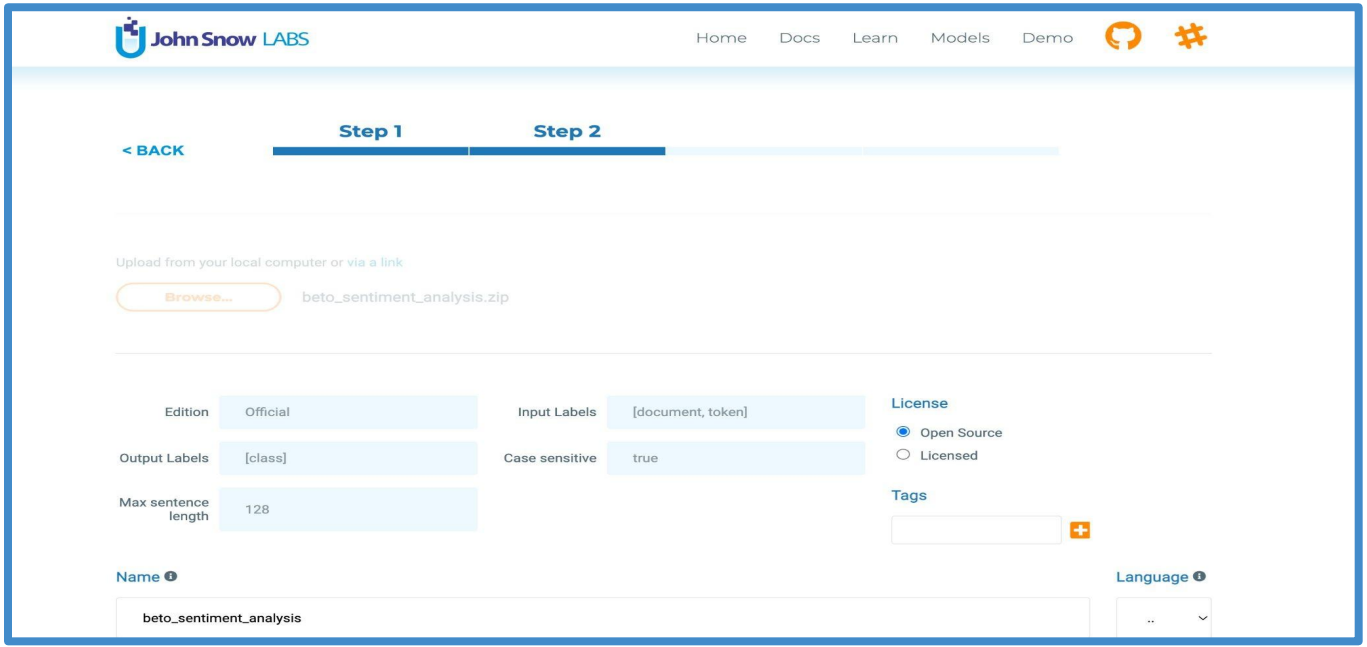
Spark NLP	HuggingFace Notebooks	Colab
BertEmbeddings	HuggingFace in Spark NLP - BERT	Open in Colab
BertSentenceEmbeddings	HuggingFace in Spark NLP - BERT Sentence	Open in Colab
DistilBertEmbeddings	HuggingFace in Spark NLP - DistilBERT	Open in Colab
CamemBertEmbeddings	HuggingFace in Spark NLP - CamemBERT	Open in Colab
RoBertaEmbeddings	HuggingFace in Spark NLP - RoBERTa	Open in Colab
DeBertaEmbeddings	HuggingFace in Spark NLP - DeBERTa	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
BertForSequenceClassification	HuggingFace in Spark NLP - BertForSequenceClassification	Open in Colab
AlbertForSequenceClassification	HuggingFace in Spark NLP - AlbertForSequenceClassification	Open in Colab
RoBertaForSequenceClassification	HuggingFace in Spark NLP - RoBertaForSequenceClassification	Open in Colab
XlmRoBertaForSequenceClassification	HuggingFace in Spark NLP - XlmRoBertaForSequenceClassification	Open in Colab
XlnetForSequenceClassification	HuggingFace in Spark NLP - XlnetForSequenceClassification	Open in Colab
LongformerForSequenceClassification	HuggingFace in Spark NLP - LongformerForSequenceClassification	Open in Colab
AlbertForQuestionAnswering	HuggingFace in Spark NLP - AlbertForQuestionAnswering	Open in Colab
BertForQuestionAnswering	HuggingFace in Spark NLP - BertForQuestionAnswering	Open in Colab
DeBertaForQuestionAnswering	HuggingFace in Spark NLP - DeBertaForQuestionAnswering	Open in Colab
DistilBertForQuestionAnswering	HuggingFace in Spark NLP - DistilBertForQuestionAnswering	Open in Colab
LongformerForQuestionAnswering	HuggingFace in Spark NLP - LongformerForQuestionAnswering	Open in Colab
RoBertaForQuestionAnswering	HuggingFace in Spark NLP - RoBertaForQuestionAnswering	Open in Colab
XlmRobertaForQuestionAnswering	HuggingFace in Spark NLP - XlmRobertaForQuestionAnswering	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

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 a zip file



Session 1 (Day 2) - Coding Time

- Notebook 5 ClassifierDL, SentimentDL, MultiClassifierDL Training
- Upload your own model via John Snow Labs Models Hub

Session 2 (Day 2)

- Spell Checking
- Keyword extraction with YAKE
- Rule-based Entity Recognition with EntityRuler
- Graph triplet extraction

Spark NLP
for Data Scientists

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))
```

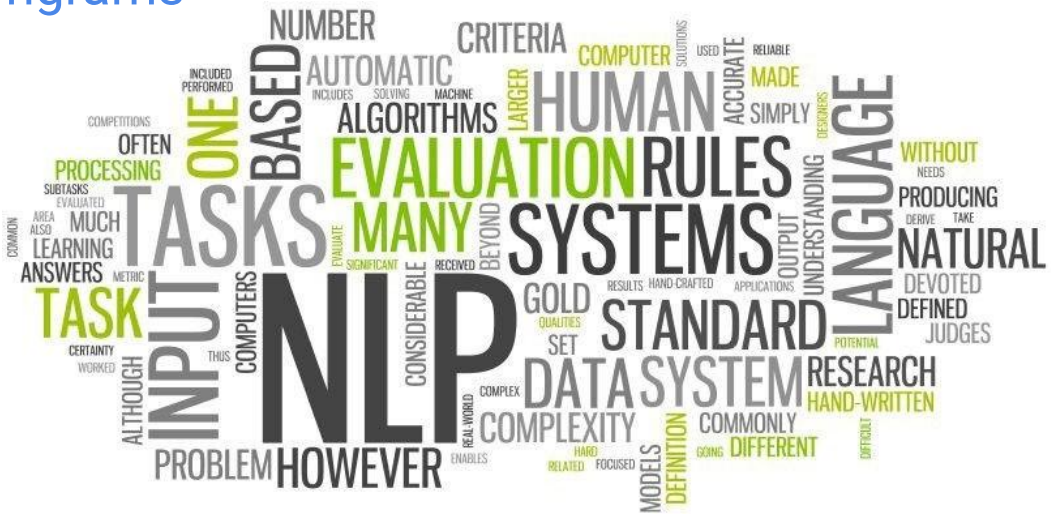
```
['During  the  summer  we  have  the  best  weather  .\n',
 'I  have  a  black  leather  jacket  ,  so  nice  .\n',
 'I  introduce  you  to  my  sister  ,  she  is  called  Heather  .\n']
```

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

Notebook 07.0 Spell Checker

Unsupervised Keyword Extraction

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



[Notebook 08.0 YAKE]

Rule-based Entity Recognition with EntityRuler

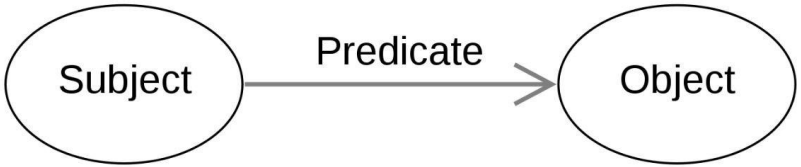
Notebook 11.0 EntityRuler

Fits an Annotator to match exact strings or regex patterns provided in a file against a Document and assigns them an named entity.

```
[
    {
      "id": "person-regex",
      "label": "PERSON",
      "patterns": ["\w+\s\w+", "\w+-\w+"]
    },
    {
      "id": "locations-words",
      "label": "LOCATION",
      "patterns": ["Winterfell"]
    }
]
```

```
{"id": "names-with-j", "label": "PERSON", "patterns": ["Jon", "John", "John Snow"]}
{"id": "names-with-s", "label": "PERSON", "patterns": ["Stark", "Snow"]}
{"id": "names-with-e", "label": "PERSON", "patterns": ["Eddard", "Eddard Stark"]}
```

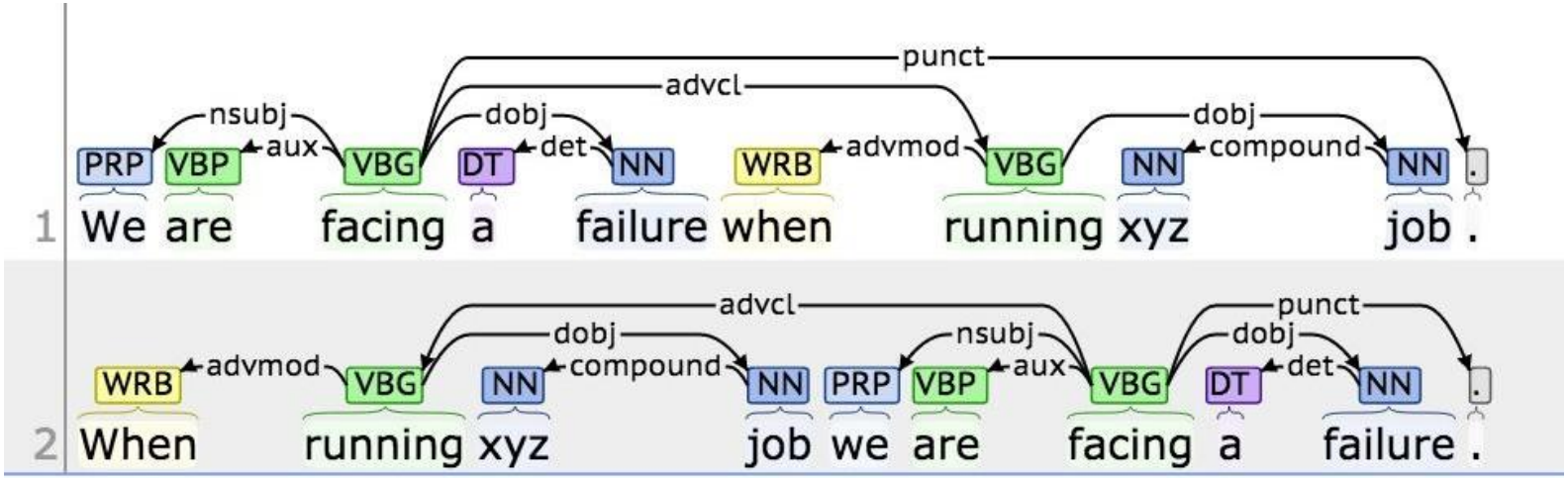
Extract RDF Semantic Triplets



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

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

Notebook 10.0 Graph Extraction



Session 2 (Day 2) - Coding Time

- Notebook 7 Context Spell Checker
- Notebook 8 YAKE
- Notebook 11 EntityRuler
- Notebook 10 RDF Graph Extraction

Spark NLP
for Data Scientists

John Snow LABS

Session 3 (Day 2)

- Sequence & Token Classification with Transformers
- Image Classification with ViT
- Speech to Text with Wav2Vec2

Spark NLP
for Data Scientists

John Snow LABS

Training & Importing Transformers

[Spark NLP - Transformers]

Import Transformers into Spark NLP

We have extended support for `HuggingFace` 🤗 and `TF Hub` exported models since `3.1.0` to equivalent Spark NLP 🚀 annotators. Starting this release, you can easily use the `saved_model` feature in HuggingFace within a few lines of codes and import any `BERT`, `DistilBERT`, `CamemBERT`, `RoBERTa`, `DeBERTa`, `XLM-RoBERTa`, `Longformer`, `BertForTokenClassification`, `DistilBertForTokenClassification`, `AlbertForTokenClassification`, `RoBertaForTokenClassification`, `DeBertaForTokenClassification`, `XlmRoBertaForTokenClassification`, `XlnetForTokenClassification`, `LongformerForTokenClassification`, `CamemBertForTokenClassification`, `CamemBertForSequenceClassification`, `CamemBertForQuestionAnswering`, `BertForSequenceClassification`, `DistilBertForSequenceClassification`, `AlbertForSequenceClassification`, `RoBertaForSequenceClassification`, `DeBertaForSequenceClassification`, `XlmRoBertaForSequenceClassification`, `XlnetForSequenceClassification`, `LongformerForSequenceClassification`, `AlbertForQuestionAnswering`, `BertForQuestionAnswering`, `DeBertaForQuestionAnswering`, `DistilBertForQuestionAnswering`, `LongformerForQuestionAnswering`, `RoBertaForQuestionAnswering`, `XlmRoBertaForQuestionAnswering`, `TapasForQuestionAnswering`, `Vision Transformers (ViT)`, `HubertForCTC`, `SwinForImageClassification`, and `ConvNextForImageClassification` models to Spark NLP. We will work on the remaining annotators and extend this support to the rest with each release 😊

Image Classification with ViT

[Notebook 18 VIT for Image Classification]

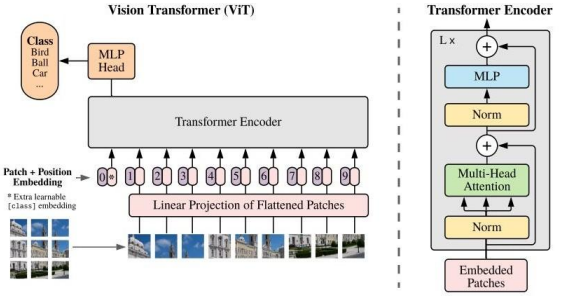
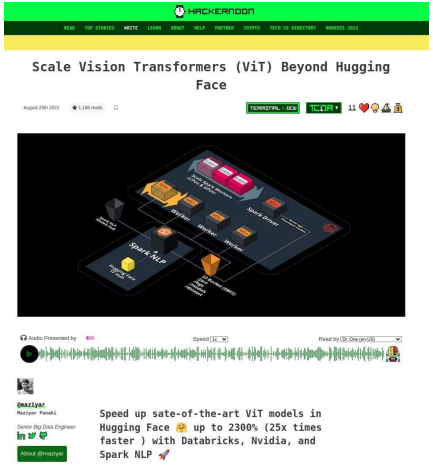
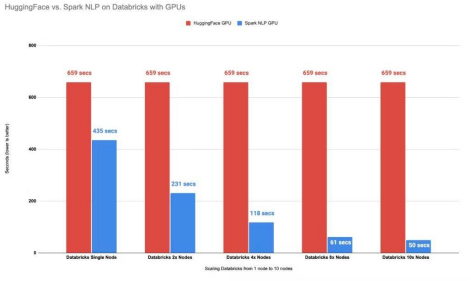


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable "classification token" to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

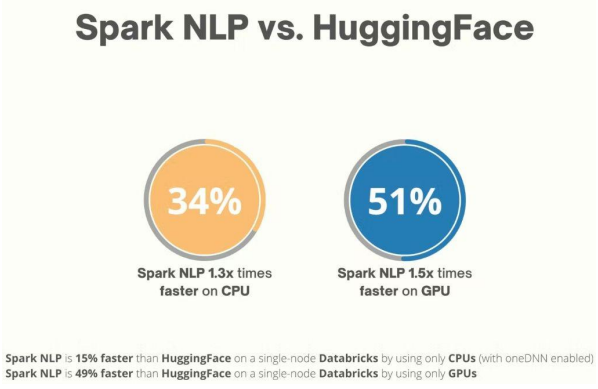


[Scale Vision Transformers (ViT) Beyond Hugging Face]



Spark NLP is **1200% faster** than Hugging Face with **10x Nodes**

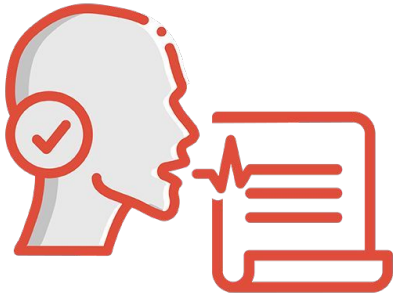
[VIT: An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale]



[Over 200 VIT Models in various languages and sizes]

Speech to Text Wav2vec 2.0

[Notebook 19 Speech2Text with Wav2Vec2]



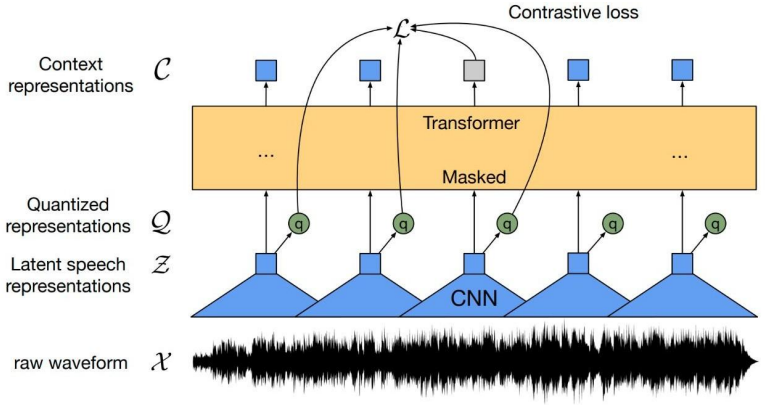


Figure 1: Illustration of our framework which jointly learns contextualized speech representations and an inventory of discretized speech units.

[wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations]

Meta

[Over 2000 Wav2Vec Models in various languages and sizes]

Session 3 (Day 2) - Coding Time

- Notebook 5.2 Transformers for Sequence Classification
- Notebook 4.2 Transformers for Token Classification
- Notebook 16 Image Classification with Transformers
- Notebook 17 Automatic Speech Recognition

Spark NLP
for Data Scientists

John Snow LABS

Session 4 (Day 2)

- Table Question Answering with TAPAS
- Question Answering, Summarization and other T5 applications
- Multilingual NLP - Train only on English data and predict for 100+ languages

Spark NLP
for Data Scientists

John Snow LABS

TAPAS for Table Classification

[Notebook 17 Table Question Answering with TAPAS]

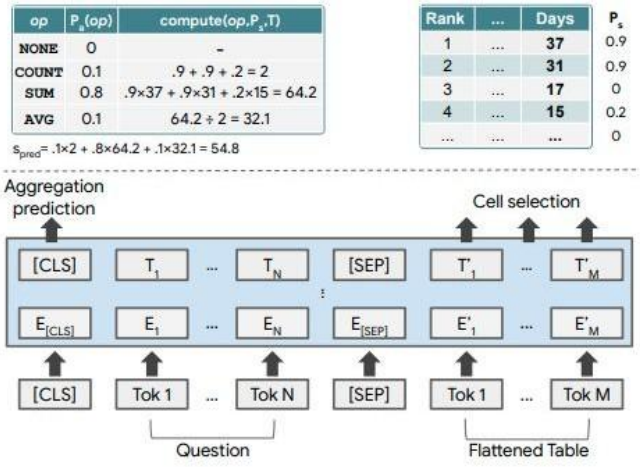


Figure 1: TAPAS model (bottom) with example model outputs for the question: *"Total number of days for the top two"*. Cell prediction (top right) is given for the selected column's table cells in bold (zero for others) along with aggregation prediction (top left).

[TAPAS: Weakly Supervised Table Parsing via Pre-training]

TAPAS for Table Question Answering using Spark NLP 🚀

TAPAS is a Zero-shot Question Answering architecture, based on Bert, to carry out Table Understanding. By asking a question on natural language using these models, you can retrieve the content of the cell or cells which best answer to those questions.

Table

Rank	Name	No. of reigns	Combined days
1	Lou Thesz	3	3,749
2	Ric Flair	8	3,103
3	Harley Race	7	1,799
4	Dory Funk Jr.	1	1,563
5	Dan Severn	2	1,559
6	Gene Kiniski	1	1,131

Example questions

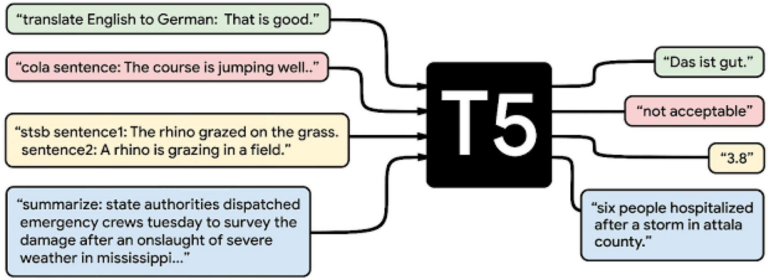
#	Question	Answer	Example Type
1	*Which wrestler had the most number of reigns?*	Ric Flair	Cell selection
2	*Average time as champion for top 2 wrestlers?*	AVG(3749,3103)=3426	Scalar answer
3	*How many world champions are there with only one reign?*	COUNT(Dory Funk Jr., Gene Kiniski)=2	Ambiguous answer
4	*What is the number of reigns for* Harley Race?	7	Ambiguous answer
5	*Which of the following wrestlers were ranked in the bottom 3?*	{Dory Funk Jr., Dan Severn, Gene Kiniski}	Cell selection
	Out of these, who had more than one reign?	Dan Severn	Cell selection

TAPAS models have been trained using a combination of three datasets:

- SQA, Sequential Question Answering by Microsoft (it was not trained to return aggregation operations as SUM, COUNT, etc - see below)
- WTQ, Wiki Table Questions by Stanford University (with aggregation operations)
- Wiki SQL, by Salesforce, also with aggregation operations.

Google

[Table Classifiers Overview]




```
# 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)
```

[Notebook 10 Question Answering and Summarization and more with T5]

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

1. Text summarization
2. Question answering
3. Translation
4. Generate SQL from natural language text
5. Text style transfer
6. Sentiment analysis
7. Natural Language inference
8. Coreference resolution
9. Sentence Completion
10. Word sense disambiguation

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

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

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

Notebook 5.2 Training Multilingual Classifier

```
# 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)
```

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		

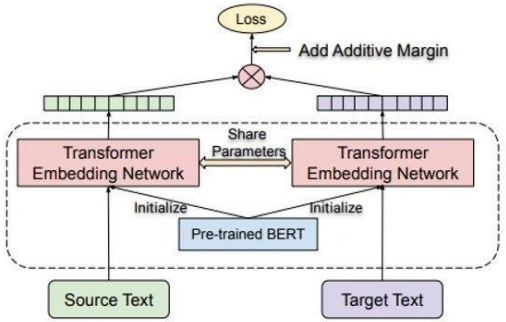


Figure 1: Dual encoder model with BERT based encoding modules.

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
https://www.udemy.com/course/spark-nlp-for-data-scientists/

John Snow LABS

Session 4 (Day 2) - Coding Time

- Notebook 15 Table Question Answering with TAPAS
- Notebook 13 Question Answering and Summarization and more with T5
- Notebook 5.3 Training Multilingual Classifier

Spark NLP
for Data Scientists

John Snow LABS

Thank You!