Spark NLP
for Data Scientists

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WELCOME!

60 minutes:	Overview and key concepts Splitting, cleaning, and connecting words
30 minutes:	Break / Code / Q&A
60 minutes:	Named entity recognition Custom pipelines & training your own models
30 minutes:	Break / Code / Q&A
60 minutes:	Document classification Model inference
Certification:	Online exam open from April 22nd to May 1st Completed in a single 90-minute session

Setup

HOUSEKEEPING:

[How to ask questions on Teams]
[How to mute / unmute / screen share]
[Notify that recording starts from next slide]

RUNNING CODE:

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

[How to set up Google Colab]

BOOKMARK:

DOCS : nlp.johnsnowlabs.com/docs/en/concepts
SLACK: spark-nlp.slack.com
CODE : github.com/johnsnowlabs/spark-nlp

Part - I

- Introducing JSL and Spark NLP
- Natural Language Processing (NLP) Basics
- Spark NLP Pretrained Pipelines
- Text Preprocessing with Spark NLP
- Spark NLP Pretrained Models

JOHN SNOW LABS

CIO Review ARTIFICIAL INTELLIGENCE SOLUTION PROVIDER OF THE YEAR - 2018

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

AI PLATFORM OF THE YEAR

CIO APPLICATIONS 2019

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

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

Introducing Spark NLP

- Natural Language Toolkit (NLTK): The complete toolkit for all NLP techniques.
- TextBlob: Easy to use NLP tools API, built on top of NLTK and Pattern.
- SpaCy: Industrial strength NLP with Python and Cython.
- Gensim: Topic Modelling for Humans
- Stanford Core NLP: NLP services and packages by Stanford NLP Group.
- Fasttext: NLP library by Facebook's AI Research (FAIR) lab
- ...

- Spark NLP is an open-source natural language processing library, built on top of Apache Spark and Spark ML. (initial release: Oct 2017)
  - A single unified solution for all your NLP needs
  - Take advantage of transfer learning and implementing the latest and greatest **SOTA** algorithms and models in NLP research
  - Lack of any NLP library that's fully supported by Spark
  - Delivering a mission-critical, enterprise grade NLP library (used by multiple Fortune 500)
  - Full-time development team (26 new releases in 2018. 30 new releases in 2019.)

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

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

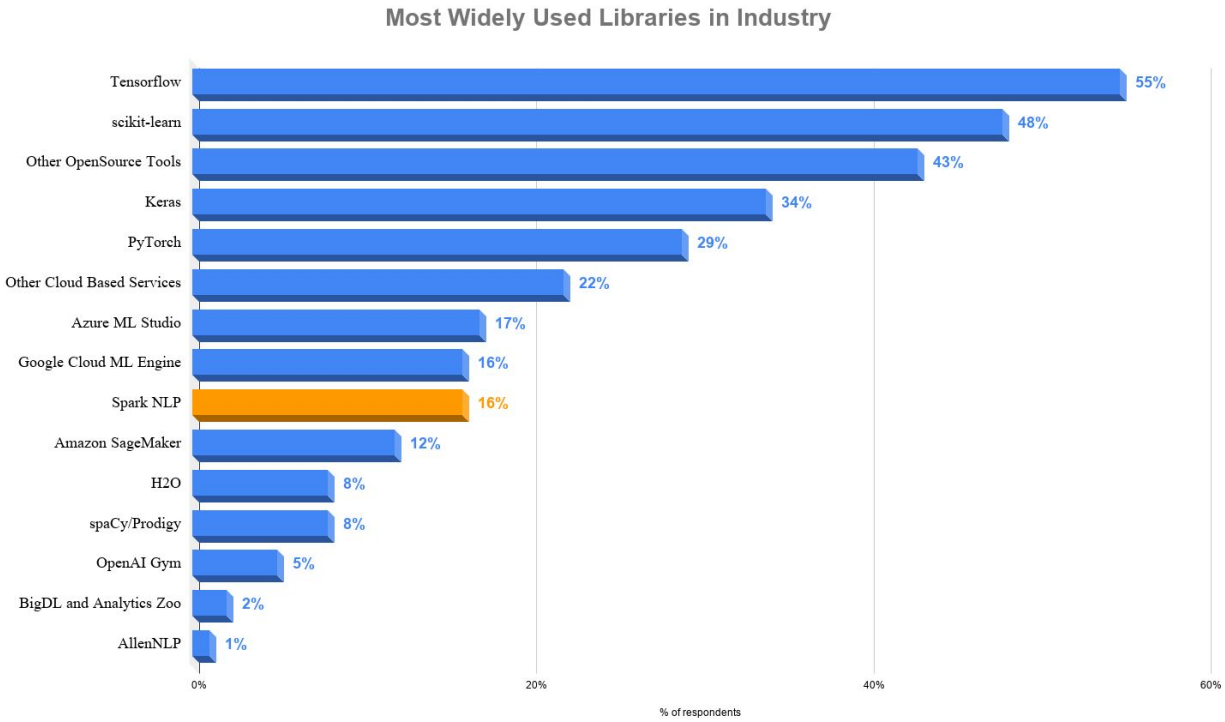

Georgia
Tech


STANFORD
UNIVERSITY

Introducing Spark NLP

Name	Spark NLP	spaCy	NLTK	CoreNLP
Sentence detection	Yes	Yes	Yes	Yes
Tokenization	Yes	Yes	Yes	Yes
Stemming	Yes	Yes	Yes	Yes
Lemmatization	Yes	Yes	Yes	Yes
POS tagger	Yes	Yes	Yes	Yes
NER	Yes	Yes	Yes	Yes
Dependency parse	Yes	Yes	Yes	Yes
Text matcher	Yes	**Yes**	**No**	Yes
Date matcher	Yes	**No**	**No**	Yes
Chunking	Yes	Yes	Yes	Yes
Spell checker	Yes	**No**	**No**	**No**
Sentiment detector	Yes	**No**	**No**	Yes
Pretrained models	Yes	Yes	Yes	Yes
Training models	Yes	Yes	Yes	Yes

Available in **Python**, **R**, **Scala** and **Java**



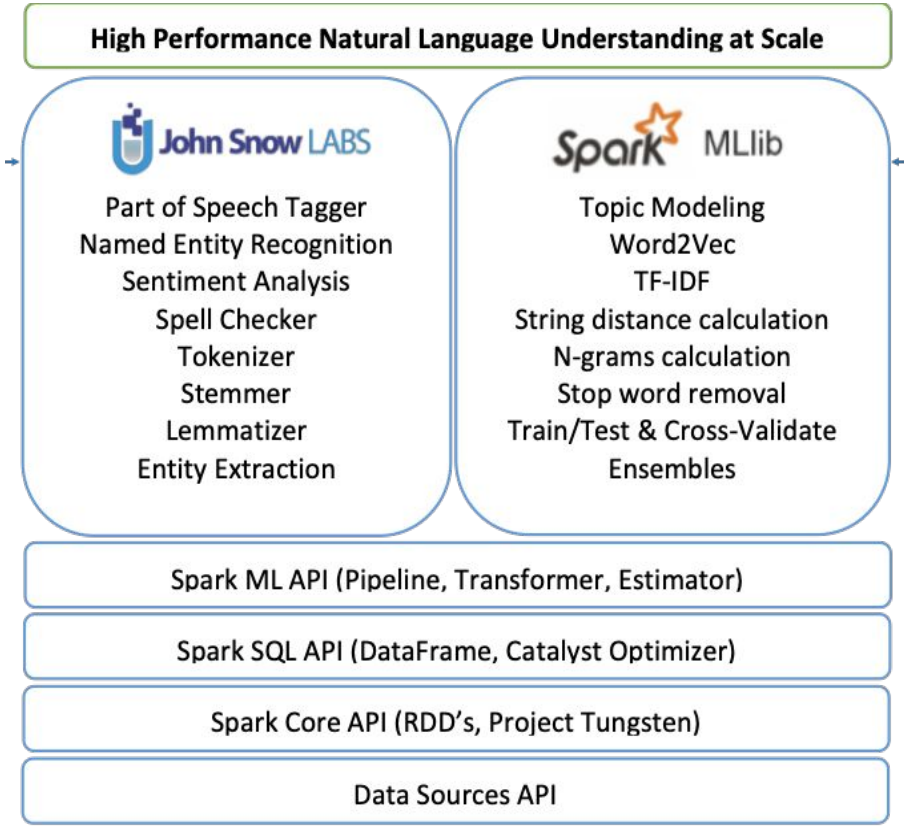
"AI Adoption in the Enterprise", February 2019
Most widely used ML frameworks and tools survey of 1,300 practitioners by O'Reilly

OFFICIALLY SUPPORTED RUNTIMES

BUILT ON THE SHOULDERS OF SPARK ML

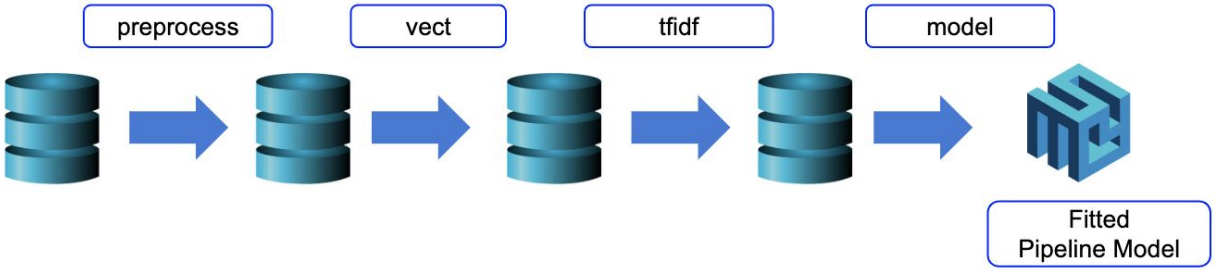
- Reusing the Spark ML Pipeline
  - Unified NLP & ML pipelines
  - End-to-end execution planning
  - Serializable
  - Distributable

- Reusing NLP Functionality
  - TF-IDF calculation
  - String distance calculation
  - Topic modeling
  - Distributed ML algorithms

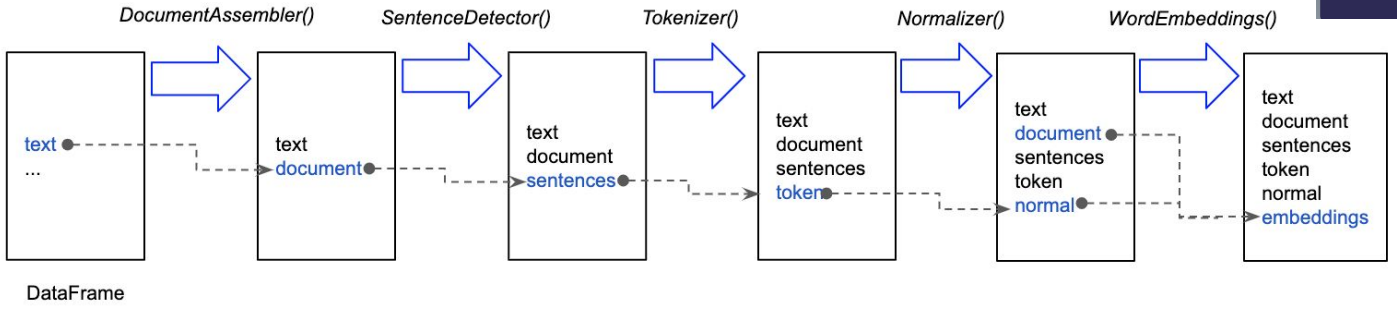


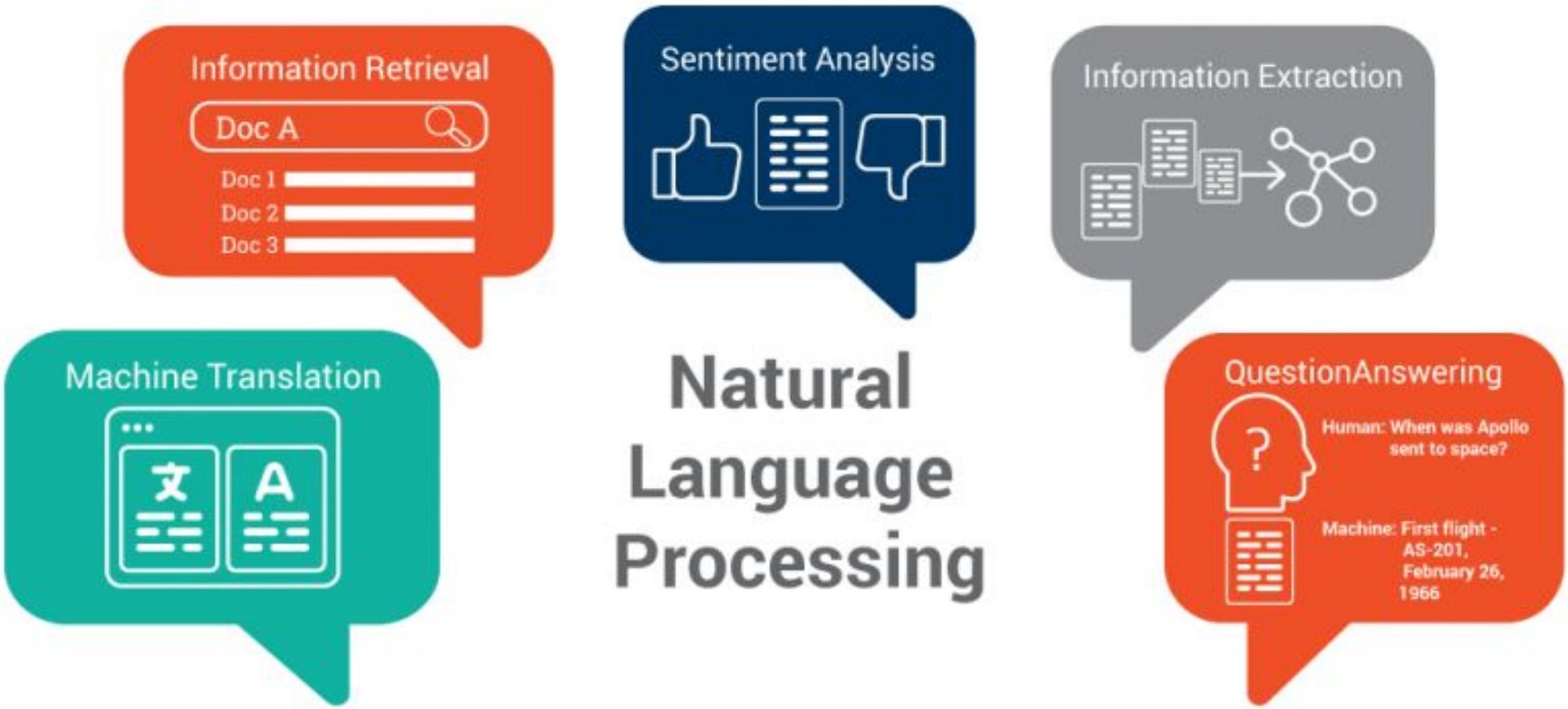
Introducing Spark NLP

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)
```




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

NLP Basics

LEMMATIZATION

Find the **lemma** of each word:

- How does it show in the dictionary?

Uses a lookup from a full dictionary.

```
am, are, is    →    be

liver          →    liver

lives          →    live
```

STEMMING

Find the **stem** of each word.

Uses rules: e.g, remove common suffixes.

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

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

NLP Basics

Remove stop words and apply stemming

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

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

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

Stopwords

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

(520 stopwords)

Spell Checking & Correction


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

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

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

NORMALIZATION

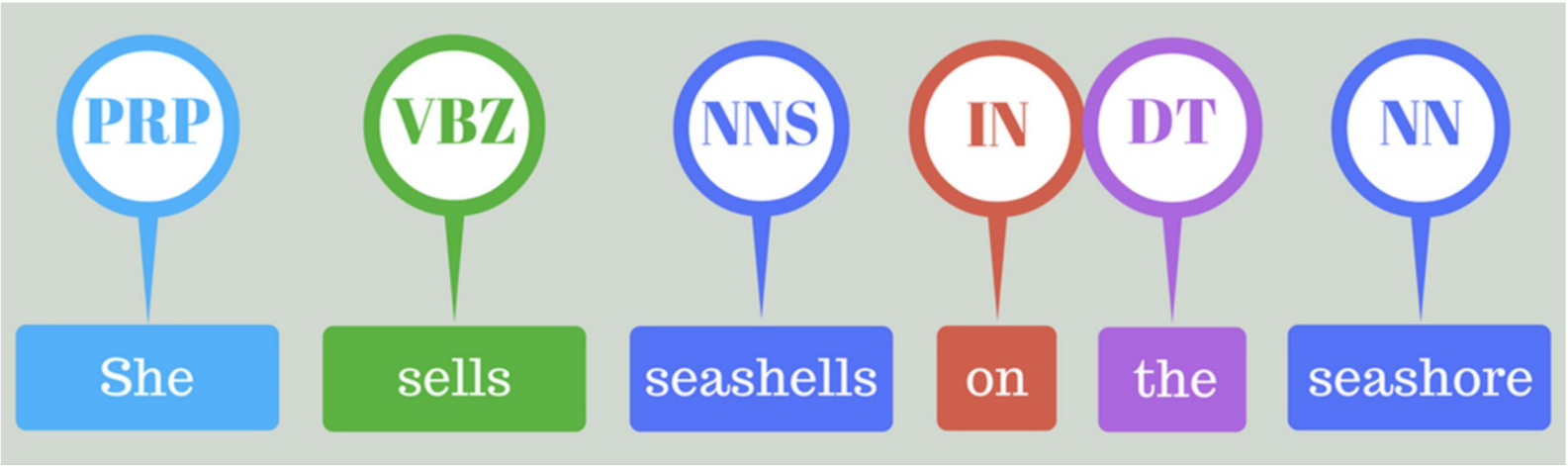
Remove or replace undesirable characters or regular expressions:

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

Spark NLP also comes with a Slang normalizer:

PART OF SPEECH TAGGING

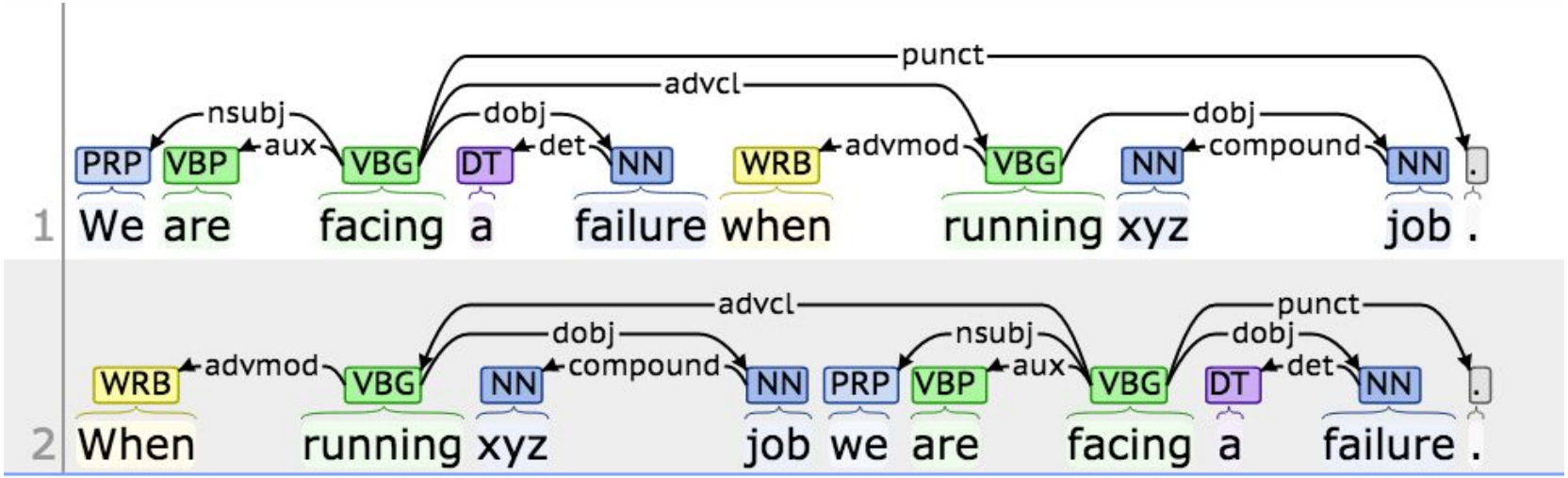
Often useful for recognizing named entities or word relationships.



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.

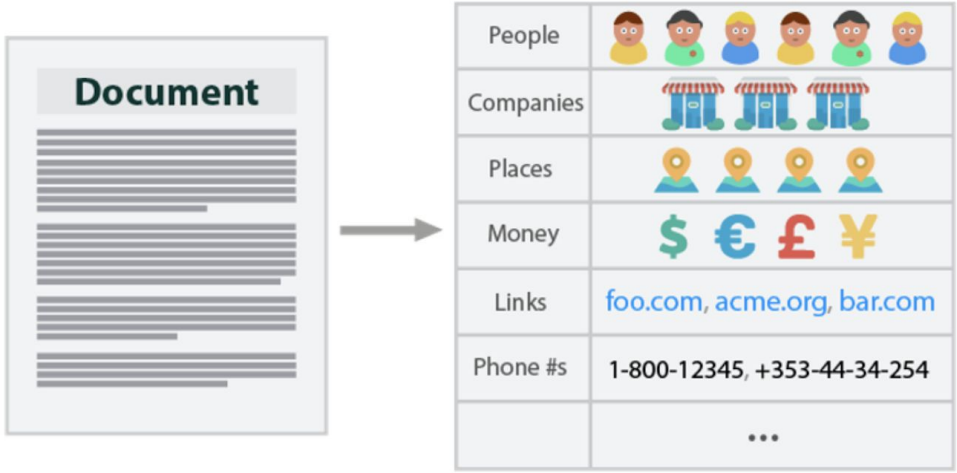
DEPENDENCY PARSING

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



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.

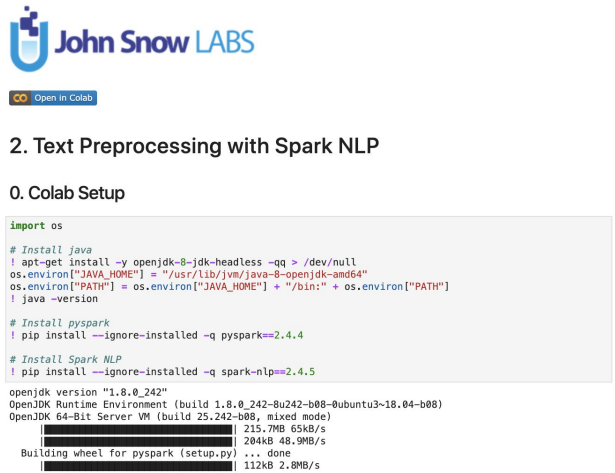
Coding ...

Open **1. Spark NLP Basics** and **2. Text Preprocessing with SparkNLP** notebooks in **Colab**

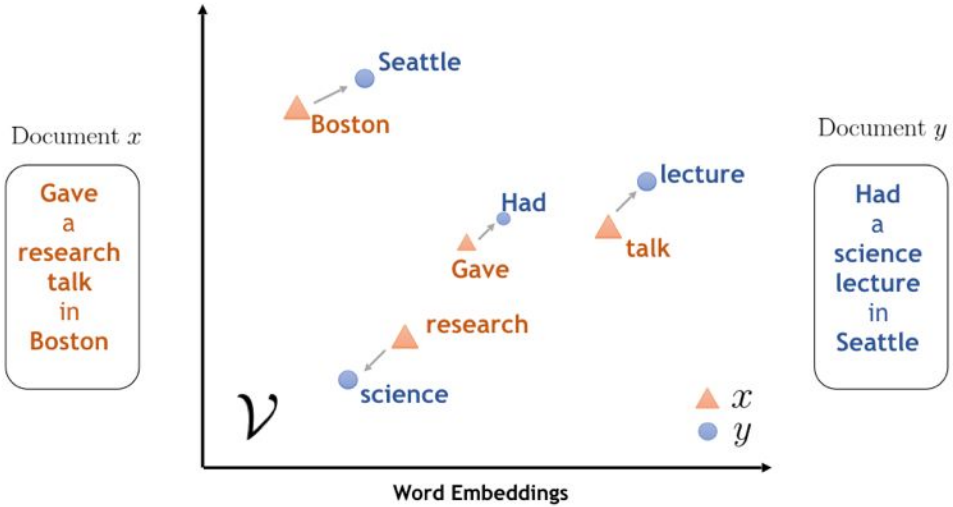
(click on Colab icon or open in a new tab)

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

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



Word & Sentence Embeddings

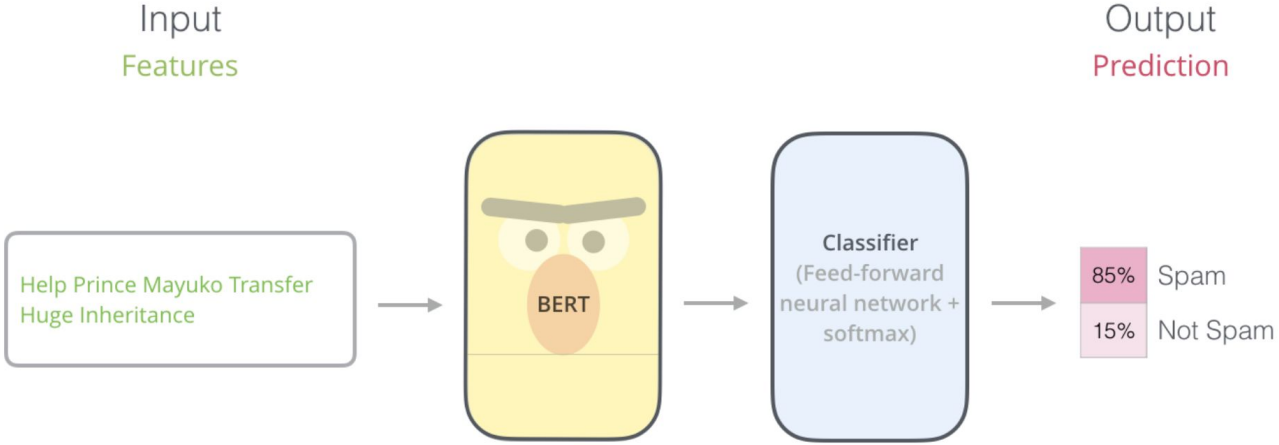



```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   , -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.
- They encode **words** and **sentences** 📜 in fixed-length dense vectors 📐 to drastically improve the processing of textual data.
- Based on **The Distributional Hypothesis**: Words that occur in the same contexts tend to have similar meanings.

Word & Sentence Embeddings

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

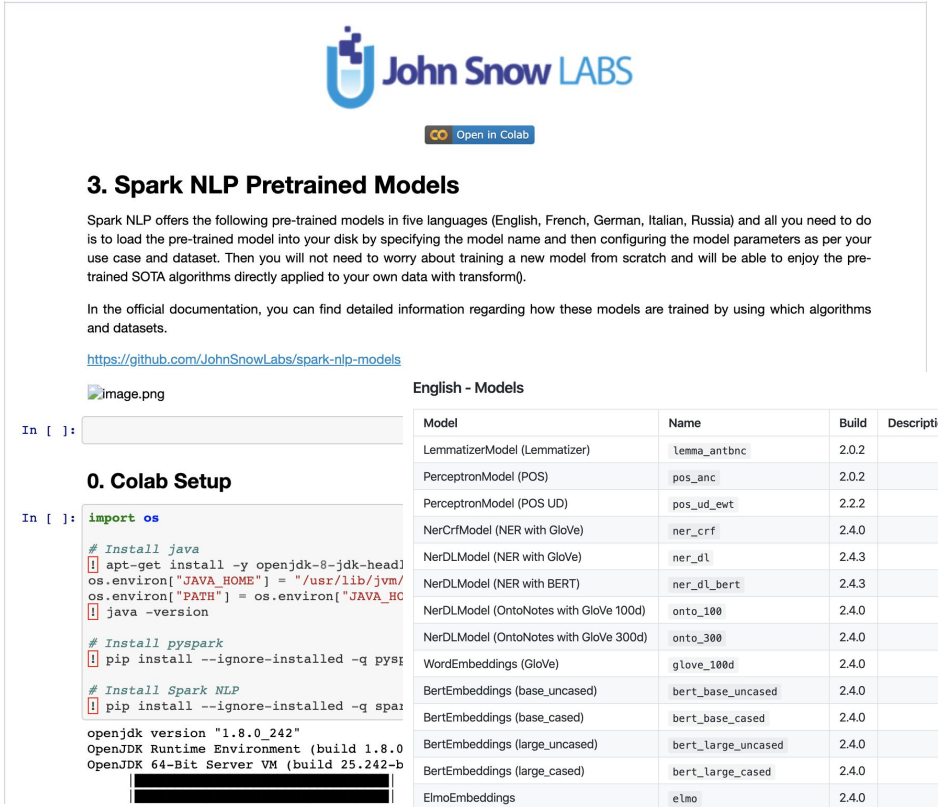


Coding ...

Open **3. Spark NLP Pretrained Models** notebooks in **Colab**

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

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



English - Models

Model	Name	Build	Description	Notes	Offline
LemmatizerModel (Lemmatizer)	lemma_antbnc	2.0.2			Download
PerceptronModel (POS)	pos_anc	2.0.2			Download
PerceptronModel (POS UD)	pos_ud_ewt	2.2.2			Download
NerCrfModel (NER with GloVe)	ner_crf	2.4.0			Download
NerDLModel (NER with GloVe)	ner_dl	2.4.3			Download
NerDLModel (NER with BERT)	ner_dl_bert	2.4.3			Download
NerDLModel (OntoNotes with GloVe 100d)	onto_100	2.4.0			Download
NerDLModel (OntoNotes with GloVe 300d)	onto_300	2.4.0			Download
WordEmbeddings (GloVe)	glove_100d	2.4.0			Download
BertEmbeddings (base_uncased)	bert_base_uncased	2.4.0			Download
BertEmbeddings (base_cased)	bert_base_cased	2.4.0			Download
BertEmbeddings (large_uncased)	bert_large_uncased	2.4.0			Download
BertEmbeddings (large_cased)	bert_large_cased	2.4.0			Download
ElmoEmbeddings	elmo	2.4.0			Download
UniversalSentenceEncoder	tfhub_use	2.4.0			Download
UniversalSentenceEncoder	tfhub_use_lg	2.4.0			Download
NerDLModel	ner_dl_sentence	2.4.0			Download
SymmetricDeleteModel (Spell Checker)	spellcheck_sd	2.0.2			Download
NorvigSweetingModel (Spell Checker)	spellcheck_norvig	2.0.2			Download
VivekNSentimentModel (Sentiment)	sentiment_vivekn	2.0.2			Download
DependencyParser (Dependency)	dependency_conllu	2.0.8			Download
TypedDependencyParser (Dependency)	dependency_typed_conllu	2.0.8			Download

Part - II

- Named Entity Recognition (NER) in Spark NLP

Named Entity Recognition (NER)

In fact, the Chinese NORP market has the three CARDINAL most influential names of the retail and tech space – Alibaba GPE , Baidu ORG , and Tencent PERSON (collectively touted as BAT ORG), and is betting big in the global AI GPE in retail industry space . The three CARDINAL giants which are claimed to have a cut-throat competition with the U.S. GPE (in terms of resources and capital) are positioning themselves to become the 'future AI PERSON platforms'. The trio is also expanding in other Asian NORP countries and investing heavily in the U.S. GPE based AI GPE startups to leverage the power of AI GPE . Backed by such powerful initiatives and presence of these conglomerates, the market in APAC AI is forecast to be the fastest-growing one CARDINAL , with an anticipated CAGR PERSON of 45% PERCENT over 2018 - 2024 DATE .

To further elaborate on the geographical trends, North America LOC has procured more than 50% PERCENT of the global share in 2017 DATE and has been leading the regional landscape of AI GPE in the retail market. The U.S. GPE has a significant credit in the regional trends with over 65% PERCENT of investments (including M&As, private equity, and venture capital) in artificial intelligence technology. Additionally, the region is a huge hub for startups in tandem with the presence of tech titans, such as Google ORG , IBM ORG , and Microsoft ORG .

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NER Benchmarks

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

- Spark NLP 2.4.x obtained the best performing academic peer-reviewed results
- State-of-the-art Deep Learning algorithms
- Achieve high accuracy within a few minutes
- Achieve high accuracy with a few lines of codes
- Blazing fast training
- Use CPU or GPU
- Easy to choose Word Embeddings
- Pre-trained GloVe models
- Pre-trained BERT models from TF Hub
- Pre-trained ELMO models from TF Hub

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NER-DL in Spark NLP

CoNNL2003 format

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

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

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

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

BIO schema

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

John Smith ⇒ PERSON
New York ⇒ LOCATION

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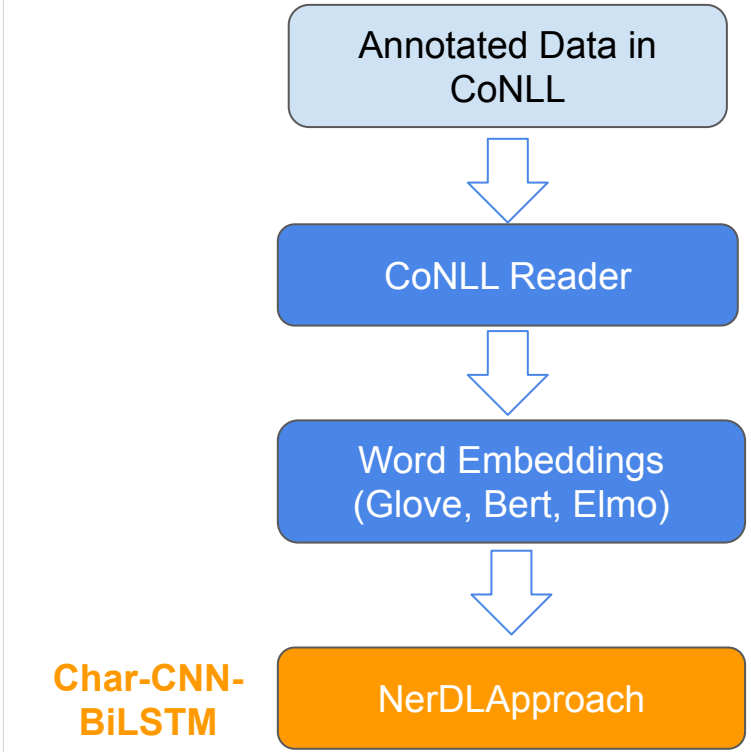
NER-DL in Spark NLP

Model	Name	Build	Description	Notes	Offline
LemmatizerModel (Lemmatizer)	lemma_antbnc	2.0.2			Download
PerceptronModel (POS)	pos_anc	2.0.2			Download
NerCrfModel (NER with GloVe)	ner_crf	2.4.0			Download
NerDLModel (NER with GloVe)	ner_dl	2.4.0			Download
NerDLModel (OntoNotes with GloVe 100d)	onto_100	2.4.0			Download
NerDLModel (OntoNotes with GloVe 300d)	onto_300	2.4.0			Download
WordEmbeddings (GloVe)	glove_100d	2.4.0			Download
BertEmbeddings (base_uncased)	bert_base_uncased	2.4.0			Download
BertEmbeddings (base_cased)	bert_base_cased	2.4.0			Download
BertEmbeddings (large_uncased)	bert_large_uncased	2.4.0			Download
BertEmbeddings (large_cased)	bert_large_cased	2.4.0			Download
ElmoEmbeddings	elmo	2.4.0			Download
UniversalSentenceEncoder	tf_hub_use	2.4.0			Download
UniversalSentenceEncoder	tf_hub_use_lg	2.4.0			Download
NerDLModel	ner_dl_sentence	2.4.0			Download
SymmetricDeleteModel (Spell Checker)	spellcheck_sd	2.0.2			Download
NorvigSweetingModel (Spell Checker)	spellcheck_norvig	2.0.2			Download
ViveknSentimentModel (Sentiment)	sentiment_vivekn	2.0.2			Download
DependencyParser (Dependency)	dependency_conllu	2.0.8			Download
TypedDependencyParser (Dependency)	dependency_typed_conllu	2.0.8			Download



You can also train your own Word Embeddings in Gensim and load in Spark NLP.

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Coding ...

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

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

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

Test set evaluation

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

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

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

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

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


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

```
              precision    recall  f1-score   support

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

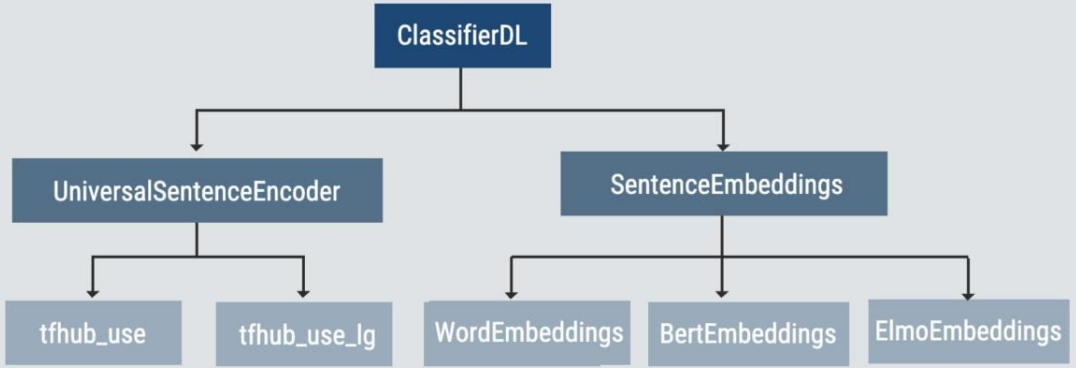
Part - III

- Text Classification with Classifier DL in Spark NLP

Text Classification with Classifier DL in Spark NLP

Spark NLP: ClassifierDL

Up to 50 classes, 11 models and 1024 dimensions

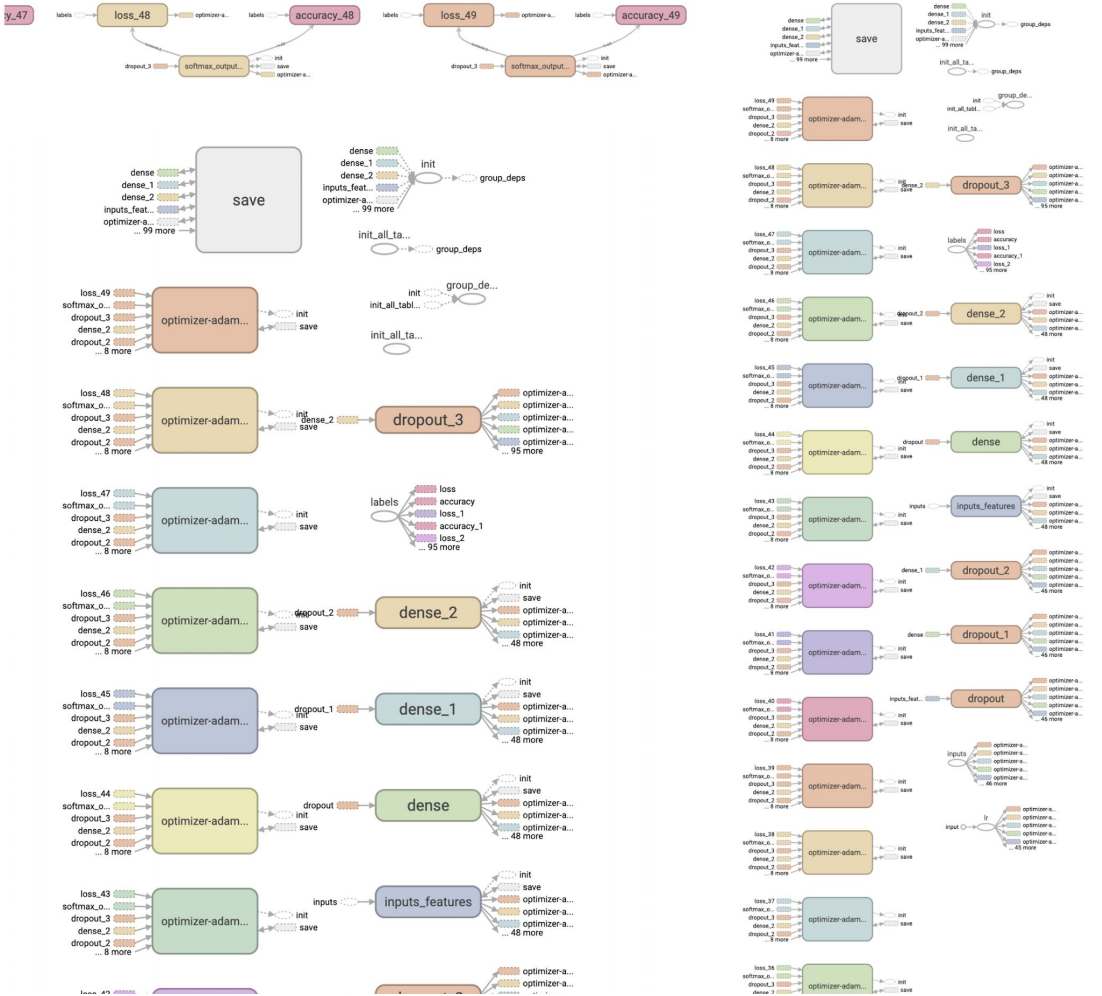


- 2 classes (positive/negative)
- 3 classes (0, 1, 2)
- 4 classes (Sports, Business, etc.)
- 5 classes (1.0, 2.0, 3.0, 4.0, 5.0)
- 50 classes!

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

- tfhub_use
- 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_cased
- elmo

Classifier DL Tensorflow Architecture



Coding ...

Open **5. Text CLassification with ClassifierDL** notebook in **Colab**

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

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

ClassifierDL with Universal Sentence Embeddings

In [ ]:
```
# actual content is inside description column
document = DocumentAssembler()\
    .setInputCol("description")\
    .setOutputCol("document")

# we can also use sentece detector here if we want to train on and get predictions for each senten
ce

use = UniversalSentenceEncoder.pretrained()\
 .setInputCols(["document"])\
 .setOutputCol("sentence_embeddings")

# the classes/labels/categories are in category column
classsifierdl = ClassifierDLApproach()\
  .setInputCols(["sentence_embeddings"])\
  .setOutputCol("class")\
  .setLabelColumn("category")\
  .setMaxEpochs(5)\
  .setEnableOutputLogs(True)

use_clf_pipeline = Pipeline(
    stages = [
        document,
        use,
        classsifierdl
    ])
```

```
tfhub_use download started this may take some time.
Approximate size to download 923.7 MB
[OK!]
```

In [ ]:
```
use_pipelineModel = use_clf_pipeline.fit(trainDataset)
# 5 epochs takes around 10 min
```

In [ ]:
```
!cd ~/annotator_logs && ls -l
```

```
total 8
-rw-r--r-- 1 root root 533 Apr  7 17:14 ClassifierDLApproach_a0fddc9e970b.log
-rw-r--r-- 1 root root 976 Apr  7 16:59 ClassifierDLApproach_f222663dfb2c.log
```

In [ ]:
```
!cat ~/annotator_logs/ClassifierDLApproach_a0fddc9e970b.log
```

```
Training started - total epochs: 5 - learning rate: 0.005 - batch size: 64 - training examples: 12
0000
Epoch 0/5 - 34.868680102%.2fs - loss: 1620.7466 - accuracy: 0.8803833 - batches: 1875
Epoch 1/5 - 35.627811455%.2fs - loss: 1604.4518 - accuracy: 0.8915333 - batches: 1875
Epoch 2/5 - 34.687788982%.2fs - loss: 1597.8773 - accuracy: 0.8966333 - batches: 1875
Epoch 3/5 - 34.629944711%.2fs - loss: 1593.4987 - accuracy: 0.900275 - batches: 1875
Epoch 4/5 - 34.714090256%.2fs - loss: 1590.3165 - accuracy: 0.90335834 - batches: 1875
```

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

John Snow LABS