John Snow LABS

Automated Text Generation & Data-Augmentation for Medicine, Finance, Law, and E-Commerce

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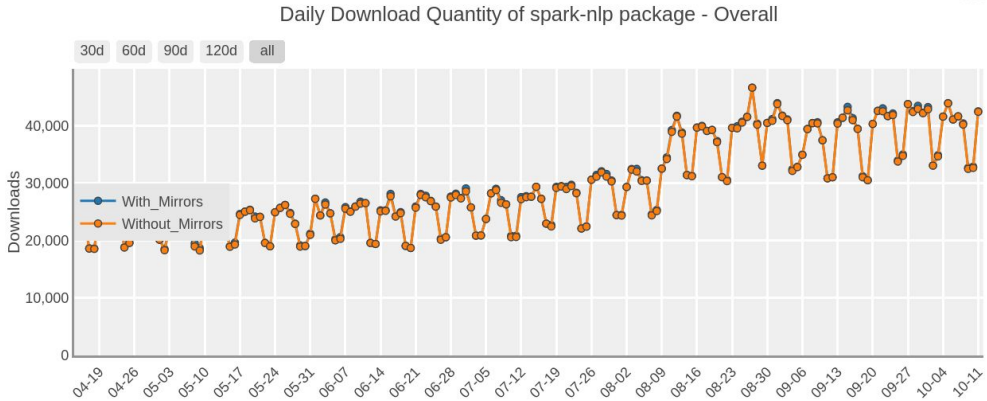
Introducing Spark NLP

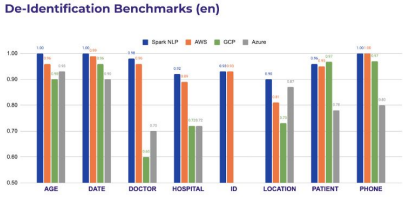
Total downloads	33,767,472
Total downloads - 30 days	2,356,291
Total downloads - 7 days	562,523

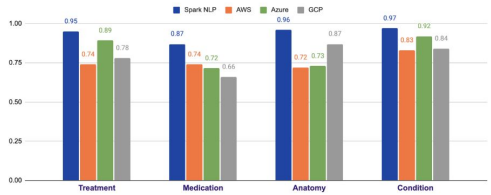


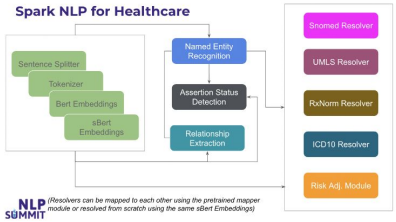
- Spark NLP is an open-source natural language processing library, built on top of Apache Spark and Spark ML. (initial release: Oct 2017)
  - A single unified solution for all your NLP needs
  - Take advantage of transfer learning and implementing the latest and greatest **SOTA** algorithms and models in NLP research
  - The most widely used NLP library in industry (5 yrs in a row)
  - Delivering a mission-critical, enterprise grade NLP library (used by multiple Fortune 500)
  - The most scalable, accurate and fastest library in NLP history

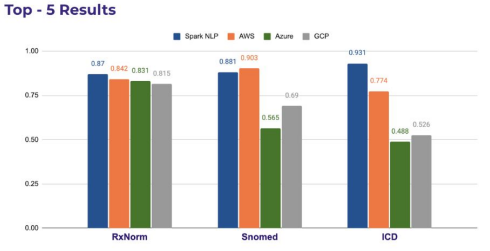
https://medium.com/spark-nlp/introduction-to-spark-nlp-foundations-and-basic-components-part-i-c83b7629ed59

Most Accurate in the Industry









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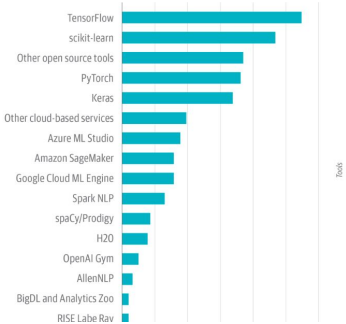
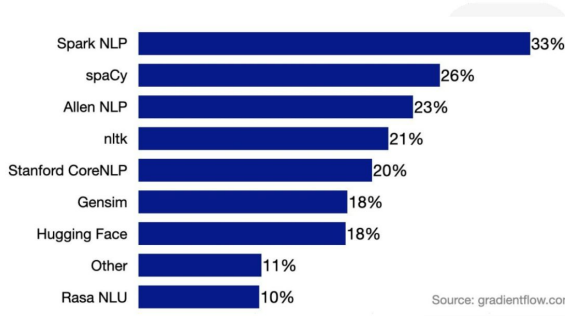
Spark NLP in Industry

Which of the following AI tools do you use?

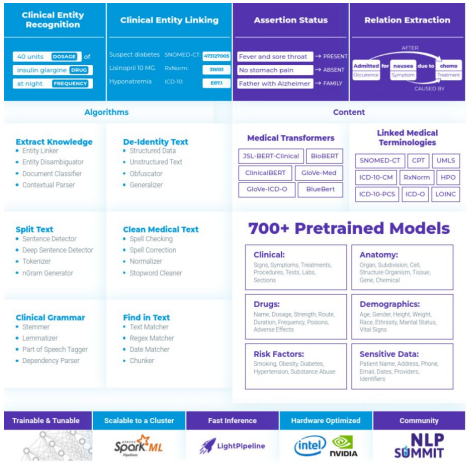


Which NLP libraries does your organization use?

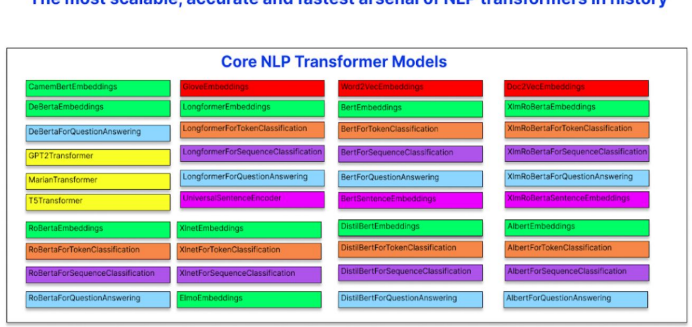


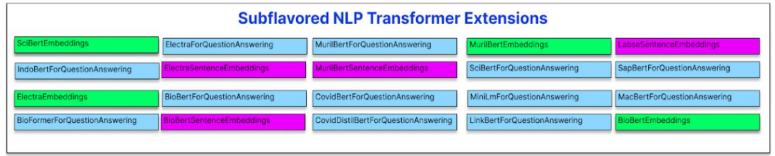
Recognized by the Technology Experts

Global 100 2021 WINNER · ghp 2021 Global Excellence Awards · 2020 Best Healthcare & Life Science AI Development Firm – USA · AI Artificial Intelligence Excellence Awards 2020 · International DataScience Awards WINNER 2019 · Most Significant Open Source Project WINNER SPARK NLP · CIO Artificial Intelligence Solution Provider Reviews of the Year 2018 · AI Platform of the Year · CIO Applications 2019



Spark NLP Modules Healthcare and Public





Biomedical Named Entity Recognition at Scale

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

I. Introduction

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

Spark NLP: Natural Language Understanding at Scale

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Accurate Clinical and Biomedical Named Entity Recognition at Scale

Anonymous NAACL-HLT 2021 submission

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

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Abstract

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

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 Bil.STM-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-

Peer-reviewed conference papers on Spark NLP NER

Optimized, Tested, Supported Integrations

NLU: All **9000+** John Snow Labs models & features in **1 line of code**

How does it work?

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

- Returns a nlu pipeline object

model.**predict**(data)

- Returns a pandas DF

How does it work?

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

- Returns a nlu pipeline object

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

- Returns a pandas DF

EMOTION DETECTION

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

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

NLU WORKS DIRECTLY ON TYPICAL PYTHON DATASETS

Strings

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

Lists

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

Pandas data frame

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

Pandas series

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

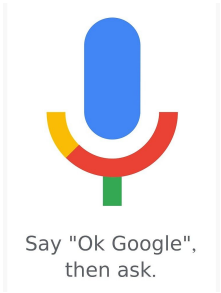
Spark
Data Frame

Ray
Data Frame

Dask
Data Frame

Where is Text Generation used in the Industry?

- Natural Language Generation (NLG) is a sub-field of natural language processing (NLP)
  - Automatically generate **coherent** and **useful** text for human consumption
- NLG Systems in use
  - Google Translate
  - Dialogue Systems (Siri, Alexa, Cortana, Google Home, Bigsby)
  - Summarizers (Google Search Results)
    - Emails, News, Papers, Reports, Conversations
  - Creative writing
    - Stories, Poetry, Narratives
    - Fake News, Botnets



Text Generation in Action : Code Time

Dipping our toes in NLG with NLU using GPT2

[GPT2 NLU Notebook]

Table of contents

Why are generation repeating and what did we just do?

A quick theory crash course follows

```
[ ] gpt2_model['gpt2'].setDoSample(False)
    generation_df = gpt2_model.predict("My Favorite Food is!")
    print(generation_df.generated.values[0])
    generation_df = gpt2_model.predict("My Favorite Food is!")
    print(generation_df.generated.values[0])
```

```
 My Favorite Food is!

I love the way the food is cooked. I love the texture. I like the way it
 My Favorite Food is!

I love the way the food is cooked. I love the texture. I like the way it
```

Why are generation repeating?

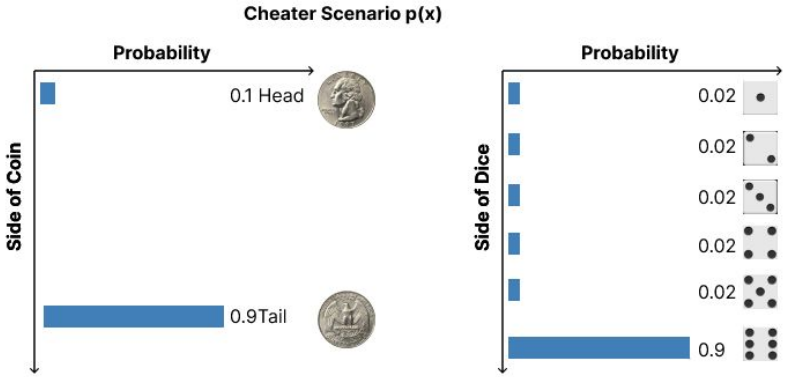
```
[ ] gpt2_model['gpt2'].setDoSample(True)
    gpt2_model['gpt2'].setMaxOutputLength(25)
    generation_df = gpt2_model.predict("My Favorite Food is!")
    print(generation_df.generated.values[0])
    generation_df = gpt2_model.predict("My Favorite Food is!")
    print(generation_df.generated.values[0])
```

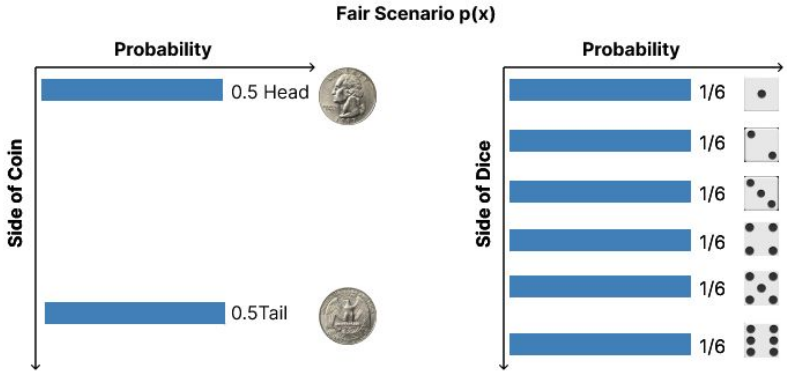
```
 My Favorite Food is!

We have a great family who loves having family gatherings with our kids. From our family gatherings to
 My Favorite Food is!

A recent "food for thought" article, entitled "How to Make a Food that is Easy
```

Why are generations **not** repeating?

What is a **Probability Distribution**?

- A probability distribution is simply a function $p : \Omega \rightarrow [0, 1]$ which returns a probability for events x form a sample space Ω
- In a coin flip scenario, sample space is $\Omega = \{Heads, Tails\}$ and for every event $p(x) = 0.5$ if the coin is fair.
- In a 6-sided-Dice throw scenario, sample space is $\Omega = \{1, 2, 3, 4, 5, 6\}$ and for every $p(x) = 1/6$ if the dice is fair.

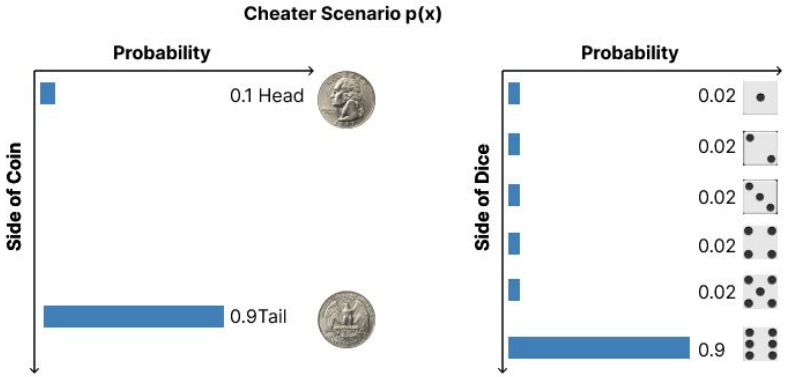


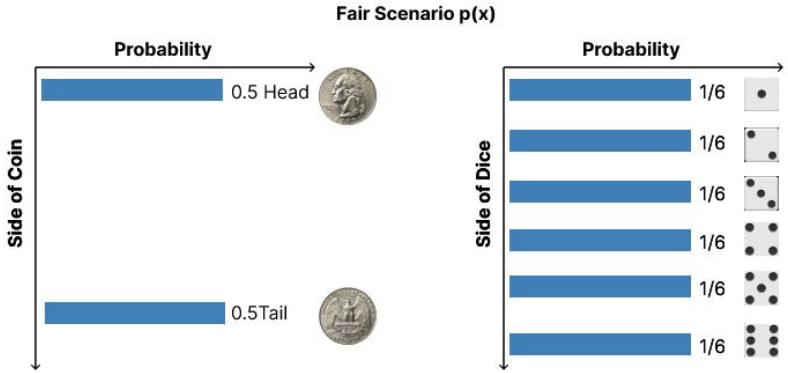


What is **drawing** from a probability distribution?

Also known as **sampling** from a distribution

- If we know the probability distribution of a sample space, we can **simulate** it
- We simulate by **drawing** elements in Ω using some **sampling algorithm**

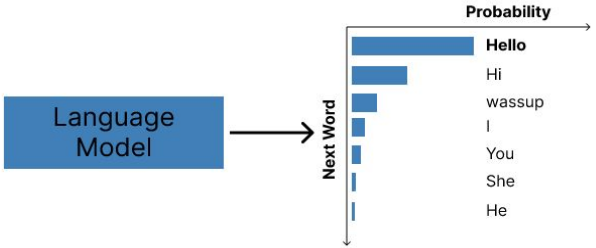




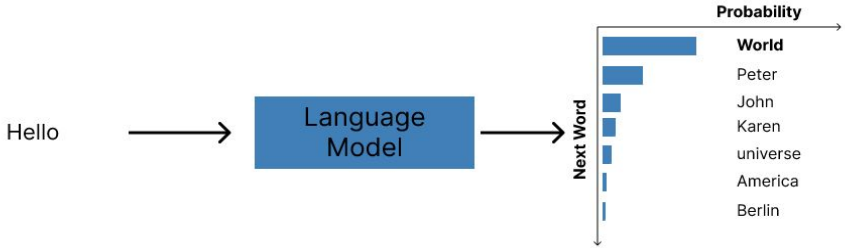
What is a **Language Model**?

- A Language Model is simply a probability distribution $p(x)$ where the sample space Ω is the **set of words in the human language**
- $p(hello)$ should tell us the probability of the word **hello** occuring as **beginning of human written text**
- $p(world \mid hello)$ should tell us the probability of the word **world** given that humman written text started with **hello**

p(x) = Softmax(Logits)



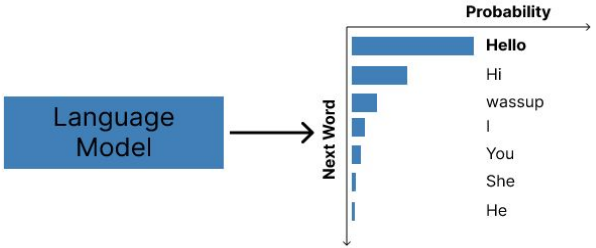
p(Hello | World) = Softmax(Logits)



How does a Language Model **generate Text**?

- The function $p(x)$ is used to draw a word from the human language
- The function $p(x|y)$ is used to draw a word from the human language, given a start word
    - We can feed the outputs of $p(x|y)$ back to itself to generate one word at a time, conditioned on preceeding words
    - **y** is reffered to as **the prompt** we are giving to the model
- Finding an decent estimation of p has been solved by Transformer based deep learning architectures like Bert,GPT,T5, etc..
- When we use these Pretrained Language Models to generate text our main concern **shaping** and **sampling** from these distrubtions
- Final layer of generative NLP Transformer exposes one logit for every word in the training vocabulary.
    - Applying Softmax function to outputs of logits, yields probability distrubtion $p(x \mid y)$ which we sample from

p(x) = Softmax(Logits)



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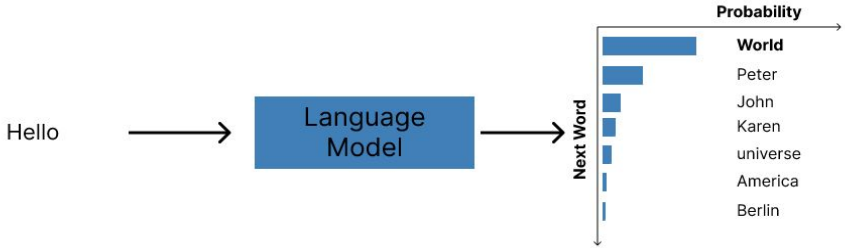
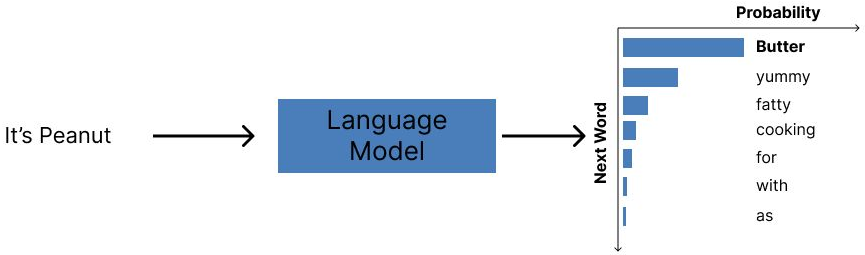
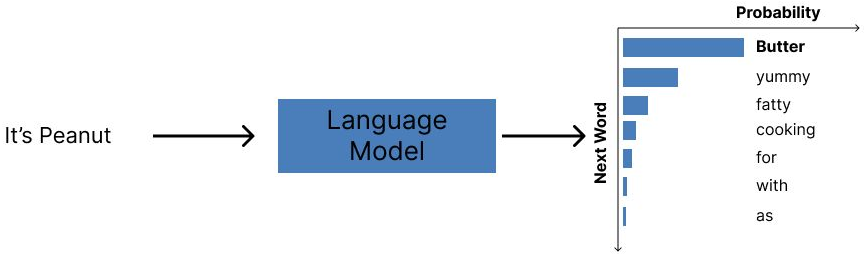


P(Next-Word | It's, Peanut) = Softmax(Logits)

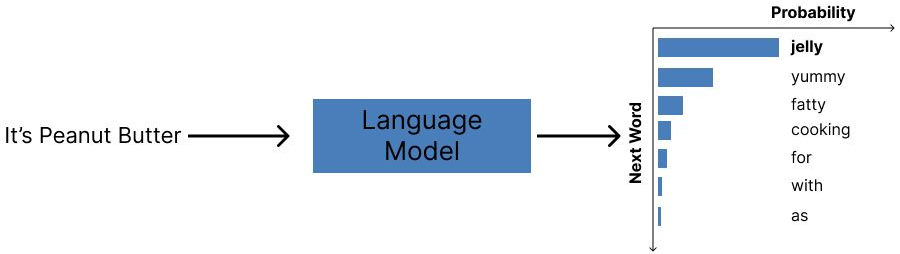


How does a Language Model **generate Text**?

P(Next-Word | It's, Peanut) = Softmax(Logits)



P(Next-Word | It's, Peanut, Butter) = Softmax(Logits)



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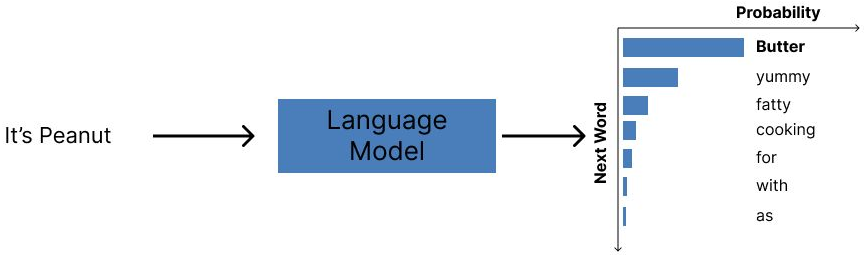
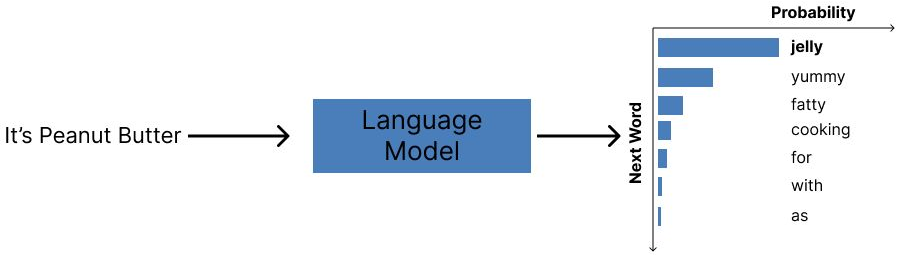
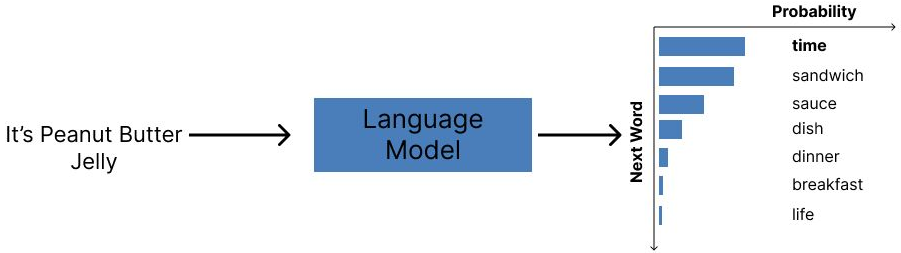
P(Next-Word | It's, Peanut) = Softmax(Logits)



P(Next-Word | It's, Peanut, Butter) = Softmax(Logits)

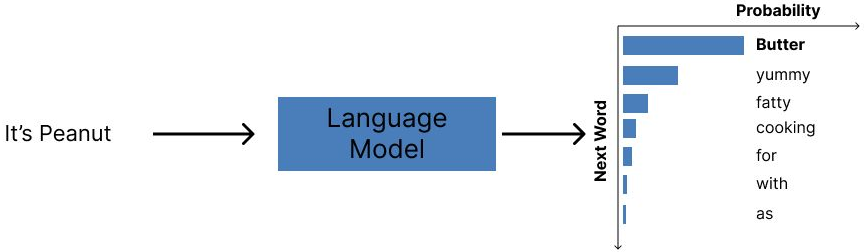


P(Next-Word | It's, Peanut, Butter,Jelly) = Softmax(Logits)

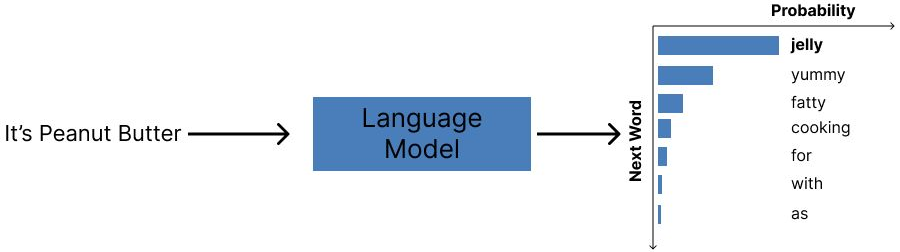


How does a Language Model **generate Text**?

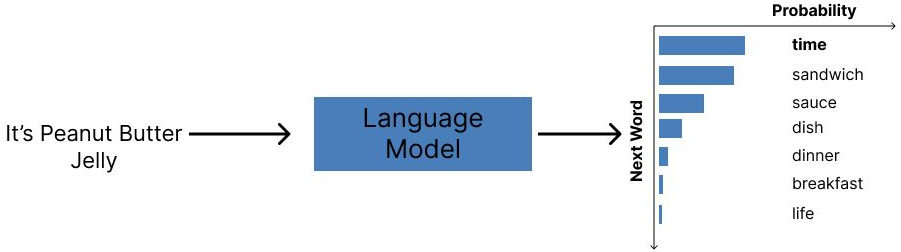
P(Next-Word | It's, Peanut) = Softmax(Logits)



P(Next-Word | It's, Peanut, Butter) = Softmax(Logits)



P(Next-Word | It's, Peanut, Butter,Jelly) = Softmax(Logits)



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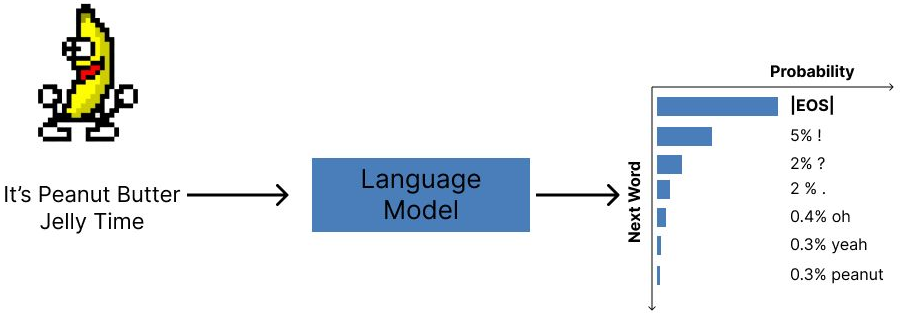
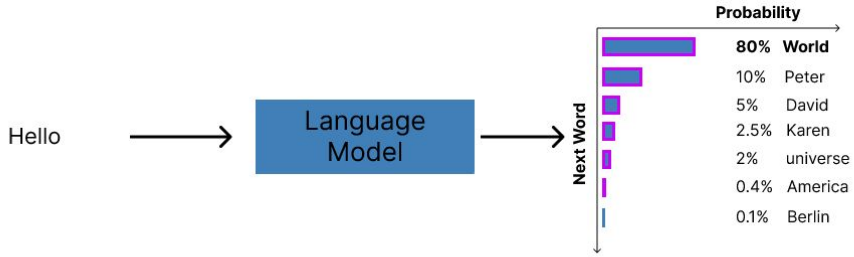


How does a Language Model **generate Text**?

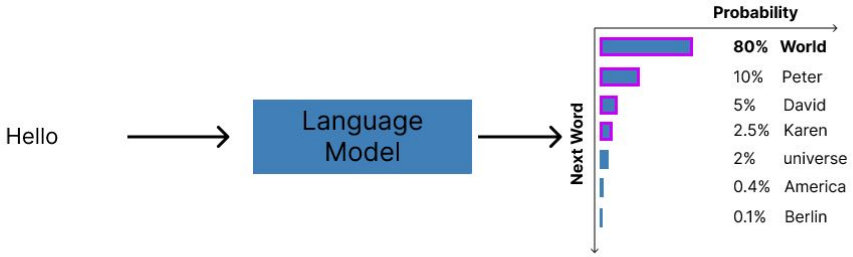
What are some **Sampling Algorithms** and **Parameters** ?

- **Parameters:**
  - Repetition Penalty: Penalize generation candidates based on how often they already exist based See CTRL
  - Max Repeated NGrams: Block some NGrams to occur more than K times
  - Temperature: Reshape distributed given by Softmax
  - Min/Max Output Length: Limit the length of generated
- **Sampling Algorithms**:
  - ArgMax based : Pick word with highest probability of occurring next, Greedy Algorithm.
    - Makes generation deterministic, i.e. always generates the same text for the same prompt
    - When **.doSample(False)** our will use this algorithm and all **previous examples used this algorithm**
  - Top-K Sampling: choose from **Top-K highest probability** words in distribution
  - Top-P Sampling: choose from words with **summed probability** equal or greater than **P**

Top-K Sampling
Choose from first K word with highest probability
For K=6



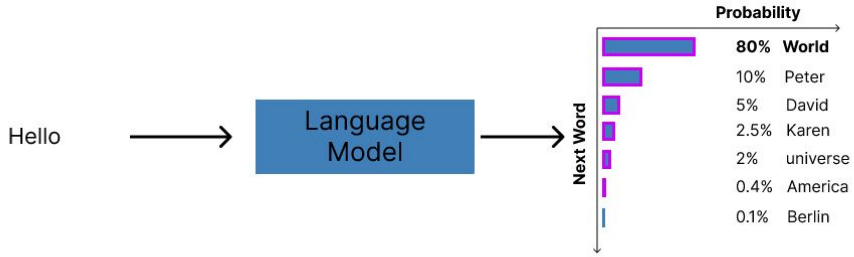
Top-P Sampling
Choose from first tokens whoose collective probability is at least P
For P = 0.95



What's the difference between **Top-P** and **Top-K Sampling**?

- **Higher K and P:** makes choices more diverse and risky. Less logical and coherent
- **Lower K and P:** makes choices more generic and safe Also more logical and coherent
- Softmax normalizes logits between 0 and 1. We can tweak the function with the T parameter
- **High T:** Make Distribution more uniform and diverse.
  Associated with creativity and randomness of generations.
- **Low T**: Make Distribution concentrate around top words, more spiky and less diverse.
  Associated with more logical and coherent generations.

Top-K Sampling
Choose from first K word with highest probability
For K=6



Top-P Sampling
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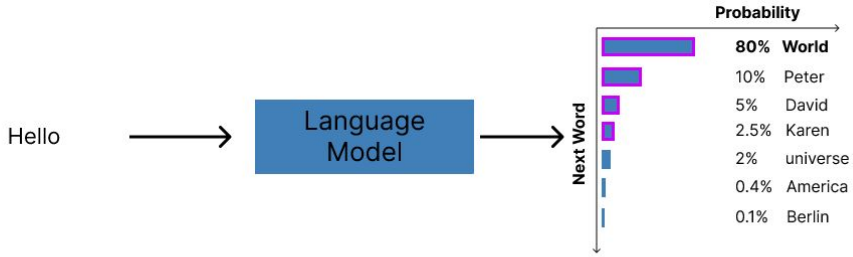


What is **Prompt Engineering**?

- Prompt Engineering is the art of **finding prompts** which shape the conditioned probability $p(x \mid y)$ such that only tokens revelant to a specific use case have a high chance of beeing sampled

```
37] # Bad prompting, the input text we condition GPT2 yields bad output, it does not understand the pattern we want from the original input
gpt2_pipe.predict("Suggest me a good Sci-Fi movie")
```

1 entry Filter

index	document	generated
0	Suggest me a good Sci-Fi movie	generate Suggest me a good Sci-Fi movie. I'm not sure if I'm going to be able to do this, but I'm sure I'll be able. (I'm sure you're going to want to do it.) So, I'm not going to do that. . , .

Show 25 per page

Like what you see? Visit the data table notebook to learn more about interactive tables.

```
# Good prompting. help GPT2 out and by giving it a few samples in the prompt we condition it on
gpt2_pipe.predict("""Generate a top 10 movie list: \n
1.The Matrix \n
2.Terminator \n
3. """)
```

1 entry Filter

index	document	generated
0	Generate a top 10 movie list: 1.The Matrix 2.Terminator 3.	generate Generate a top 10 movie list: 1.The Matrix 2.Terminator 3.The Hunger Games 4.The Dark Knight Rises 5.The Lord of the Rings 6.The Hobbit 7.The Last Crusade 8.The Lion King 9.The Lego Movie 10.The LEGO Movie 11.The King of the Hill 12.The Jungle Book 13.The Legend of Zelda 14.The Little Mermaid 15.The Princess Bride 16.The Pirates of the Caribbean 17.The Twilight Saga 18

Show 25 per page

Like what you see? Visit the data table notebook to learn more about interactive tables.

Let’s go back to the notebook and apply what we just learned

[GPT2 NLU Notebook]

Table of contents

What is **Data Augmentation** with Language Models?

- Since the largest Language Modes are trained on almost the entire Internet as text corpus, they can generate realistic text for almost any topic.

- We can **improve accuracy** of most NLP Classifiers by **augmenting our dataset** generated examples
  - Especially useful when only very little training data is available and creating new by hand is tedious
- The newly NLP classifier is likely much faster and smaller than the large Language Model
  - Essentially a distilled version or the Language Models knowledge

- How to **create more training** data and Augmented Dataset:
  - Use the label itself as prompt and suffix it with a chunk of the original text.
    Try to use chunks which have enough semantic information to justify a prediction of the label.
    One of the most simple methods is to use use the first N token or characters as suffix to the label

- The Language Model could be used for training, but the trained model is much faster, efficient and possibly more accurate

How to create **more training** data and **Augmented Dataset**?

- There are dozens of techniques and approaches, see A Survey of Data Augmentation Approaches for NLP
- For our simple demo we will :
  - Use the label itself as prompt and suffix it with a chunk of the original text.
    Try to use chunks which have enough semantic information to justify a prediction of the label.
    One of the most simple methods is to use use the first N token or characters as suffix to the label

DA Method	Ext.Know	Pretrained	Preprocess	Level	Task-Agnostic
SYNONYM REPLACEMENT (Zhang et al., 2015)	✓	×	tok	Input	✓
RANDOM DELETION (Wei and Zou, 2019)	×	×	tok	Input	✓
RANDOM SWAP (Wei and Zou, 2019)	×	×	tok	Input	✓
BACKTRANSLATION (Sennrich et al., 2016)	×	✓	Depends	Input	✓
SCPN (Wieting and Gimpel, 2017)	×	✓	const	Input	✓
SEMANTIC TEXT EXCHANGE (Feng et al., 2019)	×	✓	const	Input	✓
CONTEXTUALAUG (Kobayashi, 2018)	×	✓	-	Input	✓
LAMBADA (Anaby-Tavor et al., 2020)	×	✓	-	Input	×
GECA (Andreas, 2020)	×	×	tok	Input	×
SEQMIXUP (Guo et al., 2020)	×	×	tok	Input	×
SWITCHOUT (Wang et al., 2018b)	×	×	tok	Input	×
EMIX (Jindal et al., 2020a)	×	×	-	Emb/Hidden	✓
SPEECHMIX (Jindal et al., 2020b)	×	×	-	Emb/Hidden	Speech/Audio
MIXTEXT (Chen et al., 2020c)	×	×	-	Emb/Hidden	✓
SIGNEDGRAPH (Chen et al., 2020b)	×	×	-	Input	×
DTREEMORPH (Şahin and Steedman, 2018)	×	×	dep	Input	✓
Sub^2 (Shi et al., 2021)	×	×	dep	Input	Substructural
DAGA (Ding et al., 2020)	×	×	tok	Input+Label	×
WN-HYPERS (Feng et al., 2020)	✓	×	const+KWE	Input	✓
SYNTHETIC NOISE (Feng et al., 2020)	×	×	tok	Input	✓
UEDIN-MS (DA part) (Grundkiewicz et al., 2019)	✓	×	tok	Input	✓
NONCE (Gulordava et al., 2018)	✓	×	const	Input	✓
XLDA (Singh et al., 2019)	×	✓	Depends	Input	✓
SEQMIX (Zhang et al., 2020)	×	✓	tok	Input+Label	×
SLOT-SUB-LM (Louvan and Magnini, 2020)	×	✓	tok	Input	✓
UBT & TBT (Vaibhav et al., 2019)	×	✓	Depends	Input	✓
SOFT CONTEXTUAL DA (Gao et al., 2019)	×	✓	tok	Emb/Hidden	✓
DATA DIVERSIFICATION (Nguyen et al., 2020)	×	✓	Depends	Input	✓
DIPS (Kumar et al., 2019a)	×	✓	tok	Input	✓
AUGMENTED SBERT (Thakur et al., 2021)	×	✓	-	Input+Label	Sentence Pairs

Table 1: Comparing a selection of DA methods by various aspects relating to their applicability, dependencies, and requirements. *Ext.Know*, *KWE*, *tok*, *const*, and *dep* stand for External Knowledge, keyword extraction, tokenization, constituency parsing, and dependency parsing, respectively. *Ext.Know* refers to whether the DA method requires external knowledge (e.g. WordNet) and *Pretrained* if it requires a pretrained model (e.g. BERT). *Preprocess* denotes preprocessing required, *Level* denotes the depth at which data is modified by the DA, and *Task-Agnostic* refers to whether the DA method can be applied to different tasks. See Appendix B for further explanation.

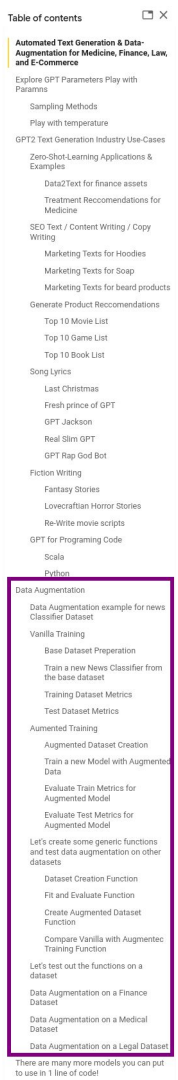
A Survey of Data Augmentation Approaches for NLP

Why does this work?

- **Universal Approximation Theorem** states: More data = more accuracy
  Holds for Neural Networks and many ML models
- Leverage this when we augment dataset size with generative models
- Bad generation can make our model perform worse though, we need to be careful how and what is generated

Data Augmentation in Action apply what we just learned

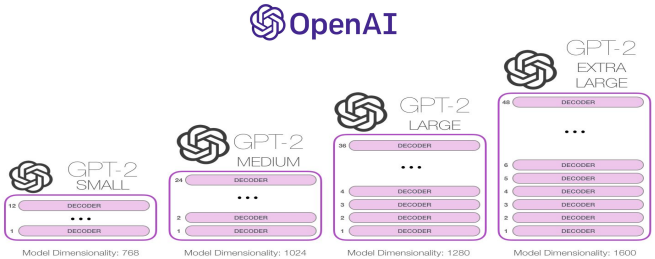
[GPT2 NLU Notebook]



Text Generating Sequence to Sequence Transformers in in NLU & Spark NLP

Every T5 Task with explanation:

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

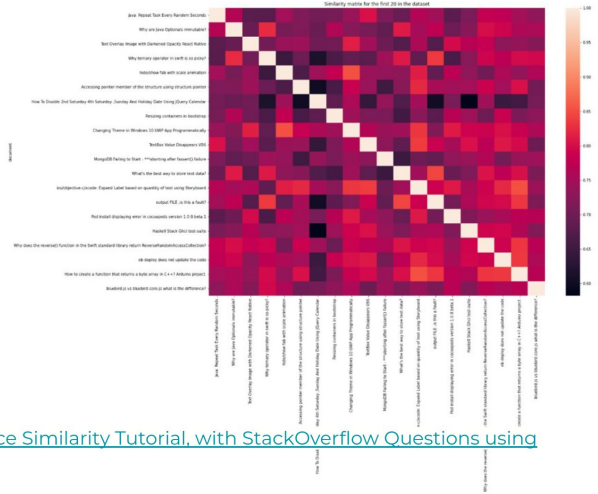


Summarize, answer questions, generate SQL and more with Google's T5
Showcased in this tutorial Webinar

Generate long sequences of text, Augment Text and more with Open AI's GPT2
Showcased today

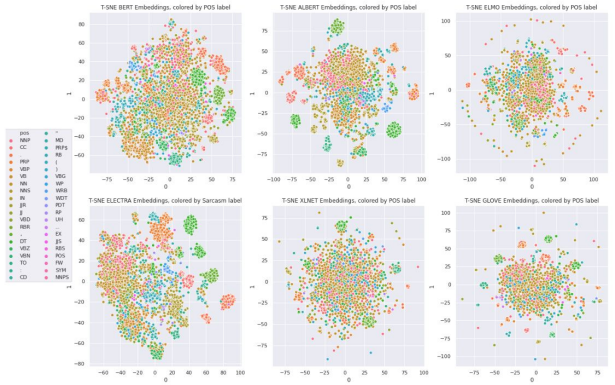
Translate between over 200 languages with Microsoft's MarianNMT
showcased on chinese in this tutorial webinar

Sentence Similarity With BERTology Embeds or T5



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

t-SNE Visualizations with NLU



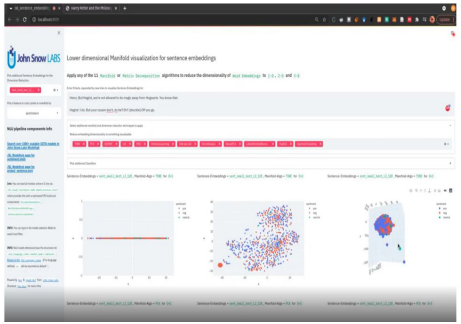
[1 line of Python code for BERT, ALBERT, ELMO, ELECTRA, XLNET, GLOVE, Part of Speech with NLU and t-SNE]

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

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

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

Compare multiple dimension reduction Techniques and Embeddings at the same time



OCR Tables from PDFs, DOC, DOCX and PPT files in 1 Line of code with NLU 4.0

```
nlu.load('pdf2table').predict('/content/tables.pdf')
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear
1	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4
2	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4
3	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4
4	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3
5	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3
6	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3
7	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3
8	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4
9	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4
10	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4
11	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4
12	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3
13	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3
14	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3
15	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3
16	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3
17	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3
18	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4
19	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4

sample.pdf

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4

Overview of all OCR features in NLU

Overview of OCR Text Extractors

These models grab the text directly from your input file and returns it as a Pandas DataFrame

NLU Spell	Transformer Class
nlu.load(`img2text`)	ImageToText
nlu.load(`pdf2text`)	PdfToText
nlu.load(`doc2text`)	DocToText

Overview of OCR Table Extractors

These models grab all Table data from the files detected and return a `list of Pandas DataFrames`, containing Pandas DataFrame for every table detected

NLU Spell	Transformer Class
nlu.load(`pdf2table`)	PdfToTextTable
nlu.load(`ppt2table`)	PptToTextTable
nlu.load(`doc2table`)	DocToTextTable

More info on
https://nlu.johnsnowlabs.com/docs/en/nlu_for_ocr

Image to Text

Sample image:

"The Old Pond" by Matsuo Bashō

An old silent pond

A frog jumps into the pond—

Splash! Silence again.

```
nlu.load('img2text').predict('path/to/haiku.png')
```

Output of IMG OCR:

text
"The Old Pond" by Matsuo Basho
An old silent pond
A frog jumps into the pond—
Splash! Silence again.

PDF to Text

haiku.pdf

Sample PDF:

"Lighting One Candle" by Yosa Buson

The light of a candle

Is transferred to another candle—

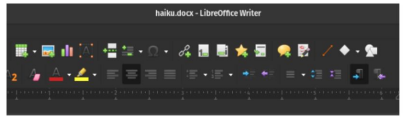
Spring twilight

```
nlu.load('pdf2text').predict('path/to/haiku.pdf')
```

Output of PDF OCR:

text
"Lighting One Candle" by Yosa Buson
The light of a candle
Is transferred to another candle—
Spring twilight

DOCX to text



Sample DOCX:

"In a Station of the Metro" by Ezra Pound

The apparition of these faces in the crowd;

Petals on a wet, black bough.

```
nlu.load('doc2text').predict('path/to/haiku.docx')
```

Output of DOCX OCR:

text
"In a Station of the Metro" by Ezra Pound
The apparition of these faces in the crowd;
Petals on a wet, black bough.

More NLU Ressources

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

Webinars and Videos

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

Thank you.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