John Snow LABS

Spark NLP for Healthcare Data Scientists

Jan 27-28, 2021

Veysel Kocaman
Lead Data Scientist
veysel@johnsnowlabs.com

Welcome

Day-1	50 min	- Intro to John Snow Labs and Spark NLP - Intro to NLP and Clinical NLP Modules in Spark NLP
	50 min	- Pretrained Clinical Pipelines - Clinical Named Entity Recognition
	50 min	- Clinical Named Entity Recognition
	50 min	- Clinical Assertion Status Model
Day-2	50 min	- Clinical Relation Extraction Model
	50 min	- Clinical Entity Resolvers
	50 min	- DeIdentification and Obfuscation of PHI
	50 min	- Spark OCR

Setup

Open in Colab

RUNNING CODE:

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

[How to set up Google Colab]

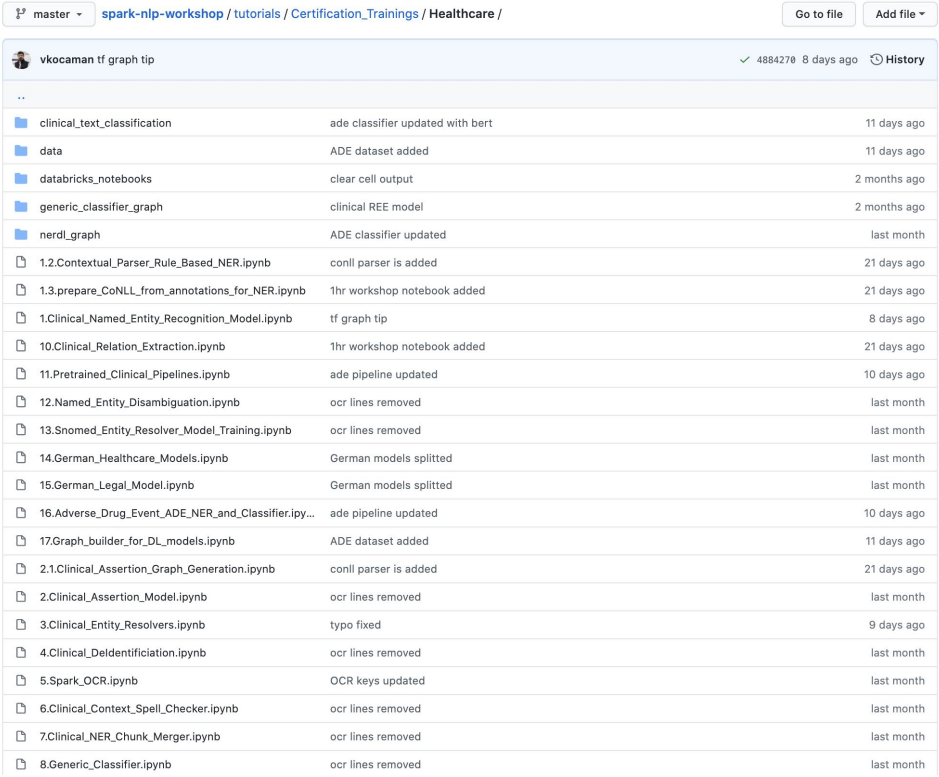
BOOKMARK:

https://nlp.johnsnowlabs.com/models

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

spark-nlp.slack.com

https://www.johnsnowlabs.com/spark-nlp-in-action/



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

vkocaman tf graph tip ✓ 4884270 8 days ago History

clinical_text_classification	ade classifier updated with bert	11 days ago
data	ADE dataset added	11 days ago
databricks_notebooks	clear cell output	2 months ago
generic_classifier_graph	clinical REE model	2 months ago
nerdl_graph	ADE classifier updated	last month
1.2.Contextual_Parser_Rule_Based_NER.ipynb	conll parser is added	21 days ago
1.3.prepare_CoNLL_from_annotations_for_NER.ipynb	1hr workshop notebook added	21 days ago
1.Clinical_Named_Entity_Recognition_Model.ipynb	tf graph tip	8 days ago
10.Clinical_Relation_Extraction.ipynb	1hr workshop notebook added	21 days ago
11.Pretrained_Clinical_Pipelines.ipynb	ade pipeline updated	10 days ago
12.Named_Entity_Disambiguation.ipynb	ocr lines removed	last month
13.Snomed_Entity_Resolver_Model_Training.ipynb	ocr lines removed	last month
14.German_Healthcare_Models.ipynb	German models splitted	last month
15.German_Legal_Model.ipynb	German models splitted	last month
16.Adverse_Drug_Event_ADE_NER_and_Classifier.ipy...	ade pipeline updated	10 days ago
17.Graph_builder_for_DL_models.ipynb	ADE dataset added	11 days ago
2.1.Clinical_Assertion_Graph_Generation.ipynb	conll parser is added	21 days ago
2.Clinical_Assertion_Model.ipynb	ocr lines removed	last month
3.Clinical_Entity_Resolvers.ipynb	typo fixed	9 days ago
4.Clinical_DeIdentificiation.ipynb	ocr lines removed	last month
5.Spark_OCR.ipynb	OCR keys updated	last month
6.Clinical_Context_Spell_Checker.ipynb	ocr lines removed	last month
7.Clinical_NER_Chunk_Merger.ipynb	ocr lines removed	last month
8.Generic_Classifier.ipynb	ocr lines removed	last month

Part - I

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

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

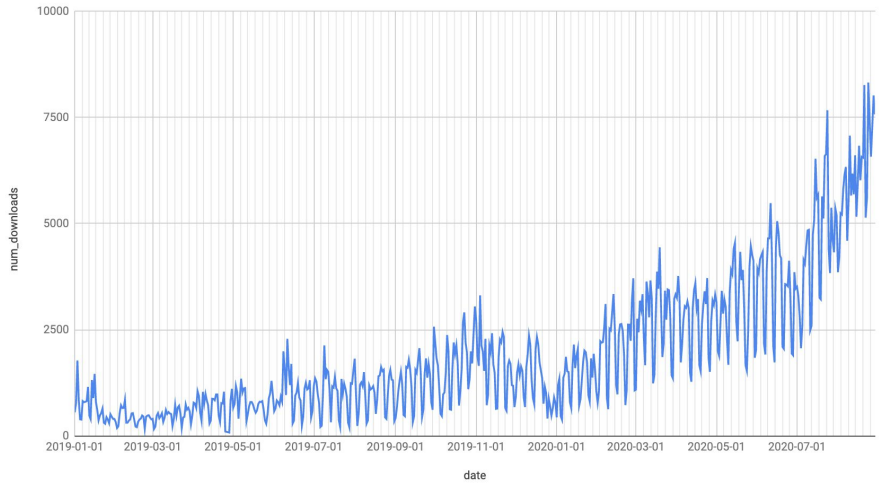
"John Snow Labs wows in both proven customer success and verifiable state-of-the-art technology – making it a natural winner of the highly competitive 2019
AI Platform of the Year Award."

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

Introducing Spark NLP

Daily ~ 12K
Monthly ~ 360K

PyPI link	https://pypi.org/project/spark-nlp
Total downloads	2,823,976
Total downloads - 30 days	360,631
Total downloads - 7 days	79,475

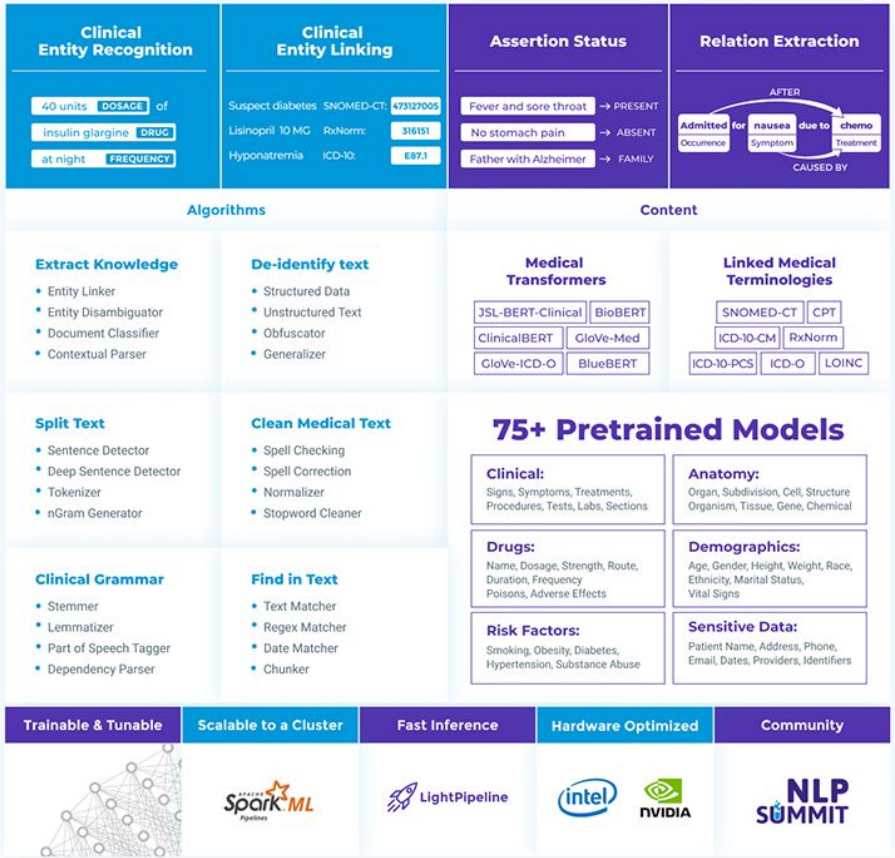


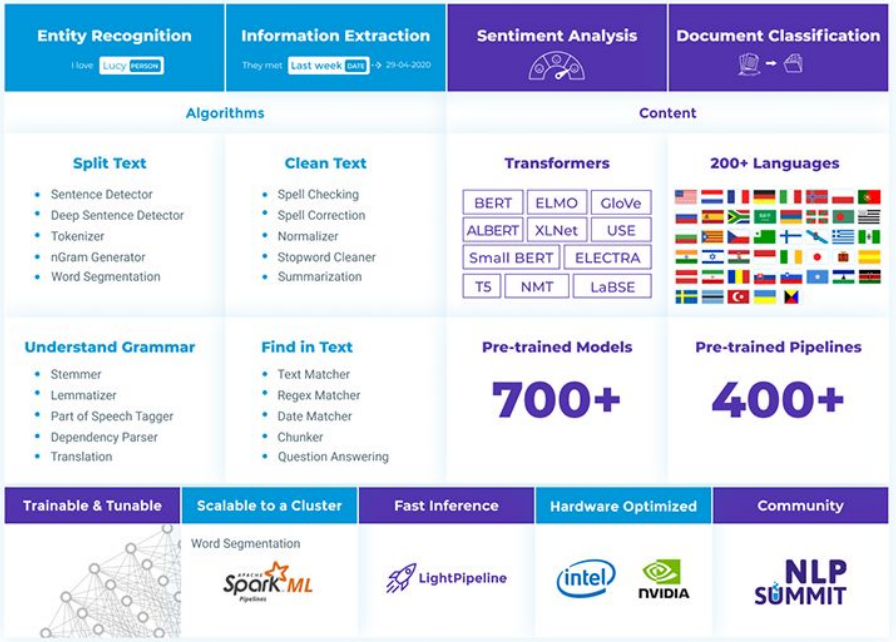
- Spark NLP is an open-source natural language processing library, built on top of Apache Spark and Spark ML. (initial release: Oct 2017)
  - A single unified solution for all your NLP needs
  - Take advantage of transfer learning and implementing the latest and greatest **SOTA** algorithms and models in NLP research
  - The most widely used NLP library in industry (3 yrs in a row)
  - Delivering a mission-critical, enterprise grade NLP library (used by multiple Fortune 500)
  - Full-time development team (26 new releases in 2020, 30 new releases in 2019.)

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

John Snow LABS

Spark NLP Modules





Spark NLP Modules (Enterprise and Public)

Spark NLP

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

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

TRUSTED BY


Microsoft


Google


amazon


intel


IBM


databricks


verizon


indeed


CapitalOne


viacom


McKESSON


MERCK


Roche


selectdata


UiPath
Reboot Work.


ASCO
CANCER·LINQ
DISCOVERY


cnrs

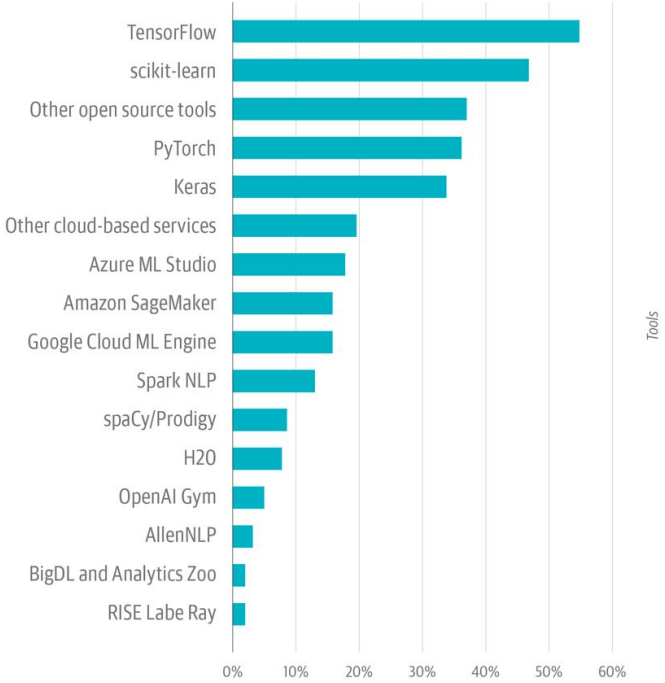

Imperial College
London


Georgia
Tech

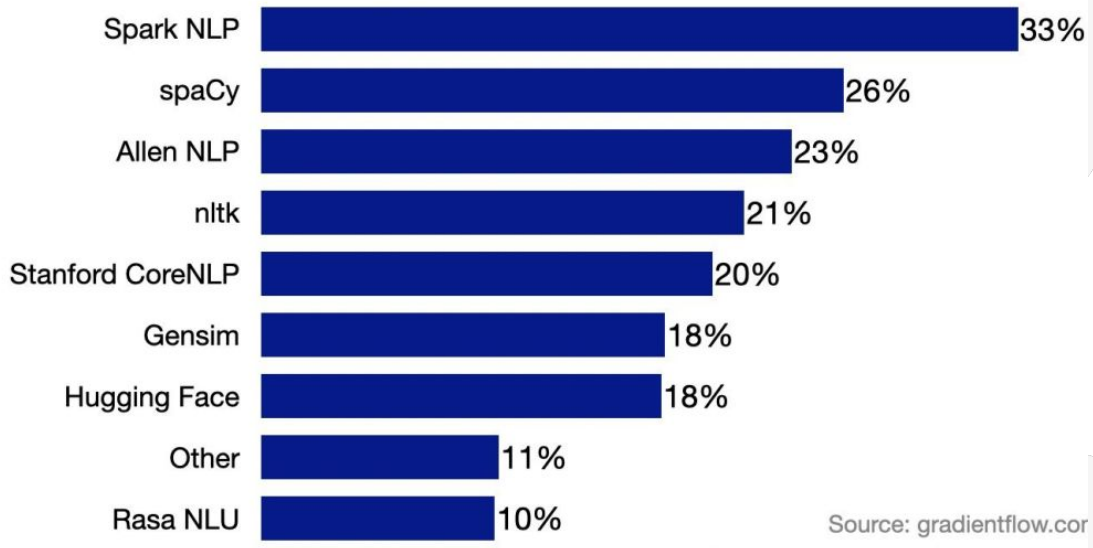

STANFORD
UNIVERSITY

Spark NLP in Industry

Which of the following AI tools do you use?



Which NLP libraries does your organization use?



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

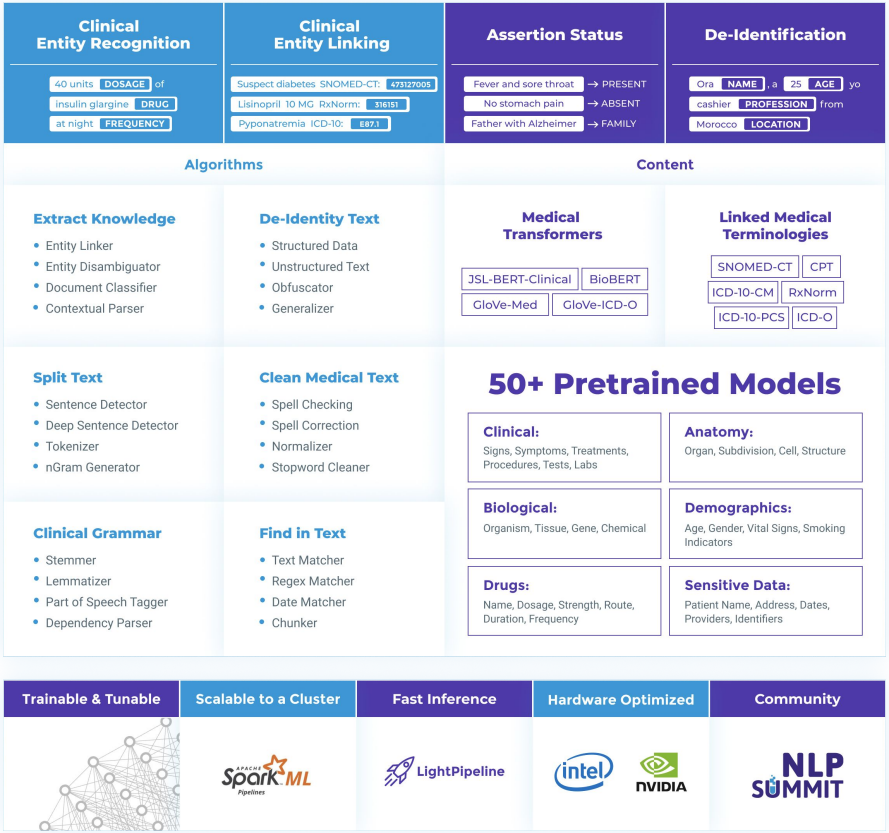
OFFICIALLY SUPPORTED RUNTIMES

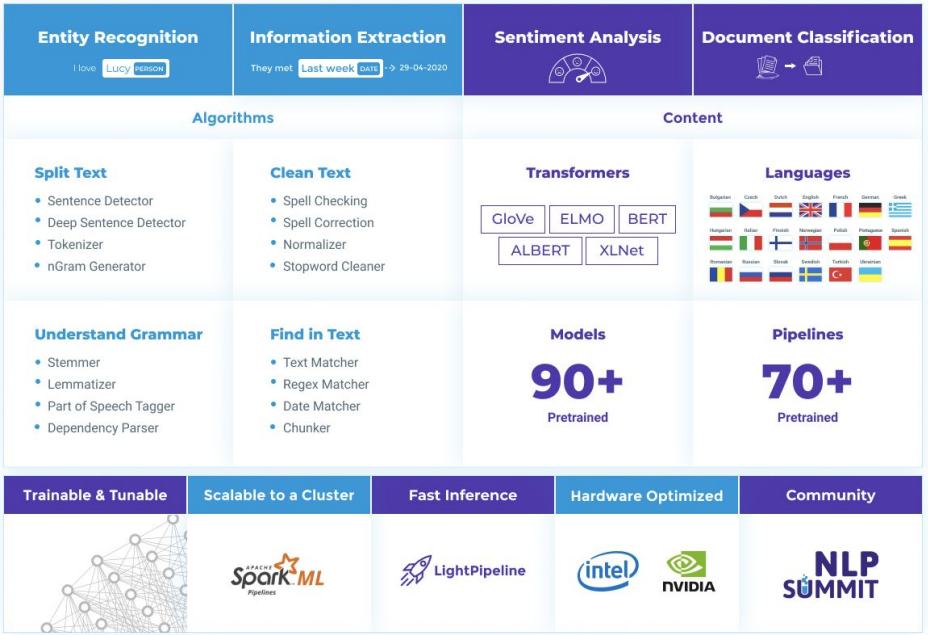
Spark NLP: Apache License 2.0

```
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)
```

- Tokenization
- Sentence Detector
- Stop Words Removal
- Normalizer
- Stemmer
- Lemmatizer
- NGrams
- Regex Matching
- Text Matching
- Chunking
- Date Matcher
- **Part-of-speech** tagging
- **Dependency** parsing
- **Sentiment** Detection (ML models)
- **Spell Checker** (ML and DL models)
- Word **Embeddings**
- **BERT** Embeddings
- **ELMO** Embeddings
- **ALBERT** Embeddings
- **XLNet** Embeddings
- **Universal Sentence Encoder**
- **BERT** Sentence Embeddings
- Sentence Embeddings
- Chunk Embeddings
- Unsupervised **keywords extraction**
- **Language Detection** & Identification
- **Multi-class** Text Classification
- **Multi-label** Text Classification
- Multi-class **Sentiment Analysis**
- **Named entity recognition**
- Easy **TensorFlow** integration
- Full integration with Spark ML functions
- **+250 pre-trained models** in 46 languages!
- **+90 pre-trained pipelines** in 13 languages!

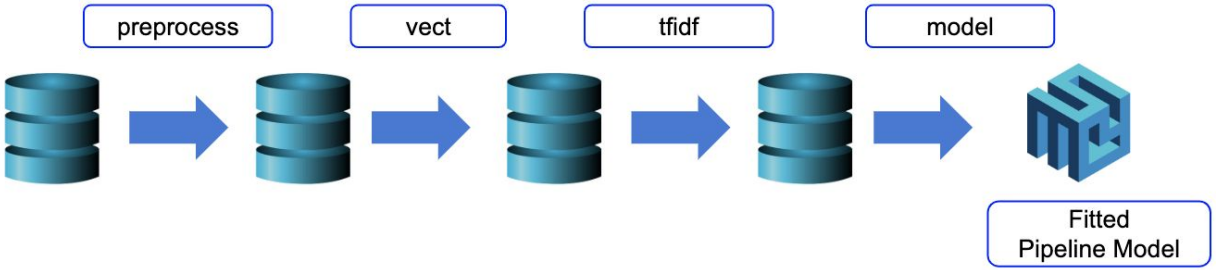
Spark NLP Modules (Enterprise and Public)



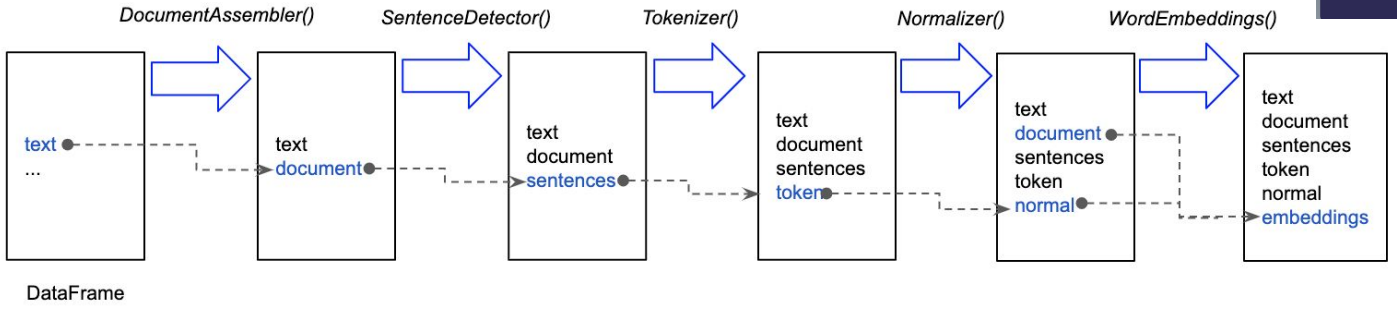


Introducing Spark NLP

Pipeline of annotators




```
from pyspark.ml import Pipeline

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

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

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

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

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

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

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



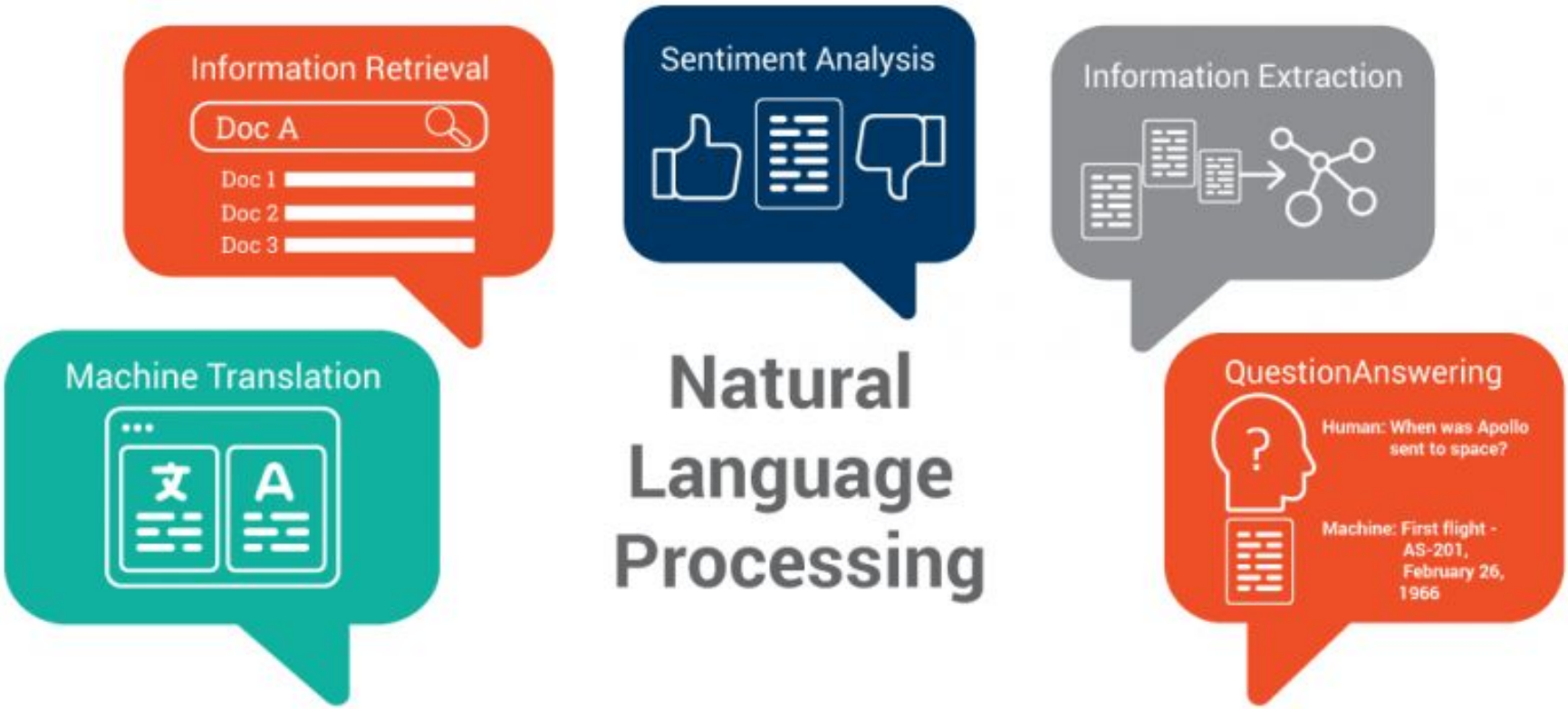
Introducing Spark NLP

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

Faster inference

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

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


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

NLP Basics

LEMMATIZATION

Find the **lemma** of each word:

- How does it show in the dictionary?

Uses a lookup from a full dictionary.

```
am, are, is    →    be

liver          →    liver

lives          →    live
```

STEMMING

Find the **stem** of each word.

Uses rules: e.g, remove common suffixes.

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

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

NLP Basics

Remove stop words and apply stemming

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

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

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

Stopwords

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

(520 stopwords)

Spell Checking & Correction


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

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

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

Context Spell Checker

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

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

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

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

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

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

NORMALIZATION

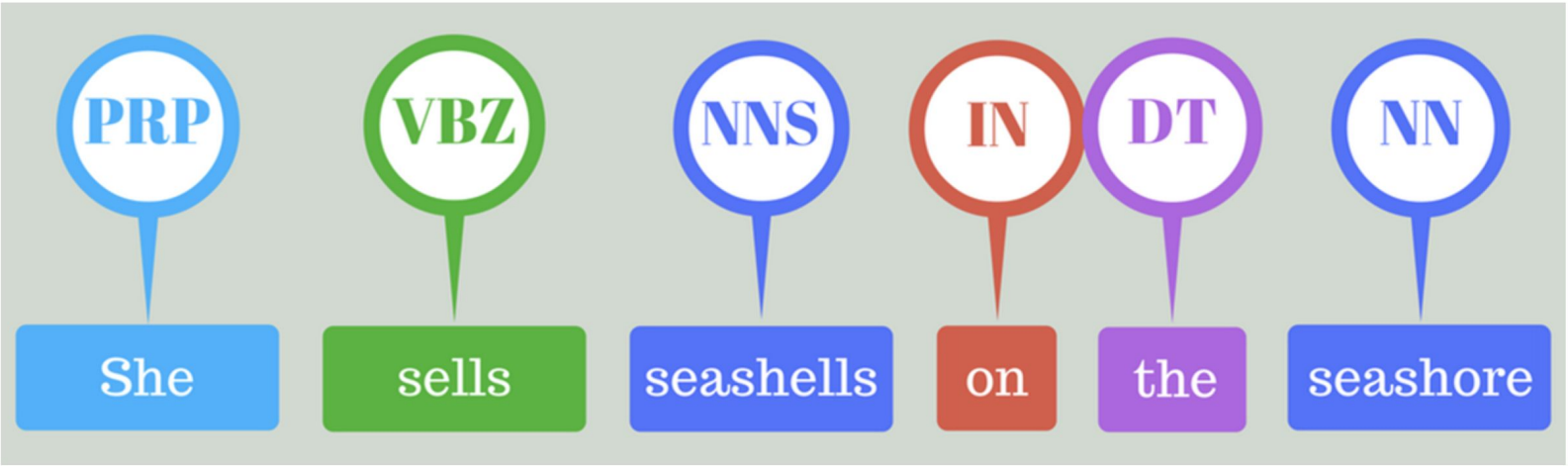
Remove or replace undesirable characters or regular expressions:

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

Spark NLP also comes with a Slang normalizer:

PART OF SPEECH TAGGING

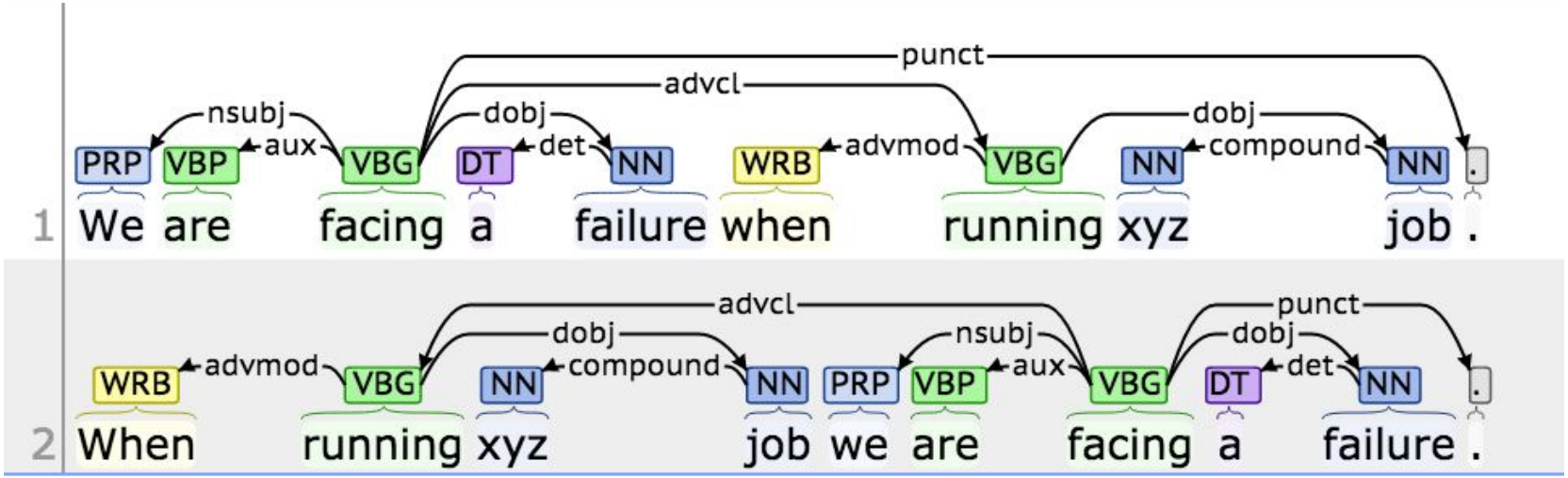
Often useful for recognizing named entities or word relationships.



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.

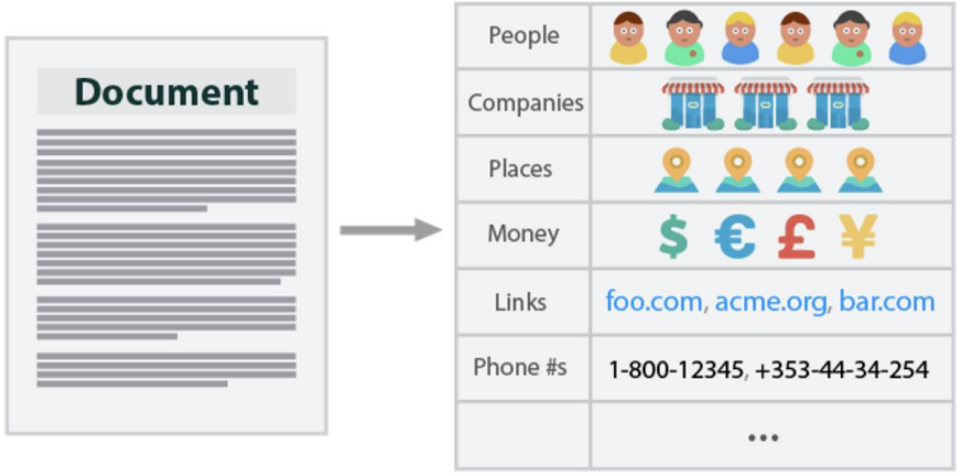
DEPENDENCY PARSING

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



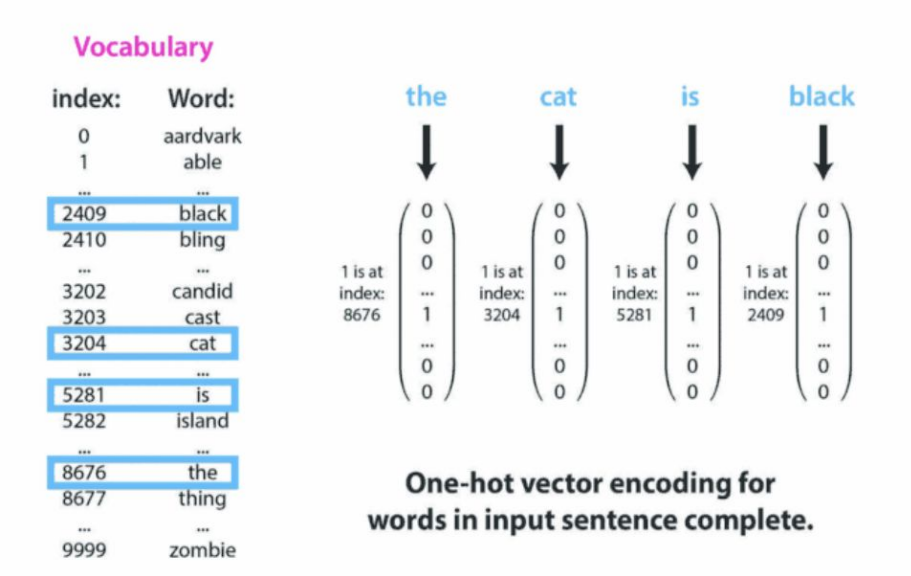
Named Entity Recognition (NER)

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.

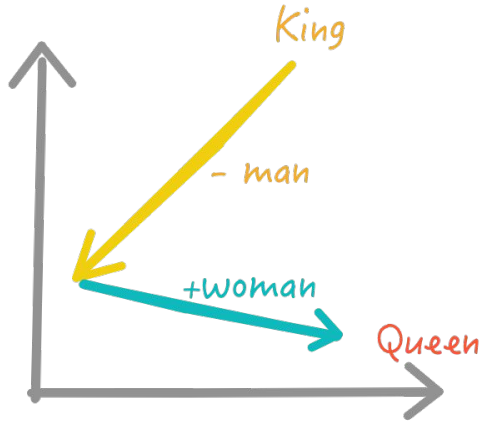
Word & Sentence Embeddings



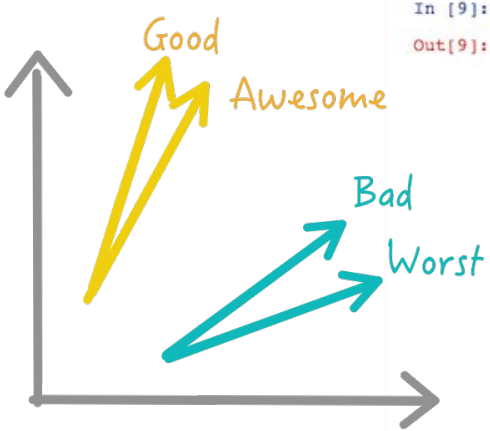

```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   ,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

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

Word & Sentence Embeddings



a) Learns Analogy



b) Similar Words have same angles

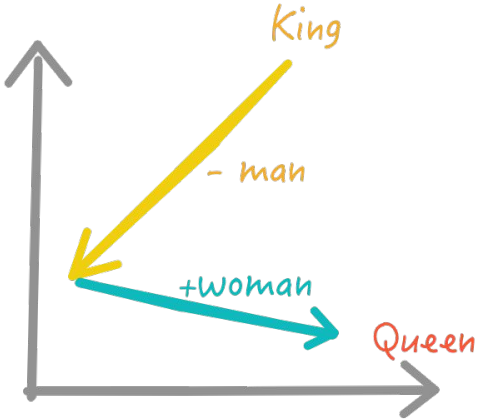
```
In [9]: doc[3].vector
Out[9]: array([ 0.037103 , -0.31259  , -0.17857  ,  0.30001  ,  0.078154 ,
                0.17958  ,  0.12048  , -0.11879  , -0.20601  ,  1.2849   ,
               -0.20409  ,  0.80613  ,  0.34344  , -0.19191  , -0.084511 ,
                0.17339  ,  0.042483 ,  2.0282   ,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

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

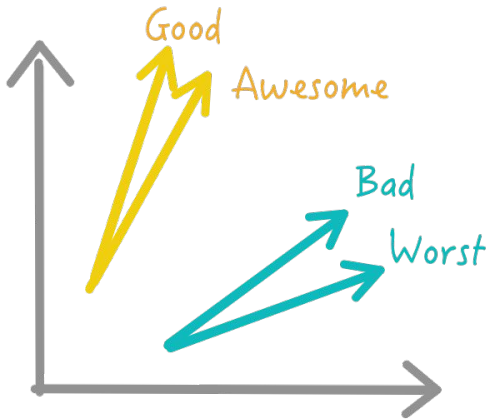
Word & Sentence Embeddings

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

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



a) Learns Analogy

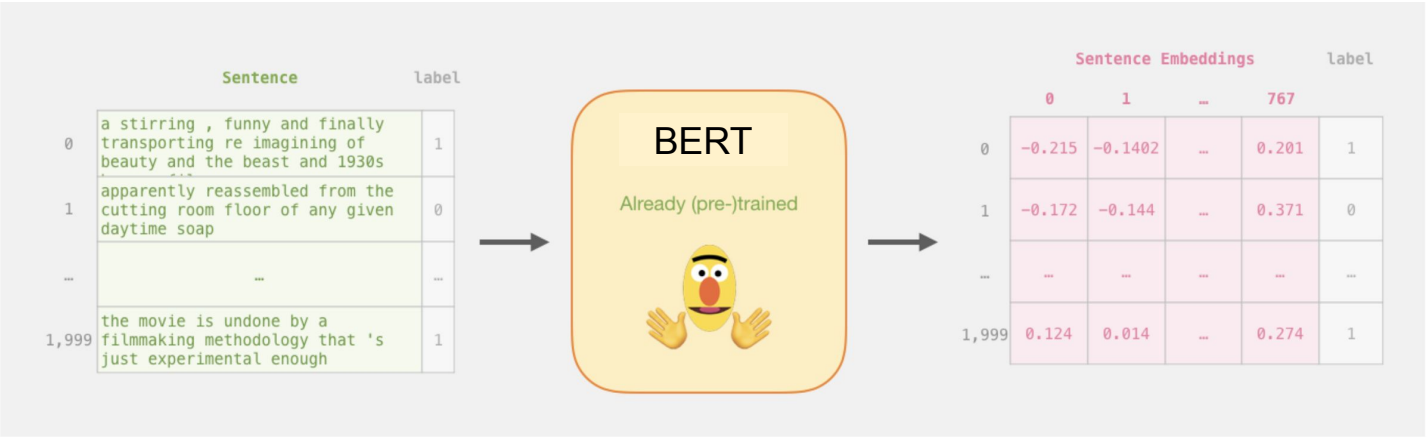


b) Similar Words have same angles

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

Text Classification with Word & Sentence Embeddings

Glove (100, 200, 300)	ELMO (512, 1024)	BERT (768d)	Universal Sentence Encoders (512)
Albert (768, 1024, 2048, 4096)	XLNet (768, 1024)	Electra (768)	Bert Sentence Embeddings (768)



Model	Name
WordEmbeddingsModel (GloVe)	`glove_100d`
BertEmbeddings	`electra_small_uncased`
BertEmbeddings	`electra_base_uncased`
BertEmbeddings	`electra_large_uncased`
BertEmbeddings	`bert_base_uncased`
BertEmbeddings	`bert_base_cased`
BertEmbeddings	`bert_large_uncased`
BertEmbeddings	`bert_large_cased`
BertEmbeddings	`biobert_pubmed_base_cased`
BertEmbeddings	`biobert_pubmed_large_cased`
BertEmbeddings	`biobert_pmc_base_cased`
BertEmbeddings	`biobert_pubmed_pmc_base_cased`
BertEmbeddings	`biobert_clinical_base_cased`
BertEmbeddings	`biobert_discharge_base_cased`
BertEmbeddings	`covidbert_large_uncased`
BertEmbeddings	`small_bert_L2_128`
BertEmbeddings	`small_bert_L4_128`
BertEmbeddings	`small_bert_L6_128`
BertEmbeddings	`small_bert_L8_128`

`WordEmbeddingsModel`	`embeddings_clinical`	`2.4.0`
`WordEmbeddingsModel`	`embeddings_healthcare_100d`	`2.5.0`
`WordEmbeddingsModel`	`embeddings_healthcare`	`2.4.4`

BertEmbeddings	`biobert_pubmed_base_cased`	2.6.0	`en`
BertEmbeddings	`biobert_pubmed_large_cased`	2.6.0	`en`
BertEmbeddings	`biobert_pmc_base_cased`	2.6.0	`en`
BertEmbeddings	`biobert_pubmed_pmc_base_cased`	2.6.0	`en`
BertEmbeddings	`biobert_clinical_base_cased`	2.6.0	`en`
BertEmbeddings	`biobert_discharge_base_cased`	2.6.0	`en`
BertEmbeddings	`covidbert_large_uncased`	2.6.0	`en`

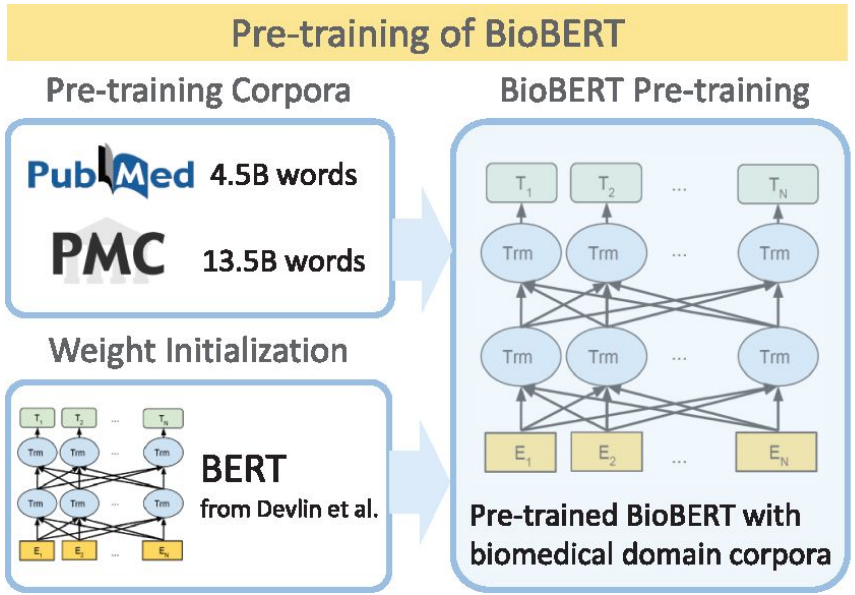
BertSentenceEmbeddings	`sent_bert_large_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_biobert_pubmed_base_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_biobert_pubmed_large_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_biobert_pmc_base_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_biobert_pubmed_pmc_base_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_biobert_clinical_base_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_biobert_discharge_base_cased`	2.6.0	`en`
BertSentenceEmbeddings	`sent_covidbert_large_uncased`	2.6.0	`en`

Clinical Word Embeddings

Clinical Glove (200d)	ICDO Glove (200d)	Bio BERT	Clinical BERT
PubMed + PMC	PubMed + ICD10 UMLS + MIMIC III	Pubmed + PMC	Fine tuned Pubmed + PMC + Discharge summaries

PubMed abstracts and PMC full-text articles

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



Spark NLP in Healthcare

Spark NLP in Healthcare

Clean & structured data

Raw & unstructured data

Healthcare data

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

Why is language understanding hard?

Human Language is:

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

Healthcare specific needs:

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

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

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

Healthcare extensions

NLP Library / Feature	State of the Art (SOTA) Research
Named Entity Recognition	"Entity Recognition from Clinical Texts via Recurrent Neural Network". *Liu et al., BMC Medical Informatics & Decision Making, July 2017.*
Word Embeddings	- "How to Train Good Word Embeddings for Biomedical NLP". *Chiu et al., In Proceedings of BioNLP'16, August 2016.* - "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". *Devlin et. al. (Google Research), October 2018.*
Assertion Status Detection	- "Improving Classification of Medical Assertions in Clinical Notes". *Kim et al., In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, 2011.* - "Neural Networks For Negation Scope Detection" *Fancellu et al., In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, 2016.*
Entity Resolution	"CNN-based ranking for biomedical entity normalization". *Li et al., BMC Bioinformatics, October 2017.*

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.

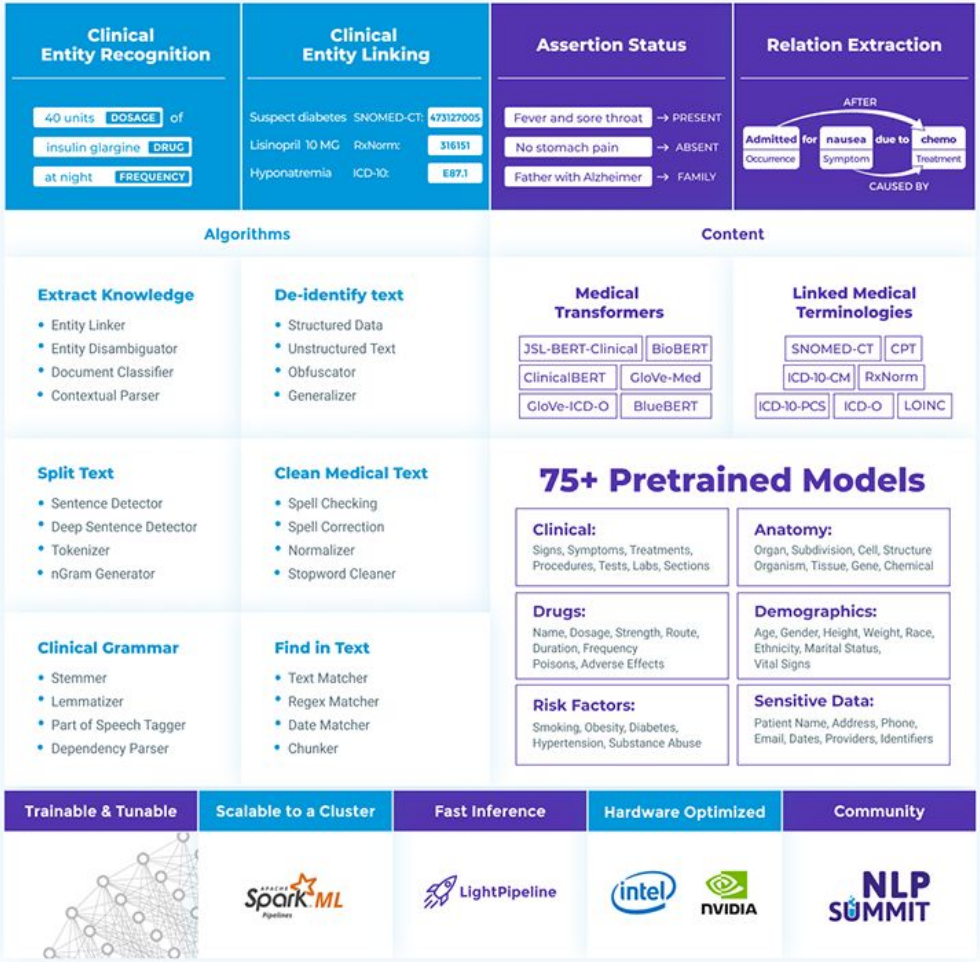
be found in structured fields for which values are inputted electronically (e.g. laboratory test orders or results) (Liede et al. 2015) but most of the time information in these records is unstructured making it largely inaccessible for statistical analysis (Murdoch and Detsky 2013). These records include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

Clinical Named Entity Recognition (NER)

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



Clinical Named Entity Recognition

Pretrained NER Models in Spark NLP

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

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

Posology NER

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

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

Anatomy NER

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

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

PHI NER

Clinical Named Entity Recognition

- ner_anatomy
- ner_bionlp
- ner_cellular
- ner_clinical
- ner_deid
- ner_diseases
- ner_drugs
- ner_events
- ner_jsl
- ner_medmentions
- ner_posology
- ner_risk_factors
- ner_human_phenotype_go
- ner_human_phenotype_gene
- ner_chemprot
- ner_ade
- ner_ade_healthcare

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

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

Posology NER

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

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

Anatomy NER

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

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

PHI NER

NER in Healthcare

- ner_anatomy
- ner_bionlp
- ner_cellular
- ner_clinical
- ner_deid
- ner_diseases
- ner_drugs
- ner_events
- ner_jsl
- ner_medmentions
- ner_posology
- ner_risk_factors
- ner_human_phenotype_go
- ner_human_phenotype_gene
- ner_chemprot
- ner_ade
- ner_ade_healthcare

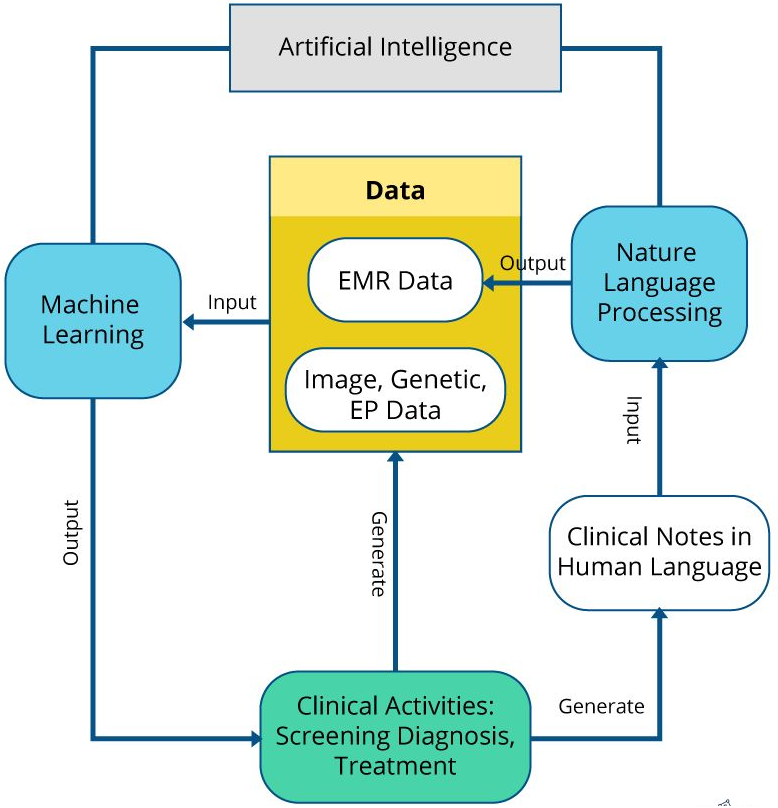
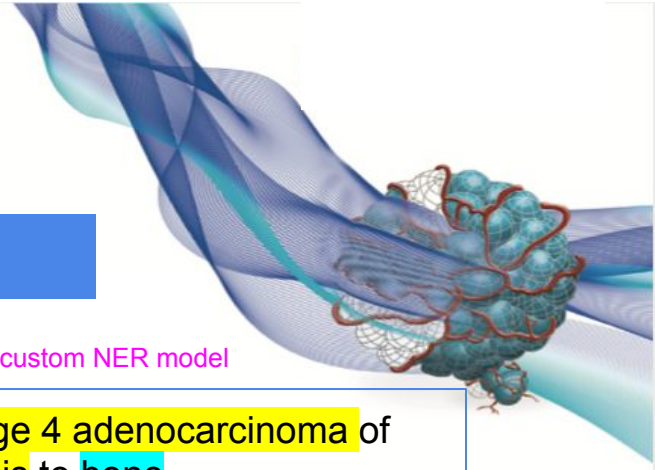
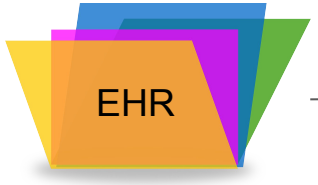


Fig. 3 | Making predictions using EHRs. a, Unstructured EHR data. Medical records are stored in idiosyncratic data structures and formats such that models built on a given hospital's record do not necessarily work with data from a different hospital. **b**, Data standardization. By mapping data from multiple sites to a single format based on FHIR, data are standardized into a homogeneous format. **c**, Sequencing. By temporally sequencing all data into a patient timeline, time-based deep-learning techniques can be applied on the entirety of EHR datasets for making predictions about single patients.

NER in Healthcare



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



Extract metastasis related sentences with mets-classifier

Annotate your own data and train a custom NER model

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

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

Feature extraction & engineering

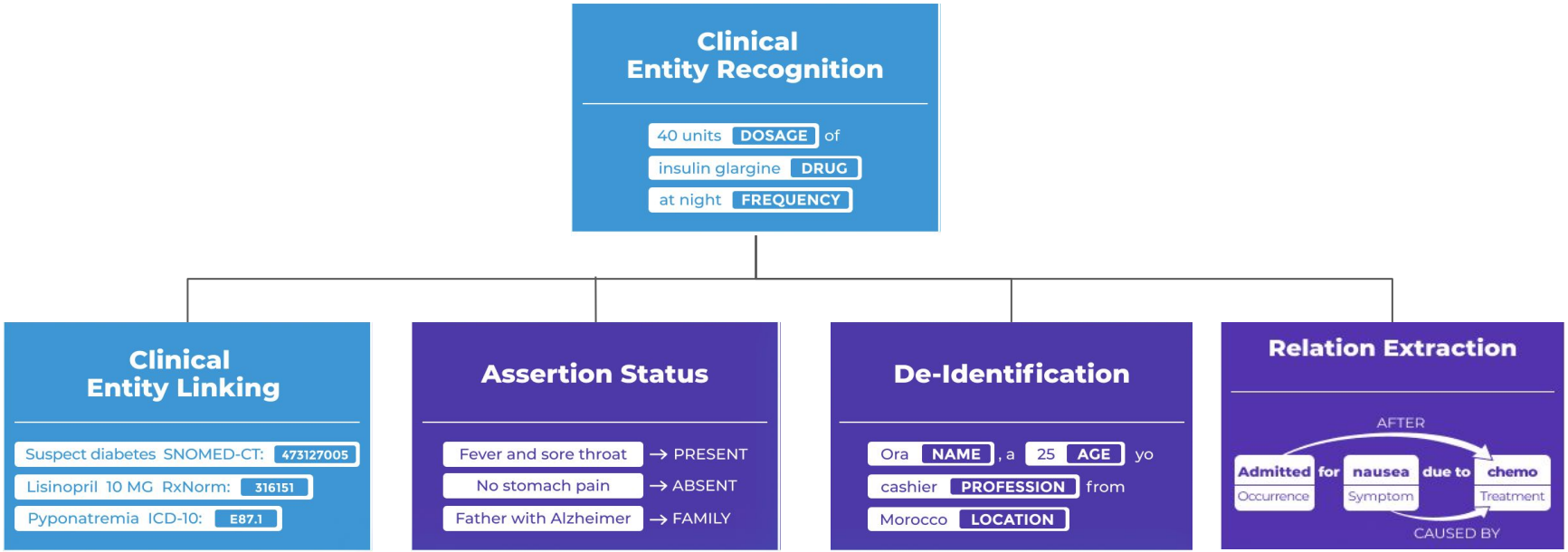
- *The frequency of clinical visits using document dates*
- *The number of positive site (organ) entities (hits by window)*
- *The number of Radiology/Oncology/Pathology reports in the last x days*
- *The number of tests applied in the last x days*
- *The number of diseases detected in the last x days*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

Text embeddings thru clinical word embeddings

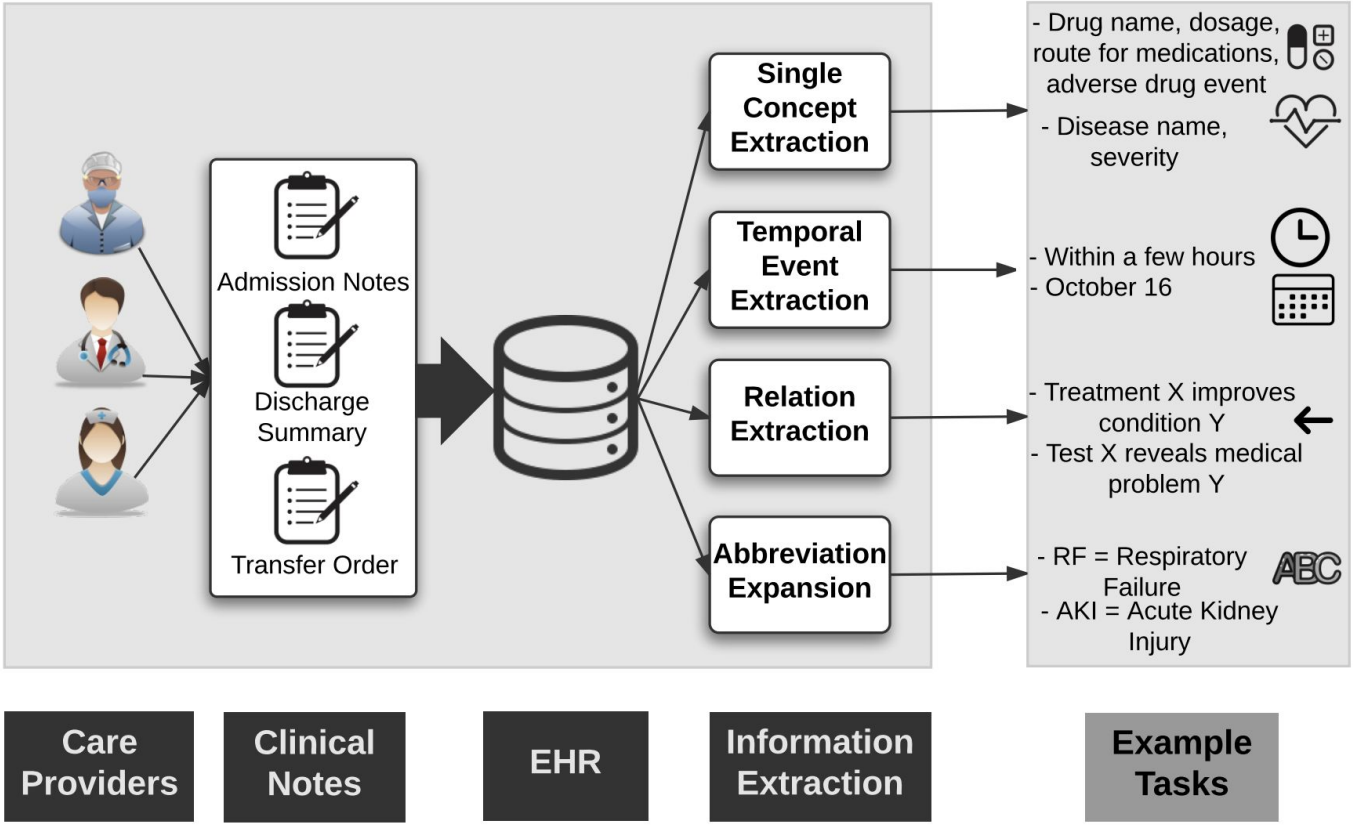
Train a DL & ML Model

Prediction: Bone metastasis on June 2018

NER in Healthcare



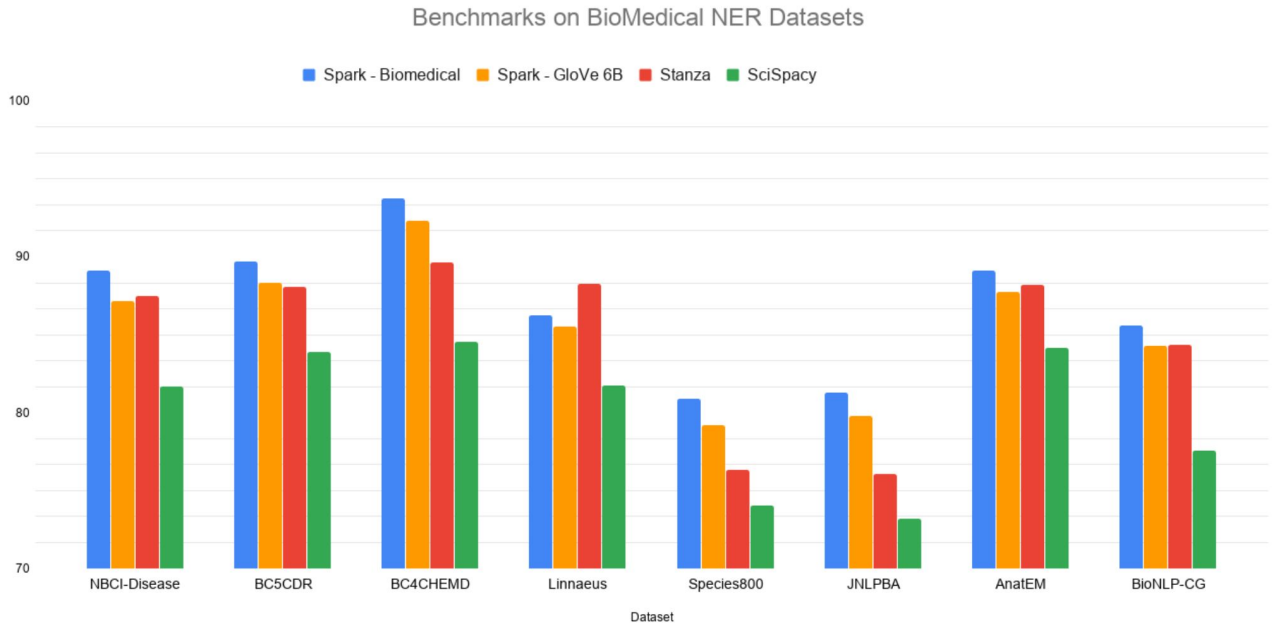
NER in Healthcare



Spark NLP NerDL

The best NER score in production

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

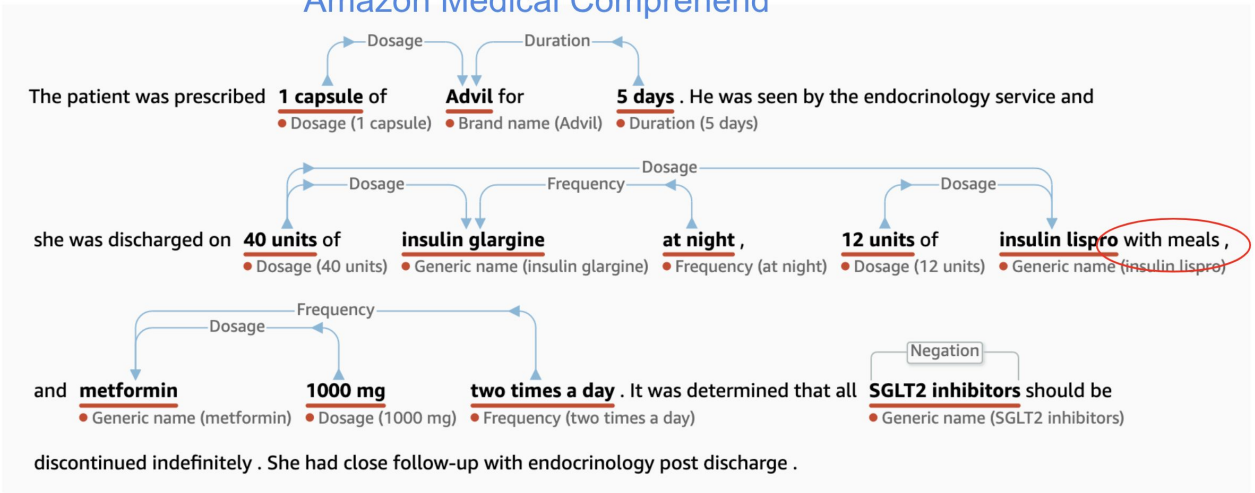


NER Comparison with AWS, GCP, and i2b2 challenges

Table 2: Performance metrics on 2010 i2b2/VA clinical concept extraction, 2014 i2b2 de-identification challenge and 2018 n2c2 medication extraction challenge. Scores indicate entity-level (span match) micro F1 scores (strict match, excluding O's) on the official test scores. BERT-based benchmarks are omitted from this study to make a fair comparison between the similar DL architectures.

	Spark NLP	Competition Best	Last Best
2010 i2b2/VA	**0.876**	0.852	0.862
2014 n2c2	**0.961**	0.936	0.955
2018 n2c2	**0.899**	0.896	0.896

Amazon Medical Comprehend



Spark NLP Posology NER

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

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

** Tested on 1000 sample text from MIMIC-III*

NER Comparison with AWS, GCP, and i2b2 challenges

Table 4: Comparison of our NER models with AWS Medical Comprehend (AMC) and Google Cloud Platform (GCP) Healthcare API on randomly sampled 1000 clinical notes from MIMIC-III database. Tests run on three major entity classes (*Problem*, *Test*, *Drug*) and Spark NLP clinical NER models are 8.9% and 6.7% better than AMC and GCP respectively in average (macro F1 score).

		Spark NLP Clinical Models			AWS Medical Comprehend			GCP Healthcare API		
Entity	Sample	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Problem	4891	0.726	0.585	**0.648**	0.539	0.478	0.507	0.850	0.516	0.642
Test	5903	0.782	0.662	**0.717**	0.594	0.703	0.644	0.576	0.461	0.512
Drug	10284	0.946	0.882	0.913	0.815	0.910	0.860	0.962	0.885	**0.922**
Avg. F1				**0.759**			0.670			0.692

** Tested on 1000 sample text from MIMIC-III*

Table 2: Performance metrics on 2010 i2b2/VA clinical concept extraction, 2014 i2b2 de-identification challenge and 2018 n2c2 medication extraction challenge. Scores indicate entity-level (span match) micro F1 scores (strict match, excluding O's) on the official test scores. BERT-based benchmarks are omitted from this study to make a fair comparison between the similar DL architectures.

	Spark NLP	Competition Best	Last Best
2010 i2b2/VA	**0.876**	0.852	0.862
2014 n2c2	**0.961**	0.936	0.955
2018 n2c2	**0.899**	0.896	0.896

Table 3: Performance evaluation on biomedical NER datasets using the same BiLSTM-CNN-Char architecture in TensorFlow and Spark NLP under the same settings for each dataset. The Spark NLP implementation beats the same architecture 7 out of 8 times in terms of macro F1 score and is faster to train in half of the datasets *(macro average F1 score, embeddings glove6B_300d, lr 0.001, dropout 0.5, LSTM state size 200, epoch 10, batch size 128, optimizer Adam)*. Bold letters represent best results.

	Tensorflow 1.15 (Keras)		Spark NLP	
Dataset	time (sec)	macro-F1	time (sec)	macro-F1
BC5CDR-disease	409	0.840	**336**	**0.858**
BC5CDR-chem	438	0.848	**367**	**0.894**
BC4CHEMD	2954	0.890	**2719**	**0.936**
NCBI-Disease	312	0.882	**269**	**0.883**
JNLPBA	**495**	0.705	743	**0.758**
Species800	**215**	0.813	232	**0.820**
Linnaeus	**709**	**0.787**	730	0.759

NER-DL in Spark NLP

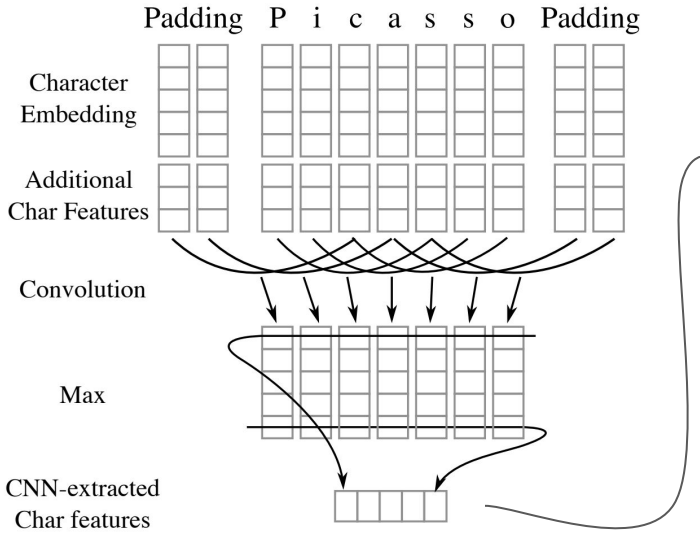


Figure 2: The convolutional neural network extracts character features from each word. The character embedding and (optionally) the character type feature vector are computed through lookup tables. Then, they are concatenated and passed into the CNN.

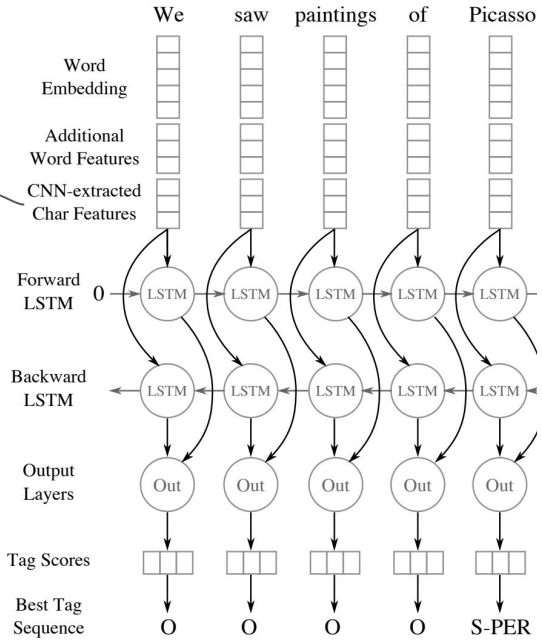


Figure 1: The (unrolled) BLSTM for tagging named entities. Multiple tables look up word-level feature vectors. The CNN (Figure 2) extracts a fixed length feature vector from character-level features. For each word, these vectors are concatenated and fed to the BLSTM network and then to the output layers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

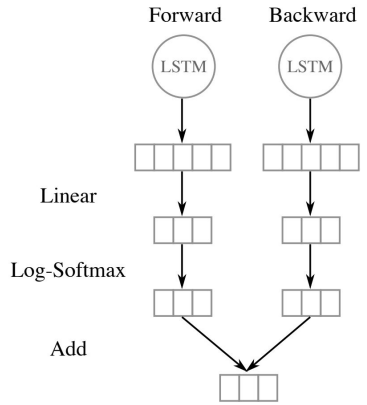


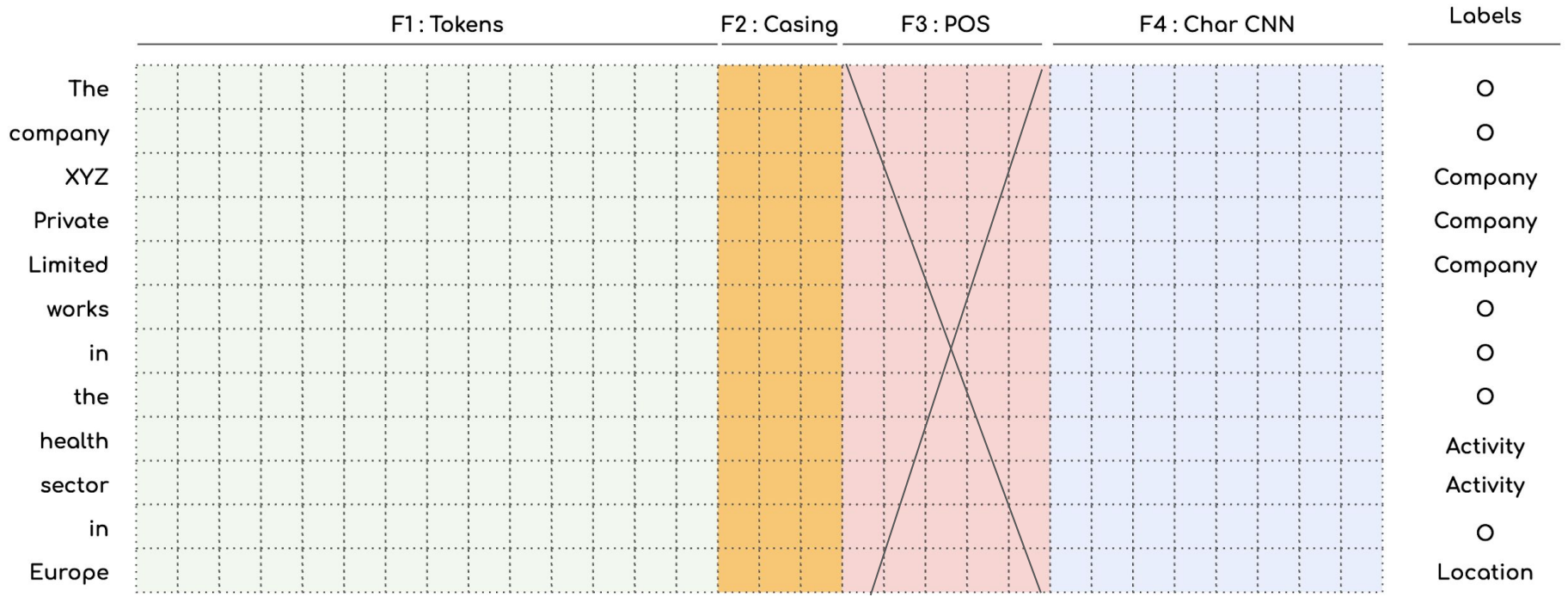
Figure 3: The output layers ("Out" in Figure 1) decode output into a score for each tag category.

Char-CNN-BiLSTM

John Snow LABS

NER-DL in Spark NLP

Char-CNN-BiLSTM

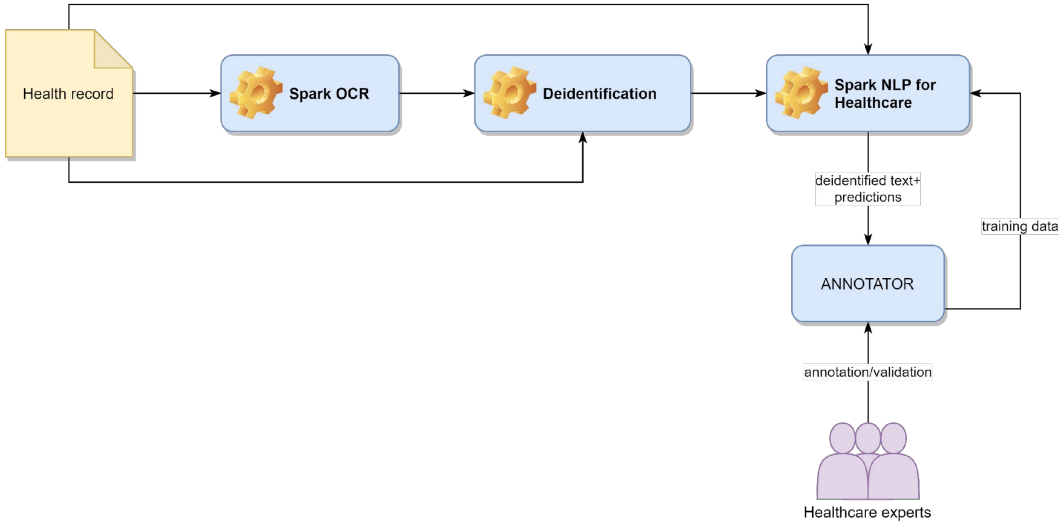


BIO schema

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

John Smith ⇒ PERSON
New York ⇒ LOCATION

NER in Healthcare



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

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

Bone negative for metastatic disease.

Patient denies any family history of cancer.

Part - II

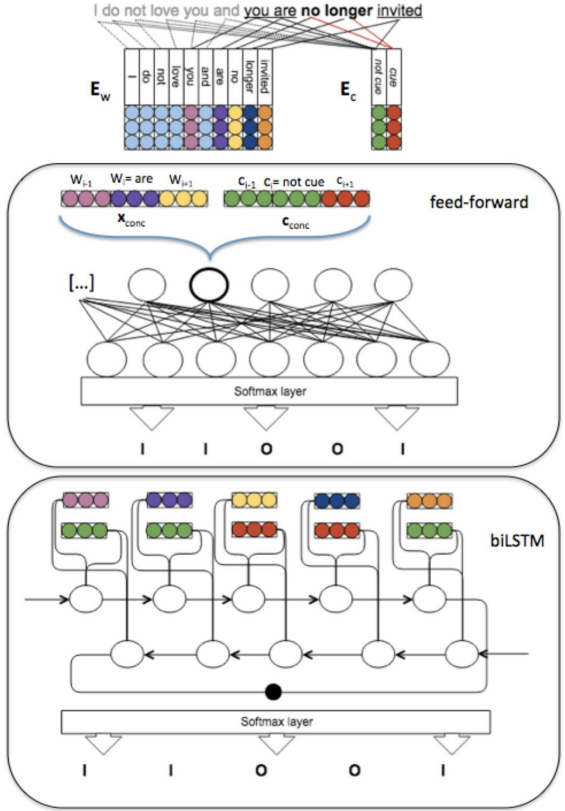
- Assertion Status detection

Clinical Assertion Model

Prescribing sick days due to diagnosis of **influenza**.	*Present*
41 yo man with CRFs of DM Type II, high cholesterol, smoking history, family hx, HTN p/w episodes of **atypical CP x 1 week**, with rest and exertion.	*Conditional*
Jane's **RIDT** came back clean.	*Absent*
Jane is at risk for **flu** if she's not vaccinated.	*Hypothetical*
There was a **dense hemianopsia** on the left side.	*Present*

F-Score	Dataset	Task
94.17%	4th i2b2/VA	Disease & problem norm.

"Neural Networks For Negation Scope Detection", Fancellu et al., In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, 2016.



scope of negation: *given a negative instance, to identify which tokens are affected by negation*

Clinical Assertion Model

Patient with severe fever and sore throat . He shows no stomach pain and he maintained on an epidural and PCA for pain control . He also became short of breath with climbing a flight of stairs . After CT , lung tumor located at the right lower lobe . Father with Alzheimer .

Color codes:PROBLEM, TREATMENT, TEST,

Entities

	chunks	entities	assertion
0	severe fever	PROBLEM	present
1	sore throat	PROBLEM	present
2	stomach pain	PROBLEM	absent
3	an epidural	TREATMENT	present
4	PCA	TREATMENT	present
5	pain control	PROBLEM	present
6	short of breath	PROBLEM	conditional
7	CT	TEST	present
8	lung tumor	PROBLEM	present
9	Alzheimer	PROBLEM	associated_with_someone_else

```
import sparknlp_jsl

spark = sparknlp_jsl.start("xxxxx")

from pyspark.ml import PipelineModel

pretrained_model = PipelineModel.load("explain_clinical_doc_dl")

from sparknlp.base import LightPipeline

ner_lightModel = LightPipeline(pretrained_model)

clinical_text = """
Patient with severe fever and sore throat.
He shows no stomach pain and he maintained on an epidural and PCA for pain control.
He also became short of breath with climbing a flight of stairs.
After CT, lung tumour located at the right lower lobe. Father with Alzheimer.
"""

result = ner_lightModel.fullAnnotate(clinical_text)

entity_tuples = [(n.result, n.metadata['entity'], m.result, n.begin, n.end)
                 for n,m in zip(result[0]['ner_chunk'],result[0]['assertion'])]

print (entity_tuples)
>>
time: 270 ms
[('severe fever', 'PROBLEM', 'present', 14, 25),
 ('sore throat', 'PROBLEM', 'present', 31, 41),
 ('stomach pain', 'PROBLEM', 'absent', 57, 68),
 ('an epidural', 'TREATMENT', 'present', 91, 101),
 ('PCA', 'TREATMENT', 'present', 107, 109),
 ('pain control', 'PROBLEM', 'present', 115, 126),
 ('short of breath', 'PROBLEM', 'conditional', 144, 158),
 ('CT', 'TEST', 'present', 200, 201),
 ('lung tumour', 'PROBLEM', 'present', 204, 214),
 ('Alzheimer', 'PROBLEM', 'associated_with_someone_else', 261, 269)]
```

Part - IV

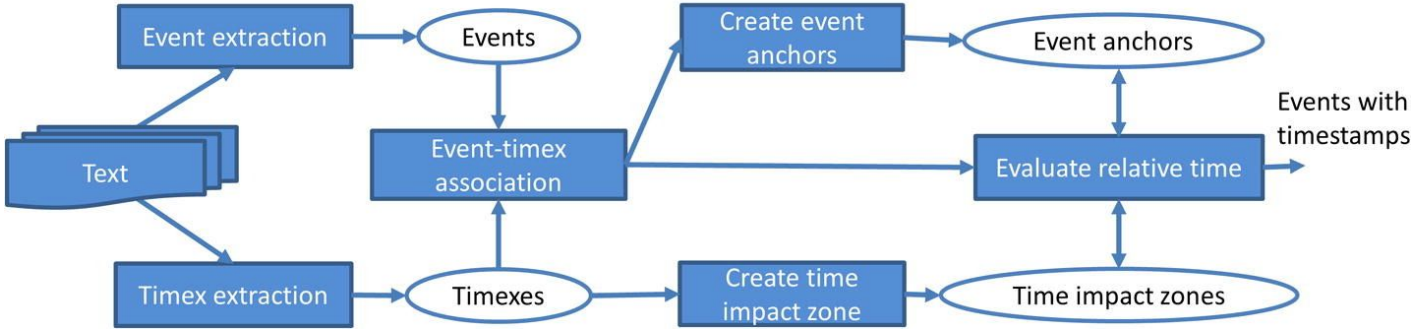
❖ Relation Extraction

`RelationExtractionModel`	`re_clinical`	`2.5.5`
`RelationExtractionModel`	`re_posology`	`2.5.5`
`RelationExtractionModel`	`re_temporal_events_clinical`	`2.6.0`
`RelationExtractionModel`	`re_temporal_events_enriched_clinical`	`2.6.0`
`RelationExtractionModel`	`re_human_phenotype_gene_clinical`	`2.6.0`
`RelationExtractionModel`	`re_drug_drug_interaction_clinical`	`2.6.0`
`RelationExtractionModel`	`re_chemprot_clinical`	`2.6.0`

Relation Extraction

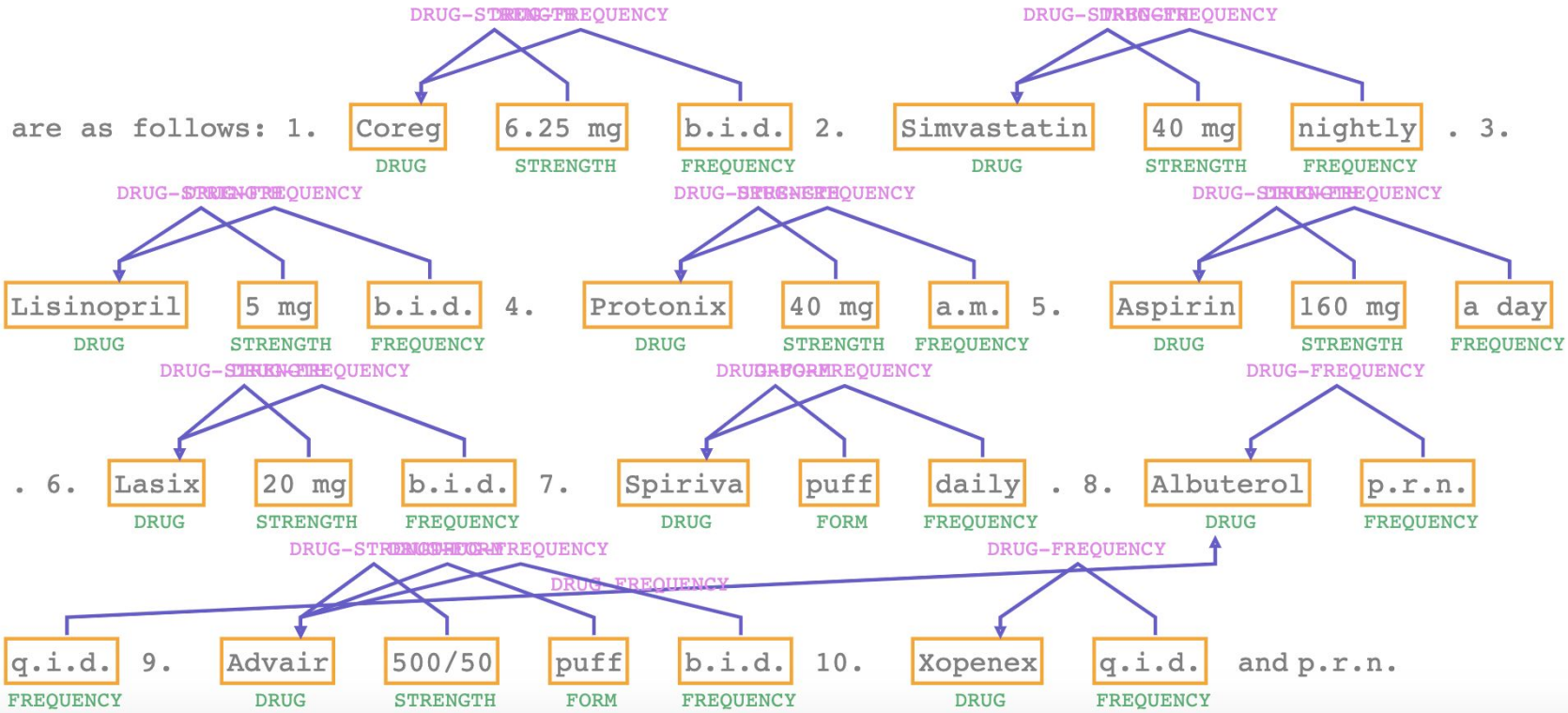
On 5/21/99, the infant received her 1st dose of vaccine A and her 2nd injection of vaccine B. The infant began vomiting and having diarrhea 5 days later. She was taken to the local ER where evaluation was ""non-diagnostic""…

Feature	Type	Date
Vaccine A	Vaccine	1999-05-21
Vaccine B	Vaccine	1999-05-21
Vomiting	Symptom	1999-05-26
Diarrhea	Symptom	1999-05-26
…	…	…



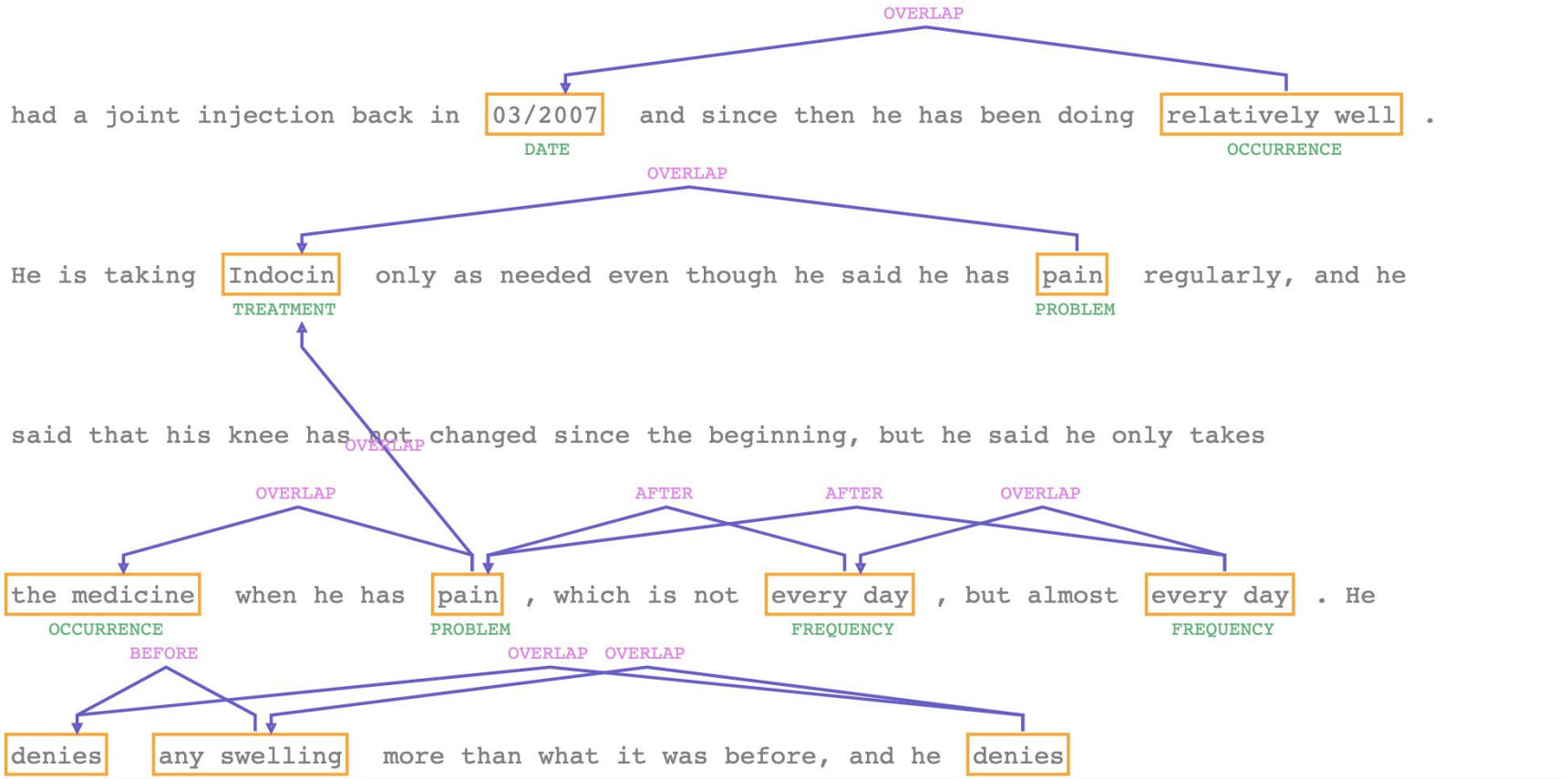
Relation Extraction

Posology



Relation Extraction

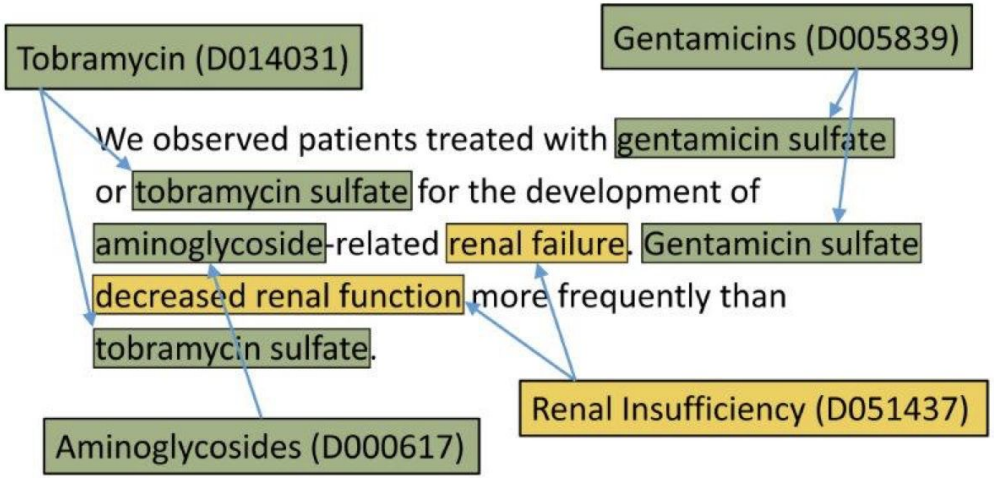
Temporal Events



Part - V

- Entity Resolution (ICD1-, RxNorm, Snomed)

Entity Resolution



"CNN-based ranking for biomedical entity normalization".

Li et al., *BMC Bioinformatics*, October 2017.

F-Score	Dataset	Task
90.30%	ShARe / CLEF	Disease & problem norm.
92.29%	NCBI	Disease norm. in literature

```
+---------+-----------------------------------------------------
|codes    |description
+---------+-----------------------------------------------------
|17473003 |Cecotomy
|17473003 |Cecotomy (procedure)
|304587000|Excision of colonic pouch
|304587000|Excision of colonic pouch (procedure)
|87279008 |Excision of lesion of colon
|174117007|Excision of lesion of colon NEC
|174117007|Excision of lesion of colon NEC (procedure)
|87279008 |Excision of lesion of colon (procedure)
|276190007|Ileocolic resection
|276190007|Ileocolic resection (procedure)
|43075005 |Partial resection of colon
|43075005 |Partial resection of colon (procedure)
|428305005|History of partial resection of colon (situation)
|428305005|History of partial resection of colon
|444165004|Partial resection of colon and resection of terminal
|738552004|Partial resection of colon with stoma (procedure)
|738552004|Partial resection of colon with stoma
|84952009 |Resection of colon for interposition
|84952009 |Resection of colon for interposition (procedure)
|445884009|Wedge resection of colon
+---------+-----------------------------------------------------
only showing top 20 rows
```

Assigns a **ICD10** (International Classification of Diseases version 10) code to chunks identified as "PROBLEMS" by the NER Clinical Model

Entity Resolution - RxNorm

the patient was prescribed 1 capsule **DRUG** of advil **DRUG** for 5 days **DURATION** . he was seen by the endocrinology service and she was discharged on 40 units **DRUG** of insulin glargine **DRUG** at night **FREQUENCY** , 12 units **DRUG** of insulin lispro **DRUG** with meals **FREQUENCY** , and metformin 1000 mg **DRUG** two times a day **FREQUENCY** . it was determined that all sglt2 inhibitors **DRUG** should be discontinued indefinitely .

advil : DRUG

	rxnorm_code	description	distance
0	153010	advil	0
1	669348	advate	0.0417

insulin lispro : DRUG

	rxnorm_code	description	distance
0	86009	insulin lispro	0
1	1157461	insulin lispro injectable product	0.0743

insulin glargine : DRUG

	rxnorm_code	description	distance
0	274783	insulin glargine	0.0000
1	1157459	insulin glargine injectable product	0.0653

metformin 1000 mg : DRUG

	rxnorm_code	description	distance
0	316255	metformin 1000 mg	0.0000
1	860995	metformin hydrochloride 1000 mg	0.0445

Entity Resolution - Snomed / ICD-10

a 28-year-old female with a history of gestational diabetes mellitus **PROBLEM** diagnosed eight years prior to presentation and subsequent type two diabetes mellitus **PROBLEM** (t2dm **PROBLEM**), one prior episode of htg-induced pancreatitis **PROBLEM** three years prior to presentation , associated with an acute hepatitis **PROBLEM** , and obesity **PROBLEM** with a body mass index **PROBLEM** (bmi) of 33.5 kg/m2 , presented with a one-week history of polyuria **PROBLEM** , polydipsia **PROBLEM** , poor appetite **PROBLEM** , and vomiting **PROBLEM** .

gestational diabetes mellitus : PROBLEM

	snomed_code	description	distance	athena_concept_id	domain_id	concept_class_id	ICD10CM_mapping
0	11687002	gestational diabetes mellitus	0.0000	4024659	Condition	Clinical Finding	O24.429, O24.439, O24.414, O24.419, O24.4, O24.410
1	40791000119105	postpartum gestational diabetes mellitus	0.0423	45757789	Condition	Clinical Finding	O24.4, O24.439

obesity : PROBLEM

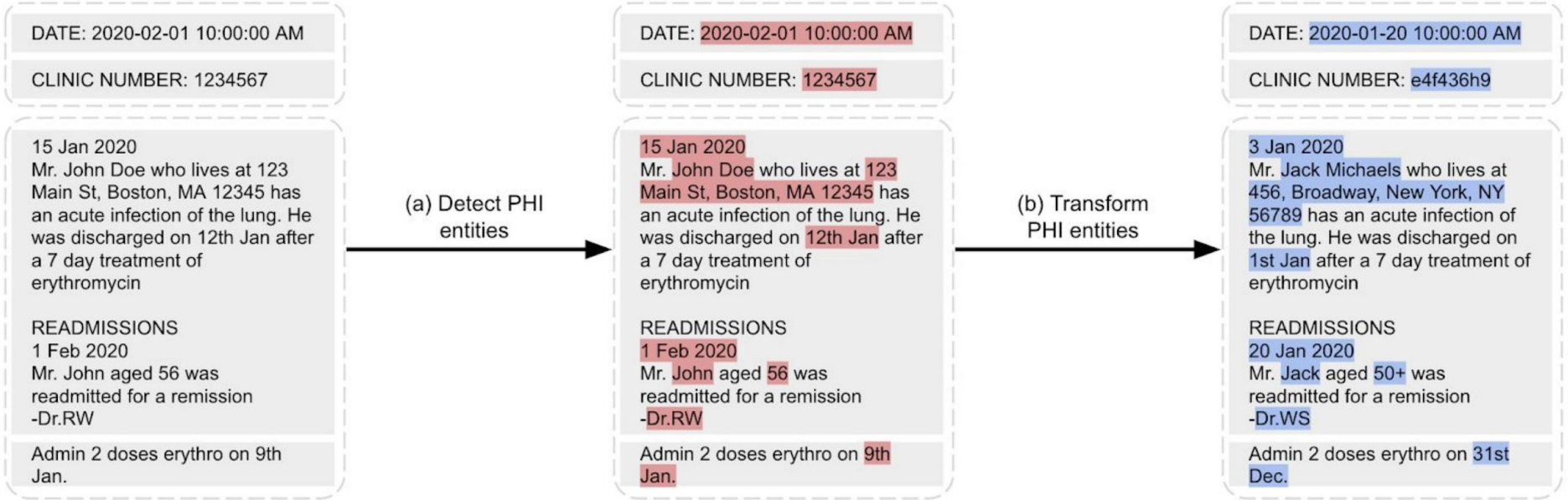
	snomed_code	description	distance	athena_concept_id	domain_id	concept_class_id	ICD10CM_mapping
0	414916001	obesity	0.0000	433736	Condition	Clinical Finding	E66.9
1	414915002	obese	0.0264	4215968	Observation	Clinical Finding	Z68.41, E66.9, E66.8

Part - VI

- De-Identification and Obfuscation of PHI data

De-Identification

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



De-Identification

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

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

De-Identification

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

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

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

Deidentified Text

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

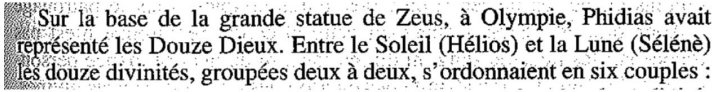
```
def get_deidentify_model():

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

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

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

    model_deidentify = deidentify_pipeline.fit(empty_data)

    return model_deidentify
```

Part - VII

- Spark OCR

Maximizing Text Recognition Accuracy with Image Transformers in Spark OCR

Spark OCR



Uploaded Image.

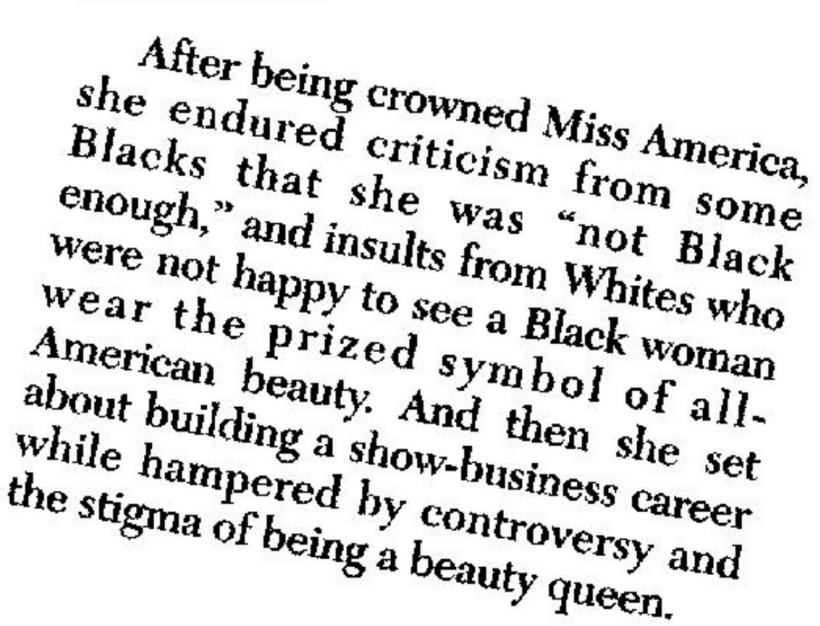
Converted Text:

; a ‘Sur. la base de la grande statue de Zeus, a ‘Olympie, Phidias avait

Teprésenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) Aes ‘douze divinités, groupées deux a a deux, Ss ordonnaient en six couples :

Converted Text:

Digital ‘ Image Processing



Uploaded Image.

Converted Text:

After being crowned Miss America, she endured criticism from some Blacks that she was “not Black cnough,” and insults from Whites who were not happy to see a Black woman wear the prized Symbol of al]. American beauty. And then she set about building a show-business career while hampered by Controversy and the stigma of being a beauty queen,

Content

10 mins	Introduction to Spark OCR
5 mins	Spark OCR pipeline examples
20 mins	Image preprocessing
10 mins	Image preprocessing with Spark OCR in action
10 mins	Q&A

Spark OCR

- Based on Spark ML.
- Offers various transformers for:
  - OCR
  - PDF processing
  - Image processing
  - Layout analysis
  - Some other utility transformers

Spark OCR Benefits

- Scalability guaranteed by Spark.
- Running in isolated environment for dealing with personal data.
- Out of the box support for different input/output formats (image, pdf, dicom)
- Existing opensource solutions provide low quality results.
- Compatibility with Spark NLP.

Common use cases

- Digitize scanned PDF's and images.
- De-identify PDF and image documents.
- Extract text from PDF, process it using Spark NLP and render back or highlight text.
- Process images using Spark.

Spark OCR Transformers

Transformers

ImageToText - OCR

Transformers for Layout analysis:

- **ImageLayoutAnalyzer** - Detect regions on page.
- **ImageSplitRegions** - Split image to regions.

Transformers for deal with text positions:

- **PositionFinder**
- **UpdateTextPosition**

PDF transformers

Transformers for dealing with PDF files:

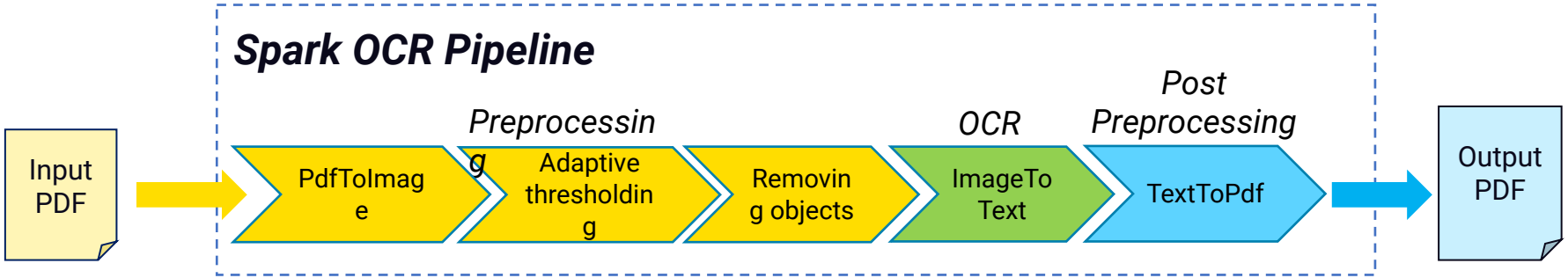
- **PdfToText** – extract text from selectable PDF
- **PdfToImage** – render each page as image
- **ImageToPdf** – store image to PDF format
- **TextToPdf** – render text with positions to PDF format
- **PdfDrawRegions** – draw regions to existing PDF

Image processing transformers

- **BinaryToImage** - Convert binary data to image
- **ImageBinarizer** – Image binarization by custom threshold.
- **ImageAdaptiveThresholding** – Image binarization using local thresholding.
  Supports *Gaussian*, *mean*, *median* methods.
- **ImageScaler** – Scale image by custom scale factor.
- **ImageAdaptiveScaler** – Detects font size and scales image to have a desired font size.
- **ImageSkewCorrector** - Autocorrect skew for images with text.
- **ImageNoiseScorer** – Compute noise score for images.
- **ImageRemoveObjects** – Remove small/big objects from image.
- **ImageMorphologyOpening** – Apply morphology opening to image.
- **ImageDrawRegions** - Draw regions to image.

Spark OCR Pipelines

OCR workflow



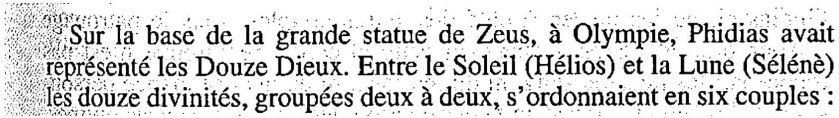
Some example of OCR pipelines

- Processing images
- Processing PDF's
- Image de-identification

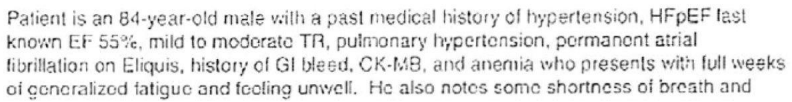
Image Preprocessing

Why do we need image preprocessing?

Background noise


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

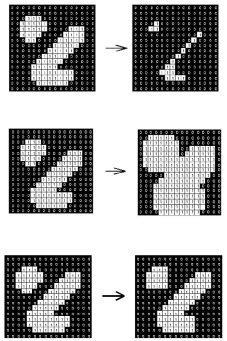
Bad quality of image


Patient is an 84-year-old male with a past medical history of hypertension, HFpEF last known EF 55%, mild to moderate TR, pulmonary hypertension, permanent atrial fibrillation on Eliquis, history of GI bleed, CK-MB, and anemia who presents with full weeks of generalized fatigue and feeling unwell. He also notes some shortness of breath and

Background in nature scene

Image preprocessing operations in Spark OCR

- Adaptive thresholding
- Morphological operations
  - Erosion
  - Dilation
  - Opening
  - Closing
- Removing objects
- Skew correction

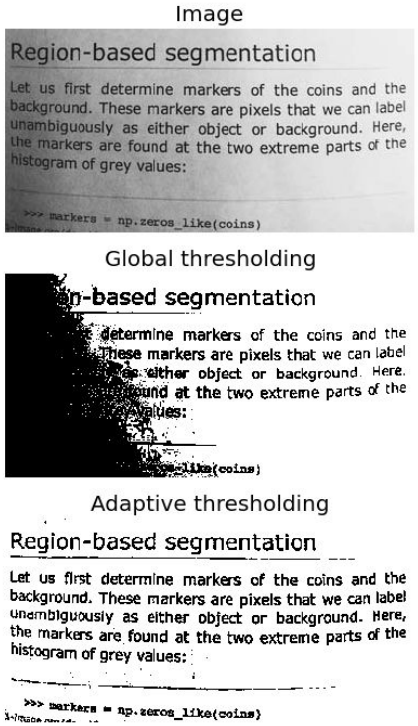


Thresholding

Thresholding is the simplest way to segment objects from a background.

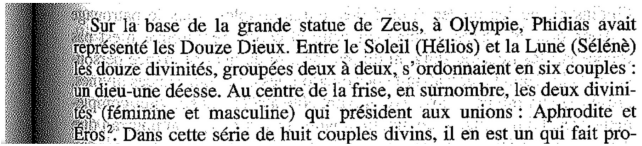
If that background is relatively ***uniform***, then you can ***use a global threshold*** value to binarize the image by pixel-intensity.

If there's ***large variation*** in the background intensity, however, ***adaptive thresholding*** may produce better results. We binarize an image using the threshold_adaptive function, which calculates thresholds in regions of size block_size surrounding each pixel (i.e. local neighborhoods). Each threshold value is the weighted mean of the local neighborhood minus an offset value.

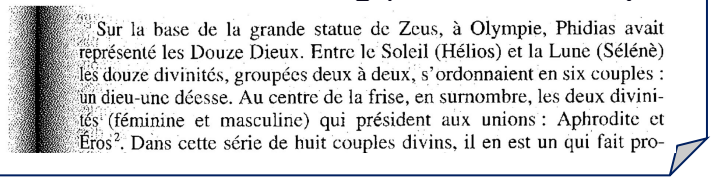


Thresholding with Spark OCR

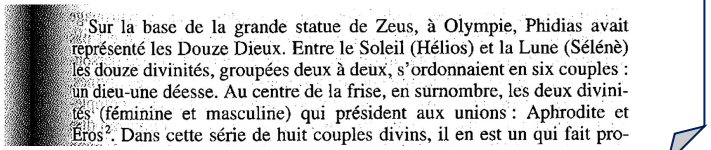
Source image


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait pro-

Global thresholding *(threshold = 80)*


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait pro-

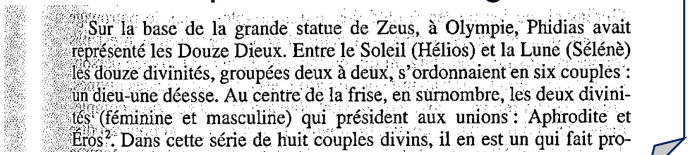
Global thresholding *(threshold = 120)*


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait pro-

```
gbinarizer = ImageBinarizer()
gbinarizer .setInputCol("scaled_image")
gbinarizer .setOutputCol("binarized_image")
gbinarizer .setThreshold(80)
```

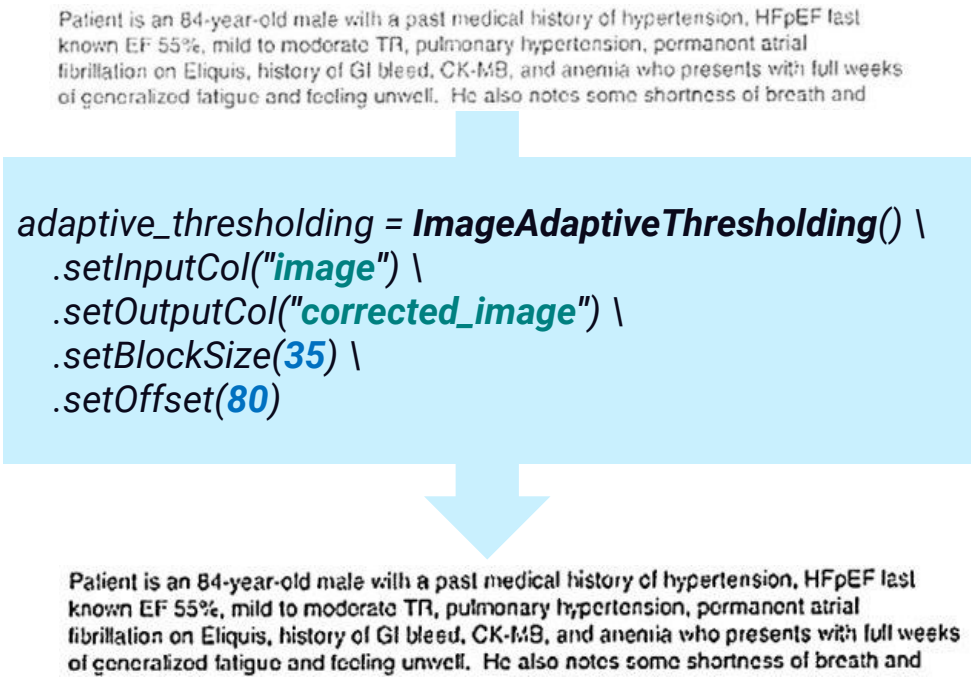
For various images usually provides better results

Adaptive thresholding


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait pro-

```
binarizer = ImageAdaptiveThresholding()
binarizer.setInputCol("scaled_image")
binarizer.setOutputCol("binarized_image")
binarizer.setBlockSize(91)
binarizer.setOffset(60)
```

ImageAdaptiveThresholding transformer



ImageAdaptiveThresholding transformer

Param name	Type	Default	Description
blockSize	int	170	Odd size of pixel neighborhood which is used to calculate the threshold value (e.g. 3, 5, 7, ..., 21, ...).
method	AdaptiveThresholdingMethod	GAUSSIAN	Method used to determine adaptive threshold for local neighborhood in weighted mean image.
offset	int	0	Constant subtracted from weighted mean of neighborhood to calculate the local threshold value.

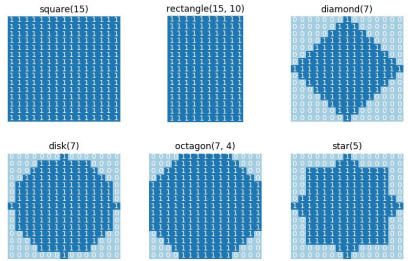
Methods:

- GAUSSIAN
- MEAN
- MEDIAN

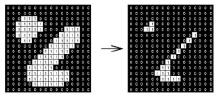
Morphological Operations

Morphological operators often take a binary image and a structuring element (kernel) as input and combine them using a set operator (intersection, union, inclusion, complement). They process objects in the input image based on characteristics of its shape, which are encoded in the structuring element. The mathematical details are explained in Mathematical Morphology.

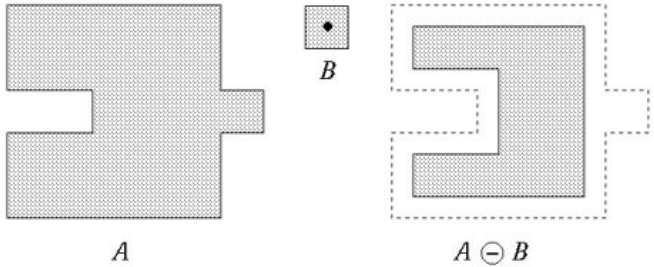
The structuring element used in practice is generally much smaller than the image, often a 3x3 matrix.



Erosion



The erosion operation uses a structuring element for reducing the shapes contained in the input image.



Let *E* be a Euclidean space or an integer grid, and *A* a binary image in *E*. The **erosion** of the binary image *A* by the structuring element *B* is defined by:

$$A \ominus B = \{z \in E | B_z \subseteq A\}$$

where B_z is the translation of *B* by the vector z, i.e.,

$$B_z = \{b + z | b \in B\}$$

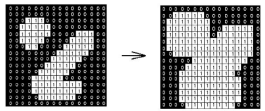
Source image

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

Image after applying erosion

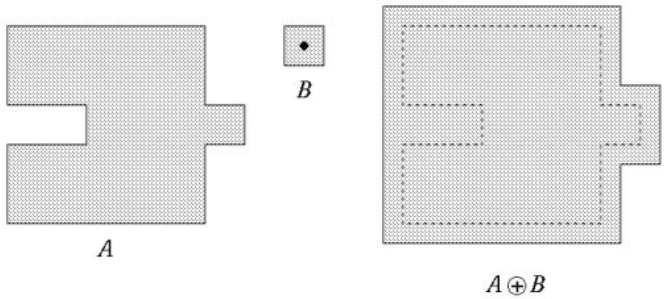
Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

Dilation



The dilation operation uses a structuring element for expanding the shapes contained in the input image.

$$A \oplus B = \bigcup_{b \in B} A_b,$$



Source image

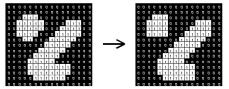
Patient is an 84-year-old male with a past medical history of hypertension, HFpEF last known EF 55%, mild to moderate TR, pulmonary hypertension, permanent atrial fibrillation on Eliquis, history of GI bleed, CK-MB, and anemia who presents with full weeks of generalized fatigue and feeling unwell. He also notes some shortness of breath and

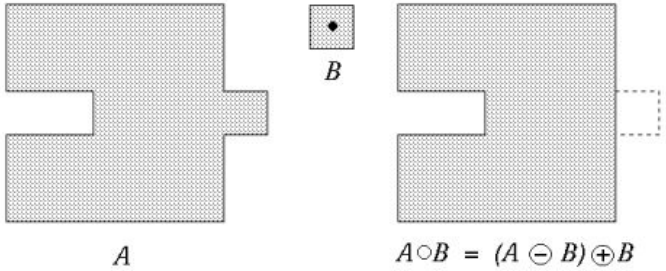
Image after applying dilation

Patient is an 84-year-old male with a past medical history of hypertension, HFpEF last known EF 55%, mild to moderate TR, pulmonary hypertension, permanent atrial fibrillation on Eliquis, history of GI bleed, CK-MB, and anemia who presents with full weeks of generalized fatigue and feeling unwell. He also notes some shortness of breath and

Opening

Very simply, an opening is defined as an erosion followed by a dilation *using the same structuring element for both operations*.





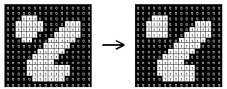
Source image

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

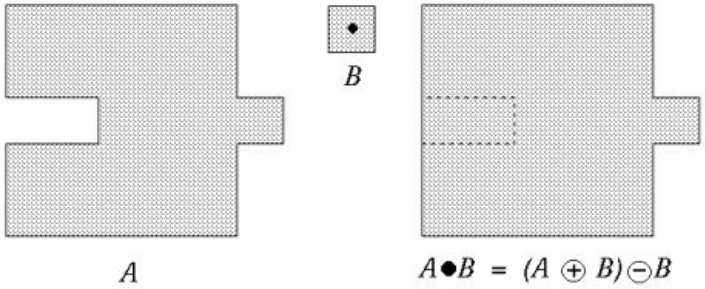
Image after applying opening

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

Closing



Closing is opening performed in reverse. It is defined simply as a dilation followed by an erosion *using the same structuring element for both operations*.



Source image

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

Image after applying opening

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

ImageMorphologyOperation transformer

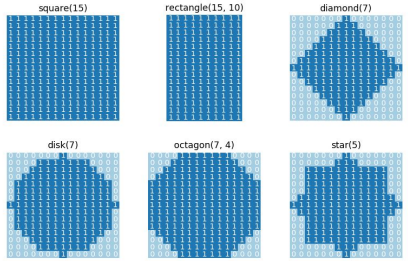
```
ImageMorphologyOperation() \
    .setKernelShape(KernelShape.SQUARE) \
    .setKernelSize(3) \
    .setOperation(MorphologyOperationType.EROSION) \
    .setInputCol("image") \
    .setOutputCol("corrected_image")
```

Kernel Shapes:

- ***SQUARE***
- ***DIAMOND***
- ***DISK***
- ***OCTAGON***
- ***STAR***

Morphology Operations:

- ***EROSION***
- ***DILATION***
- ***OPENING***
- ***CLOSING***



Removing objects

- Removing small objects
- Remove small holes
- Removing small objects with specifying min font size
- Removing big objects (images, lines etc)

Source image

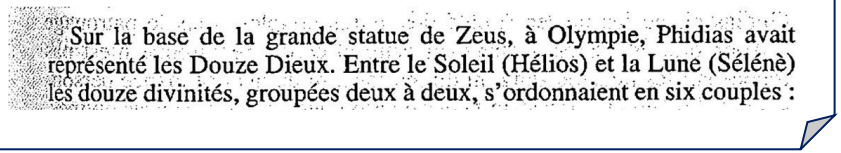
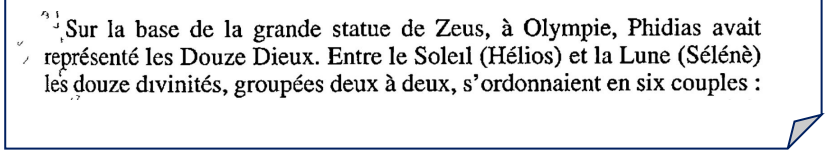
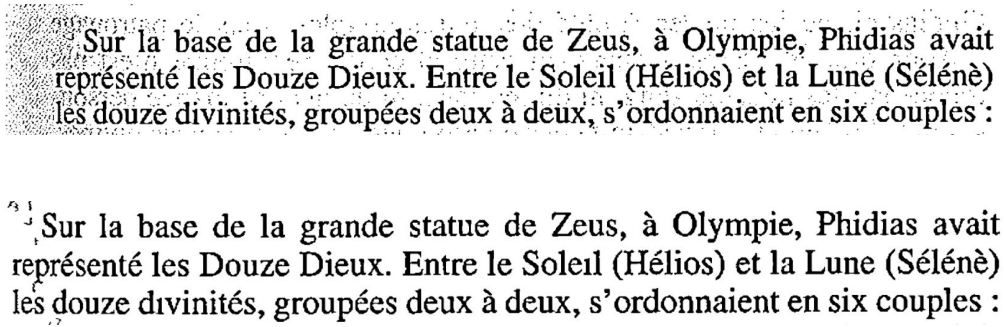

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

Image after applying removing objects


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples :

ImageRemoveObject transformer

```
ImageRemoveObjects() \
    .setInputCol("binarized_image") \
    .setOutputCol("corrected_image") \
    .setMinSizeObject(50)
```

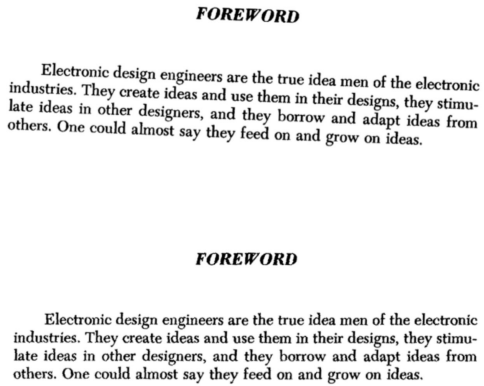


Param name	Type	Default	Description
minSizeFont	int	10	Min size of font in pt.
minSizeObject	int	None	Min size of object which will keep on image [*].
minSizeHole	int	None	Min size of hole which will keep on image [*].
maxSizeObject	int	None	Max size of object which will keep on image [*].

[*] : *None* value disables removing objects

Skew correction

```
ImageSkewCorrection() \
    .setInputCol("image") \
    .setOutputCol("corrected_image") \
    .setAutomaticSkewCorrection(True)
```

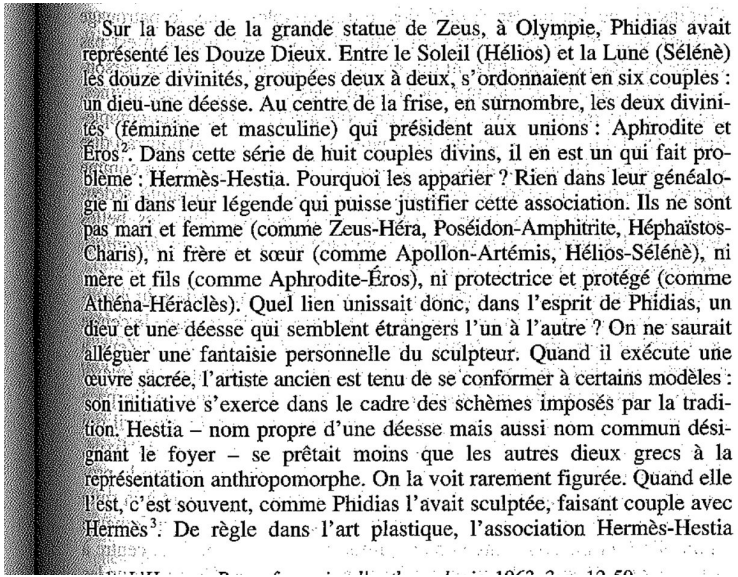


Param name	Type	Description
rotationAngle	double	rotation angle
automaticSkewCorrection	boolean	enables/disables adaptive skew correction

OCR in action

Tesseract

F1 score - 0.2610

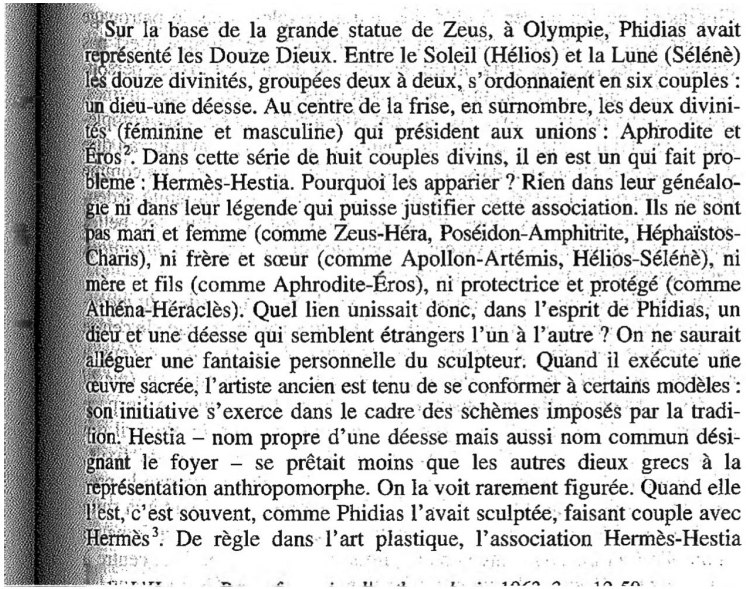


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait problème : Hermès-Hestia. Pourquoi les apparier ? Rien dans leur généalogie ni dans leur légende qui puisse justifier cette association. Ils ne sont pas mari et femme (comme Zeus-Héra, Poséidon-Amphitrite, Héphaïstos-Charis), ni frère et sœur (comme Apollon-Artémis, Hélios-Séléné), ni mère et fils (comme Aphrodite-Éros), ni protectrice et protégé (comme Athéna-Héraclès). Quel lien unissait donc, dans l'esprit de Phidias, un dieu et une déesse qui semblent étrangers l'un à l'autre ? On ne saurait alléguer une fantaisie personnelle du sculpteur. Quand il exécute une œuvre sacrée, l'artiste ancien est tenu de se conformer à certains modèles : son initiative s'exerce dans le cadre des schèmes imposés par la tradition. Hestia – nom propre d'une déesse mais aussi nom commun désignant le foyer – se prêtait moins que les autres dieux grecs à la représentation anthropomorphe. On la voit rarement figurée. Quand elle l'est, c'est souvent, comme Phidias l'avait sculptée, faisant couple avec Hermès[3]. De règle dans l'art plastique, l'association Hermès-Hestia

on base de la Basie. statue de Zeus, a Olympie, Phidias 'avait
"Das cette série de huit couples divins, il en est. un qui 'fait | pro-
Hermés-Hestia. Pourquoi les apparier ? ? Rien dans leur 'généalo-
ati, et femme (comme Zeus-Héra, Poséidon-Amphittite, 'Héphaistos-
; ni ffére et sccur (comme Apolion-Antémis, Hélios-Séléné), ni
t une: déesse qui semblent étrangers r un a l'autre ?' On ne saurait
ler une fantaisie personnelle du sculpteur. Quand il exécute' une
t le foyer — se prétait moins que les autres dieux grecs a la
Stésentation anthropomorphe. On la voit rarement figurée: Quand elle
est souvent, comme Phidias |' avait sculptée; faisant couple avec
3s°: De régle dans- l'art 'Plastique, Passociation Henmes-Hestia
—_ _ . wt a. wo et anhserh A an om *
on base de la Basie. statue de Zeus, a Olympie, Phidias 'avait
"Das cette série de huit couples divins, il en est. un qui 'fait | pro-
Hermés-Hestia. Pourquoi les apparier ? ? Rien dans leur 'généalo-
ati, et femme (comme Zeus-Héra, Poséidon-Amphittite, 'Héphaistos-
; ni ffére et sccur (comme Apolion-Antémis, Hélios-Séléné), ni
t une: déesse qui semblent étrangers r un a l'autre ?' On ne saurait
ler une fantaisie personnelle du sculpteur. Quand il exécute' une
t le foyer — se prétait moins que les autres dieux grecs a la
Stésentation anthropomorphe. On la voit rarement figurée: Quand elle
est souvent, comme Phidias |' avait sculptée; faisant couple avec
3s°: De régle dans- l'art 'Plastique, Passociation Henmes-Hestia
—_ _ . wt a. wo et anhserh A an om *

ABBYY FineReader

F1 score - 0.8972

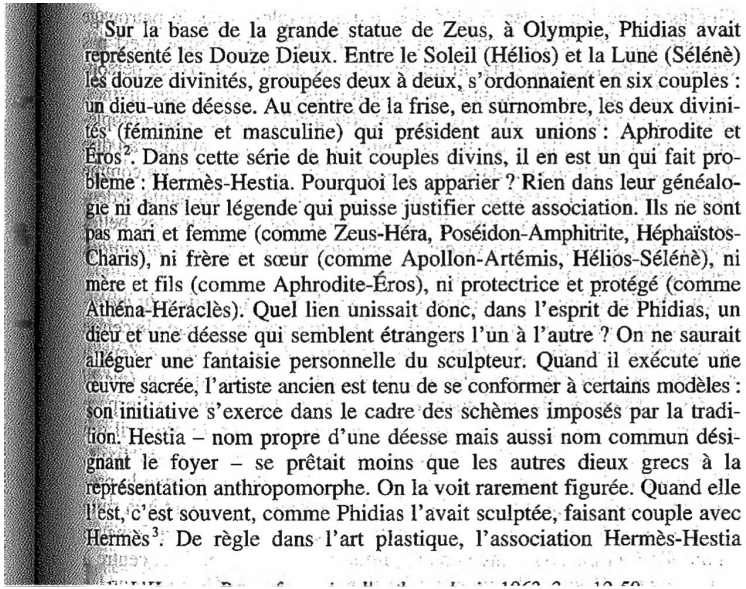


Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait problème : Hermès-Hestia. Pourquoi les apparier ? Rien dans leur généalogie ni dans leur légende qui puisse justifier cette association. Ils ne sont pas mari et femme (comme Zeus-Héra, Poséidon-Amphitrite, Héphaïstos-Charis), ni frère et sœur (comme Apollon-Artémis, Hélios-Séléné), ni mère et fils (comme Aphrodite-Éros), ni protectrice et protégé (comme Athéna-Héraclès). Quel lien unissait donc, dans l'esprit de Phidias, un dieu et une déesse qui semblent étrangers l'un à l'autre ? On ne saurait alléguer une fantaisie personnelle du sculpteur. Quand il exécute une œuvre sacrée, l'artiste ancien est tenu de se conformer à certains modèles : son initiative s'exerce dans le cadre des schèmes imposés par la tradition. Hestia – nom propre d'une déesse mais aussi nom commun désignant le foyer – se prêtait moins que les autres dieux grecs à la représentation anthropomorphe. On la voit rarement figurée. Quand elle l'est, c'est souvent, comme Phidias l'avait sculptée, faisant couple avec Hermès[3]. De règle dans l'art plastique, l'association Hermès-Hestia

Sur la base de la grande statue de Zeus, à Olympie, Phidias avait
présenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Sëlénè)
& douze divinités, groupées deux à deux, s'ordonnaient en six couples :
n dieu-une déesse. Au centre de la frise, en surnombre, les deux divini-
(féminine et masculine) qui président aux unions : Aphrodite et
ms2;; Dans cette série de huit couples divins, il en est un qui fait prolemé :
Hermès-Hestia. Pourquoi les apparier ? Rien dans leur généaloJfêfrïï dans
leur légende qui puisse justifier cette association: Ils rie sont
M m ari et femme (comme Zeus-Héra, Poséidon-Amphitrite,
HéphaïstosÊHaris), ni frère et sœur (comme Apollon-Artémis, Hélios-Séléribè),
ni
mère et fils (comme Aphrodite-Eros), ni protectrice et protégé (comme
théna Héraclès). Quel lien unissait donc, dans T esprit de Phidias, un
lieu et une dée s s e qui semblent étrangers l'un à l'autre ? On ne saurait
'"eguer une fantaisie personnelle du sculpteur. Quand il exécuté une
livre sacrée, T artiste ancien est tenu de se conformer à certains modèles :
|®ihitiative s'exerce dans le cadre des schèmes imposes par la tradiipnV
Hestia - nom propre d'une déesse mais aussi nom commun désignant le
foyer - se prêtait moins que les autres dieux grecs à la
èprésentation anthropomorphe. On la voit rarement figurée. Quand elle
'est,5c'est souvent, comme Phidias l'avait sculptée, faisant couple avec
érmës3. De règle dans l'art plastique, l'association Hermès-Hestia
RpvÆ îi. -4'i 1 T I T i A r o a -i a

AWS Text Ract

F1 score - 0.9323



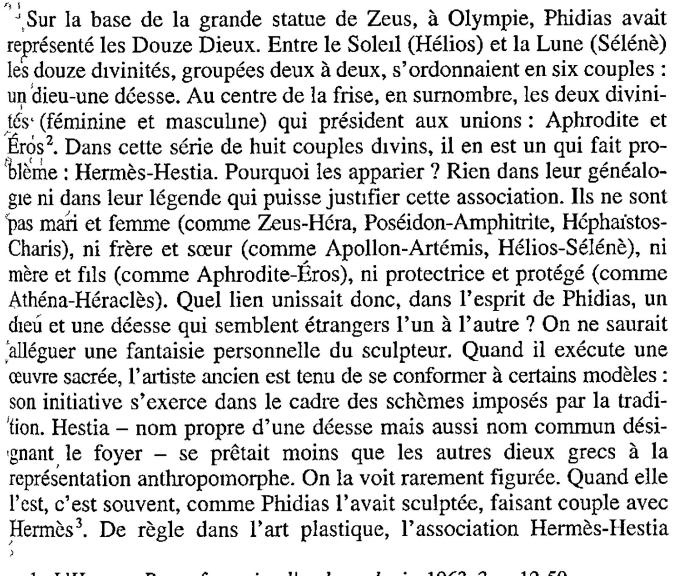
Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait problème : Hermès-Hestia. Pourquoi les apparier ? Rien dans leur généalogie ni dans leur légende qui puisse justifier cette association. Ils ne sont pas mari et femme (comme Zeus-Héra, Poséidon-Amphitrite, Héphaïstos-Charis), ni frère et sœur (comme Apollon-Artémis, Hélios-Séléné), ni mère et fils (comme Aphrodite-Éros), ni protectrice et protégé (comme Athéna-Héraclès). Quel lien unissait donc, dans l'esprit de Phidias, un dieu et une déesse qui semblent étrangers l'un à l'autre ? On ne saurait alléguer une fantaisie personnelle du sculpteur. Quand il exécute une œuvre sacrée, l'artiste ancien est tenu de se conformer à certains modèles : son initiative s'exerce dans le cadre des schèmes imposés par la tradition. Hestia – nom propre d'une déesse mais aussi nom commun désignant le foyer – se prêtait moins que les autres dieux grecs à la représentation anthropomorphe. On la voit rarement figurée. Quand elle l'est, c'est souvent, comme Phidias l'avait sculptée, faisant couple avec Hermès[3]. De règle dans l'art plastique, l'association Hermès-Hestia

Sur la base de la grande statue de Zeus, a Olympie, Phidias avait represente les Douze Dieux. Entre le Soleil (Helios) et la Lune (Selene) les douze divinites, groupees deux a deux, s ordonnaient en six couples : un dieu-une deesse. Au centre de la frise, en surnombre, les deux divinites (feminine et masculine) que president aux unions : Aphrodite et Eros?. Dans cette serie de huit couples divins, il en est un qui fait probleme': Hermes-Hestia. Pourquoi les apparier ? Rien dans leur genealogre nl dans leur legende qui puisse justifier cette association. Ils ne sont pas mari et femme (comme Zeus-Hera, Poseidon-Amphitrite, Hephaistos-Charis), ni frere et soeur (comme Apollon-Artemis, Helios-Selene), ni mere et fils (comme Aphrodite-Eros), ni protectrice et protege (comme Athena-Heracles): Quel lien unissait donc, dans l'esprit de Phidias; un dieu et une deesse qui semblent etrangers 'un a 1'autre ? On ne saurait alleguer une fantaisie personnelle du sculpteur: Quand il execute une ceuvre sacree, T'artiste ancien est tenu de se conformer a certains modeles : son initiative 'exerce dans le cadre des schemes imposes par la tradition. Hestia - nom propre d'une deesse mais aussi nom commun designant le foyer - se pretait moins que les autres dieux grecs a la representation anthropomorphe. On la voit rarement figuree. Quand elle Pest, c est souvent, comme Phidias 'avait sculptee, faisant couple avec Hermes3 De regle dans l'art plastique, l'association Hermes-Hestia TYy„

Spark OCR

F1 score - 0.9812

Image after preprocessing:



Sur la base de la grande statue de Zeus, à Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux à deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de la frise, en surnombre, les deux divinités (féminine et masculine) qui président aux unions : Aphrodite et Éros[2]. Dans cette série de huit couples divins, il en est un qui fait problème : Hermès-Hestia. Pourquoi les apparier ? Rien dans leur généalogie ni dans leur légende qui puisse justifier cette association. Ils ne sont pas mari et femme (comme Zeus-Héra, Poséidon-Amphitrite, Héphaïstos-Charis), ni frère et sœur (comme Apollon-Artémis, Hélios-Séléné), ni mère et fils (comme Aphrodite-Éros), ni protectrice et protégé (comme Athéna-Héraclès). Quel lien unissait donc, dans l'esprit de Phidias, un dieu et une déesse qui semblent étrangers l'un à l'autre ? On ne saurait alléguer une fantaisie personnelle du sculpteur. Quand il exécute une œuvre sacrée, l'artiste ancien est tenu de se conformer à certains modèles : son initiative s'exerce dans le cadre des schèmes imposés par la tradition. Hestia – nom propre d'une déesse mais aussi nom commun désignant le foyer – se prêtait moins que les autres dieux grecs à la représentation anthropomorphe. On la voit rarement figurée. Quand elle l'est, c'est souvent, comme Phidias l'avait sculptée, faisant couple avec Hermès[3]. De règle dans l'art plastique, l'association Hermès-Hestia

Sur la base de la grande statue de Zeus, a Olympie, Phidias avait représenté les Douze Dieux. Entre le Soleil (Hélios) et la Lune (Séléné) les douze divinités, groupées deux a deux, s'ordonnaient en six couples : un dieu-une déesse. Au centre de 1a frise, en surnombre, les deux divinités: (féminine et masculine) qui président aux unions: Aphrodite et Eros", Dans cette série de huit couples divins, il en est un qui fait probléme : Hermés-Hestia. Pourquoi les apparier ? Rien dans leur généalogie ni dans leur légende qui puisse justifier cette association. Ils ne sont pas mari et femme (comme Zeus-Héra, Poséidon-Amphitrite, Héphaistos-Charis), ni frére et sccur (comme Apollon-Artémis, Hélios-Séléné), ni mére et fils (comme Aphrodite-Eros), ni protectrice et protégé (comme Athéna-Héraclés). Quel lien unissait donc, dans l'esprit de Phidias, un dieu et une déesse qui semblent étrangers l'un a l'autre ? On ne saurait alléguer une fantaisie personnelle du sculpteur. Quand il exécute une ceuvre sacrée, l'artiste ancien est tenu de se conformer a certains modeéles : son initiative s'exerce dans le cadre des schémes imposés par la tradition. Hestia — nom propre d'une déesse mais aussi nom commun désignant le foyer — se prétait moins que les autres dieux grecs a la représentation anthropomorphe. On la voit rarement figurée. Quand elle Vest, c'est souvent, comme Phidias l'avait sculptée, faisant couple avec Hermés*, De régle dans l'art plastique, l'association Hermés-Hestia

Coding ...

Spark NLP Resources

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

John Snow LABS


NOW ANNOUNCING
NLP
SUMMIT
Applied Natural
Language Processing
Boston, Oct 27-28 | San Francisco, Nov 17-18