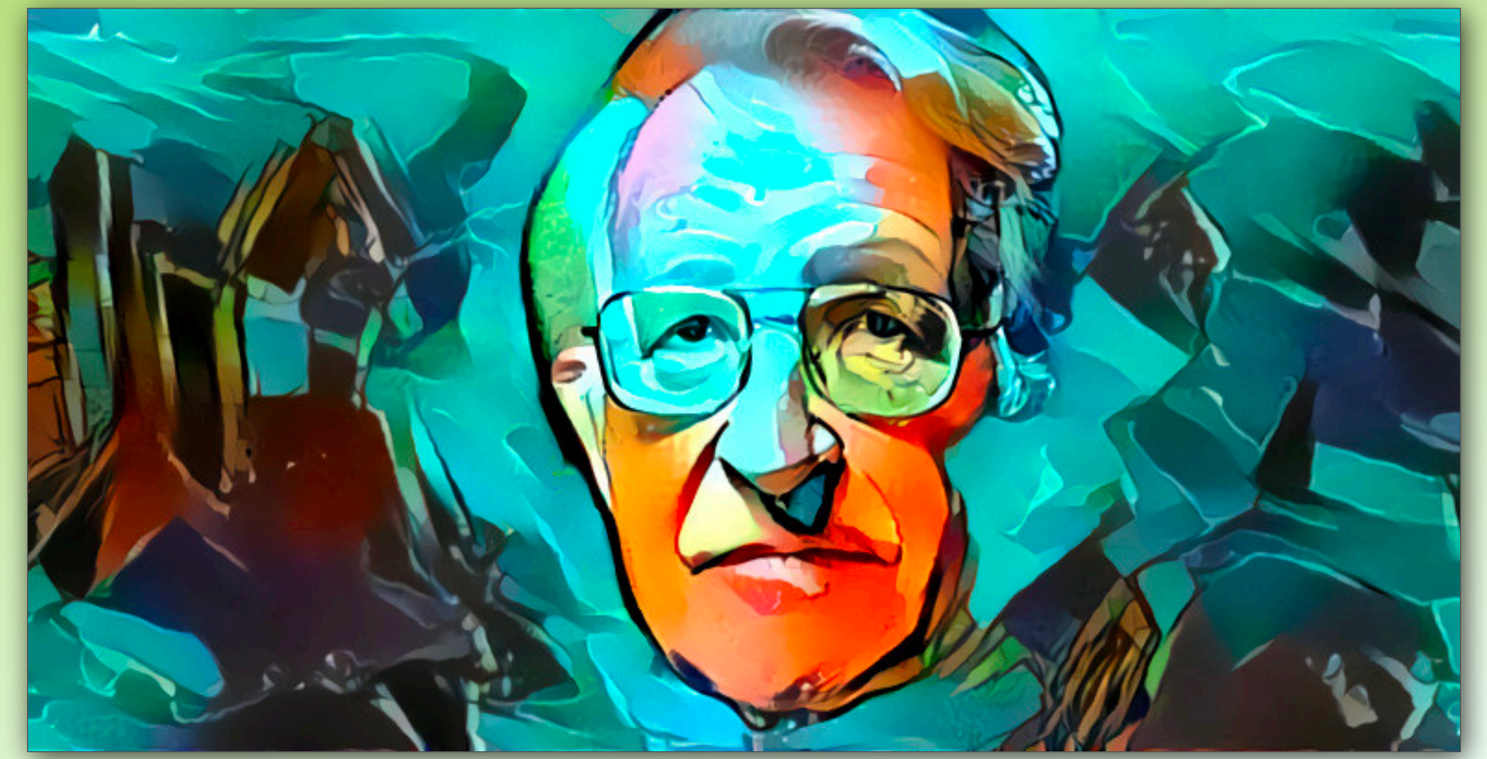
spaCy tuTorial

Paco Nathan @pacoid

derwen.ai

https://bit.ly/31wal51



part 01:
parsing natural language

Parsing Natural Language

NLP used to be mostly concerned about **transformational grammars**, linguistic theory by Chomsky, etc. Other former approaches such as **link grammars** have since been largely overlooked.

However, ML techniques allow much simpler approaches called *statistical parsing*. With the rise of Big Data, these techniques became even more effective – **Google won the NIST 2005 Machine Translation Evaluation** and remains a leader.

Probabilistic methods split texts into sentences, annotate words with part-of-speech, chunk noun phrases, resolve named entities, calculate similarity of documents, etc.

The Era of Formal Grammars

terminals

{generate, hate, great, green, ideas, linguists}

nonterminals

{SENTENCE, NOUNPHRASE, VERBPHRASE, NOUN, VERB, ADJ}

production rules

SENTENCE → *NOUNPHRASE VERBPHRASE*

NOUNPHRASE → *ADJ NOUNPHRASE*

NOUNPHRASE → *NOUN*

VERBPHRASE → *VERB NOUNPHRASE*

VERBPHRASE → *VERB*

NOUN → ideas

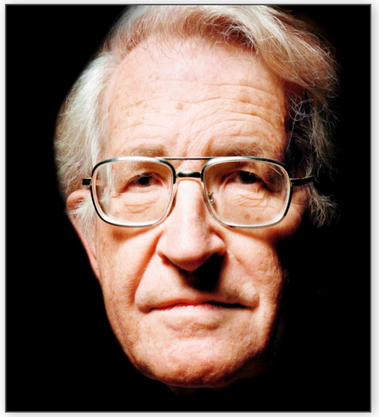
NOUN → linguists

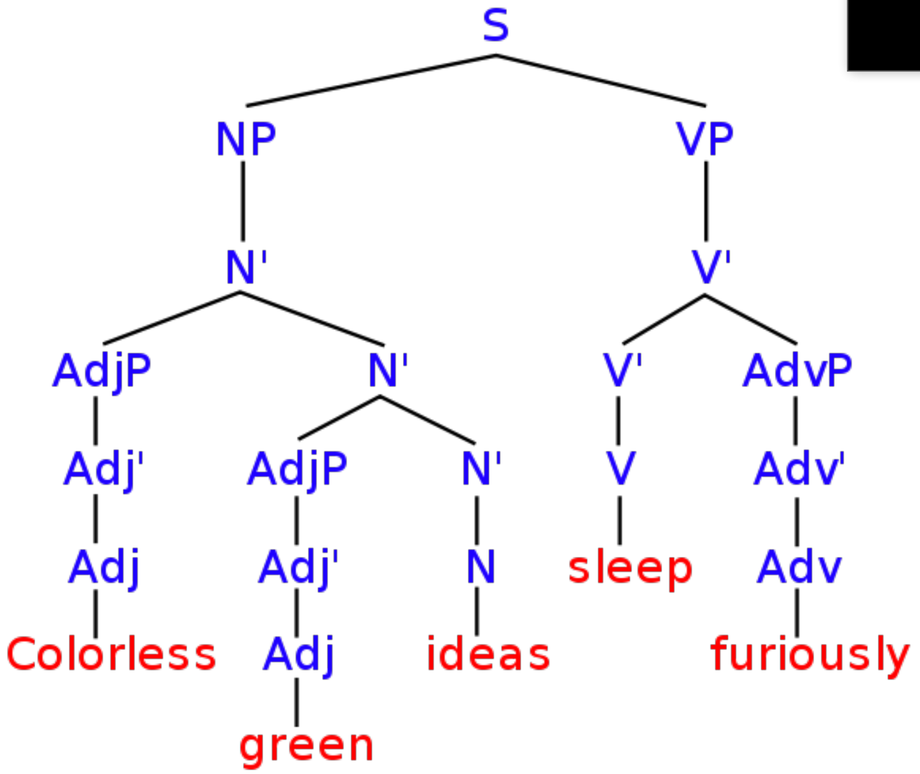
VERB → generate

VERB → hate

ADJ → great

ADJ → green





Statistical Parsers

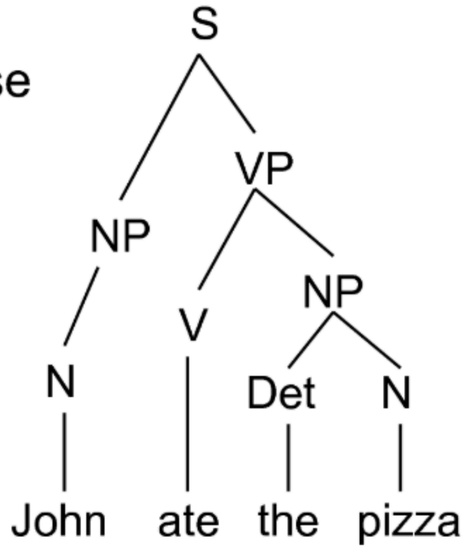
“Statistical Relational Learning”

Pedro Domingos

see slides 96-97

Statistical Parsing

- **Input:** Sentence
- **Output:** Most probable parse
- **PCFG:** Production rules with probabilities
  E.g.: 0.7 NP → N
  0.3 NP → Det N
- **WCFG:** Production rules with weights (equivalent)
- Chomsky normal form:
  A → B C or A → a

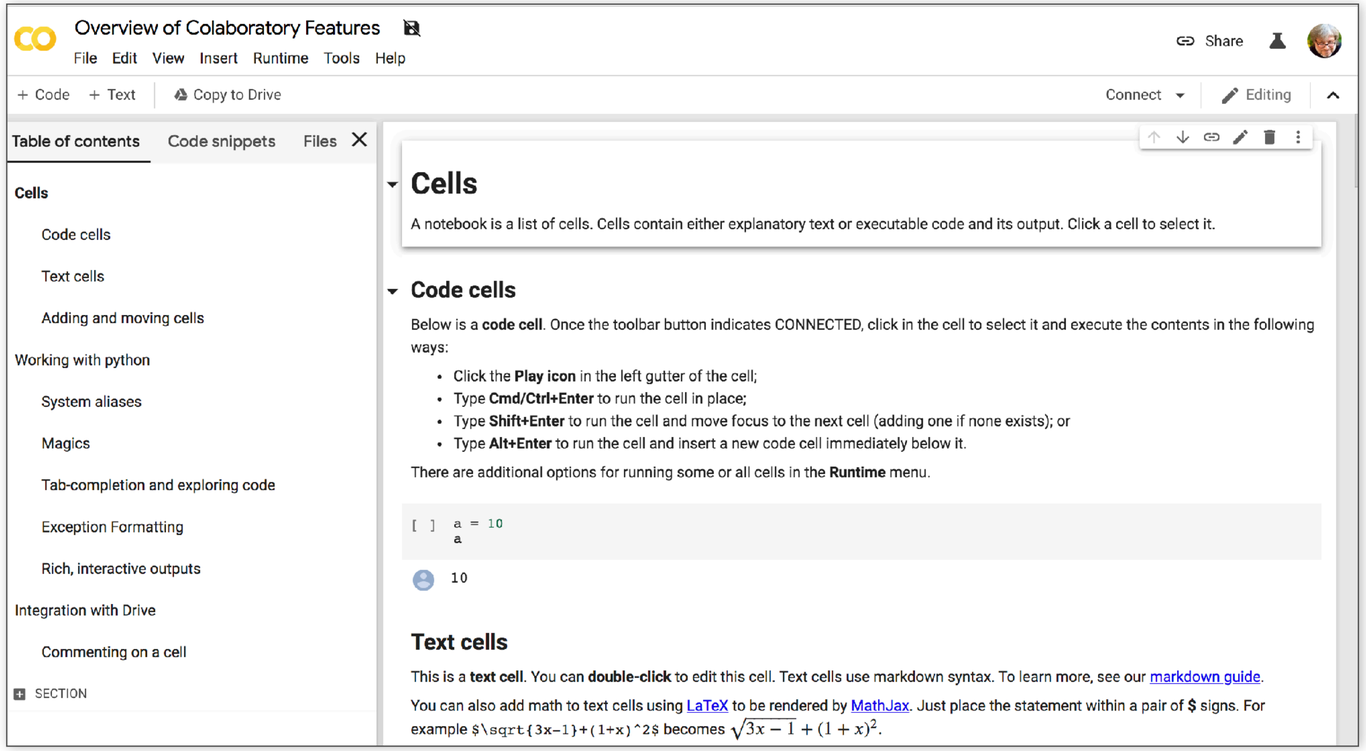


part 02:
intro to spaCy

Using Google Colab

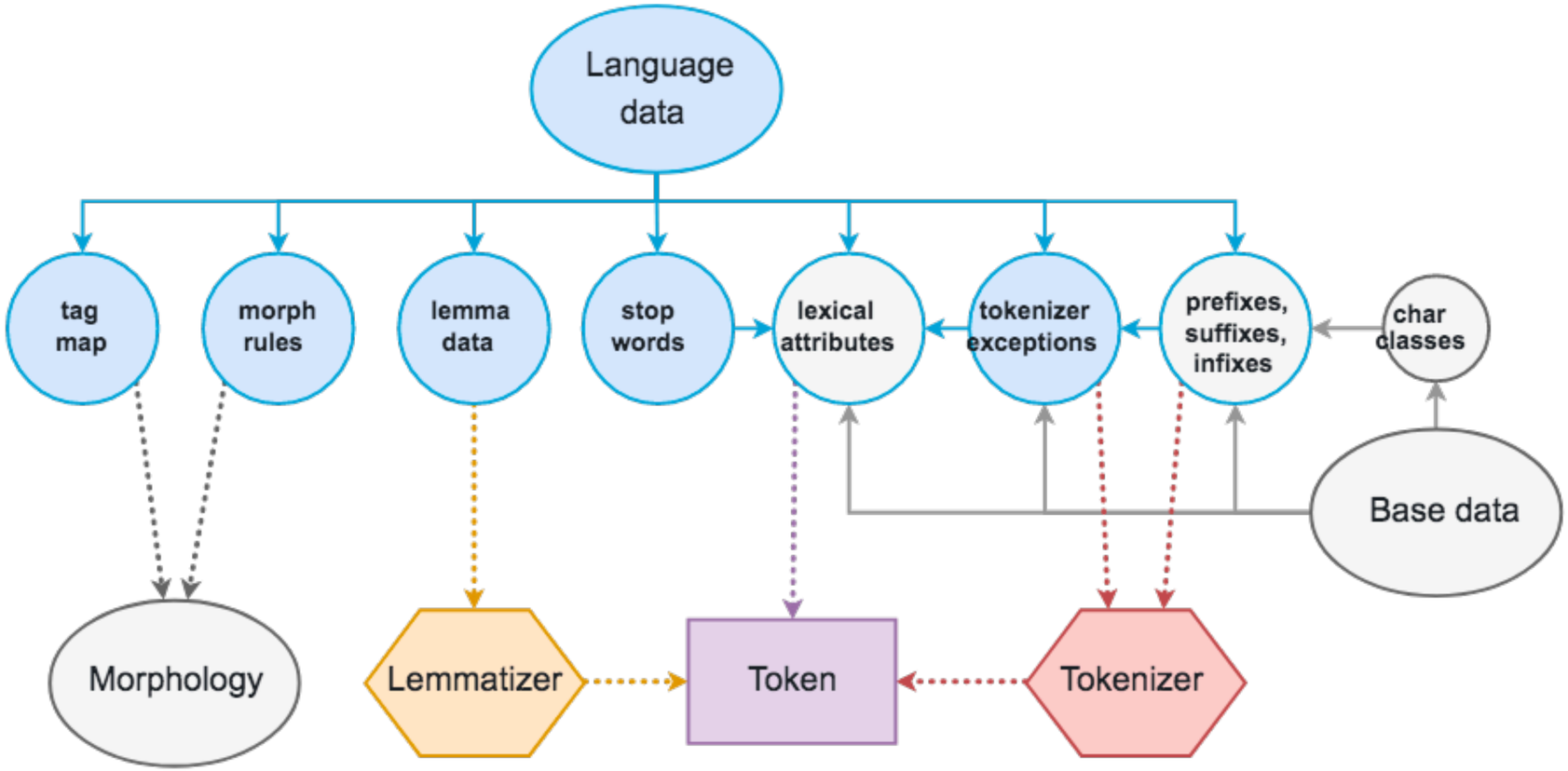
We'll be working with Jupyter notebooks, loaded from GitHub, then running inside **Google Colab**

Use this URL: **https://github.com/DerwenAI/spaCy_tuTorial**



Intro to spaCy

Let's get started with **spaCy**… open this **notebook** in **Google Colab** from GitHub then go to the section titled **"Getting Started"**



Other Popular NLP Frameworks

Stanford Core

nlp.stanford.edu/software/

Spark NLP

nlp.johnsnowlabs.com/

Flair NLP

research.zalando.com/welcome/mission/research-projects/flair-nlp/

Multiple Language Support

One frequently asked question is about *multi-language support* for NLP tools. Here are some links:

- **https://spacy.io/usage/adding-languages**
- **http://globalwordnet.org/wordnets-in-the-world/**
- **https://wordnet.princeton.edu/related-projects**
- **http://compling.hss.ntu.edu.sg/omw/**
- **https://nlp.stanford.edu/software/lex-parser.shtml**

part 03:
acquiring text

Character Encoding

The example text that we've used is relatively "clean" …
that rarely happens in practice!

- "**Text vs. Data Instead of Unicode vs. 8-bit**"
- **ligatures** used in publishing add to the fun
- **codecs** become especially important for storing text in files
- See also about **Unicode equivalence** and how to **normalize** text in Python.

Open the **`ex02.ipynb`** notebook

Character Encoding

Resolving character encoding issues is a hard problem, and will continue to be so – perhaps it's suitable as a use case for AI research…

For more details and further context about use cases in search, check the excellent article "**Character Filtering**" by **Daniel Tunkelang**, along with his entire series about **Query Understanding**.

Semantic Similarity

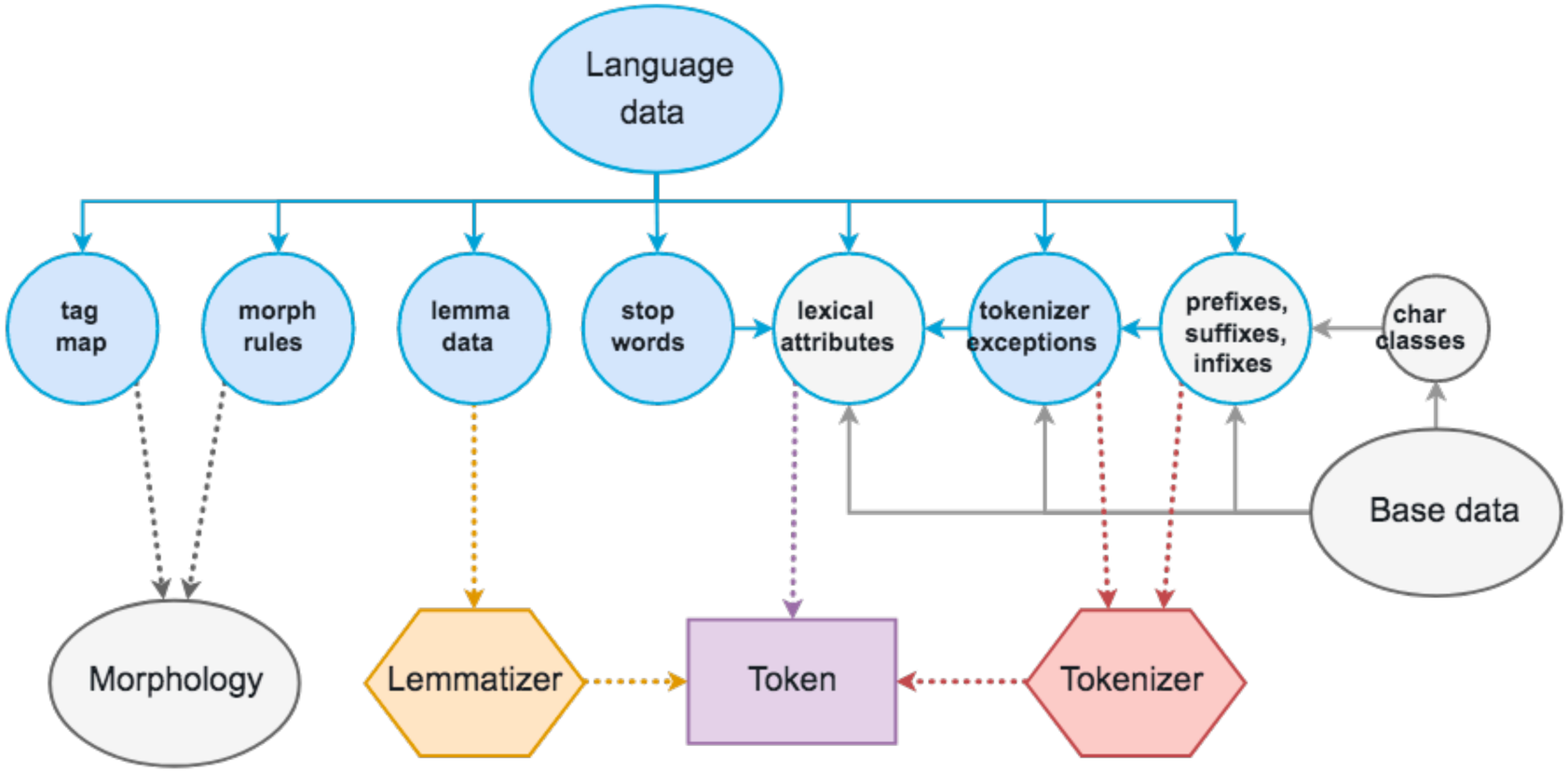
Semantic similarity between two texts can be measured using a variety of approaches. **Jaccard and Tanimoto** are two statistical measures.

We can approximate a Jaccard similarity with **MinHash** – the **Probabilistic Data Structures in Python** tutorial has more detailed background about this approach.

That is mostly based on the **datasketch** library, building on work by **Philippe Flajolet**, et al.

spaCy

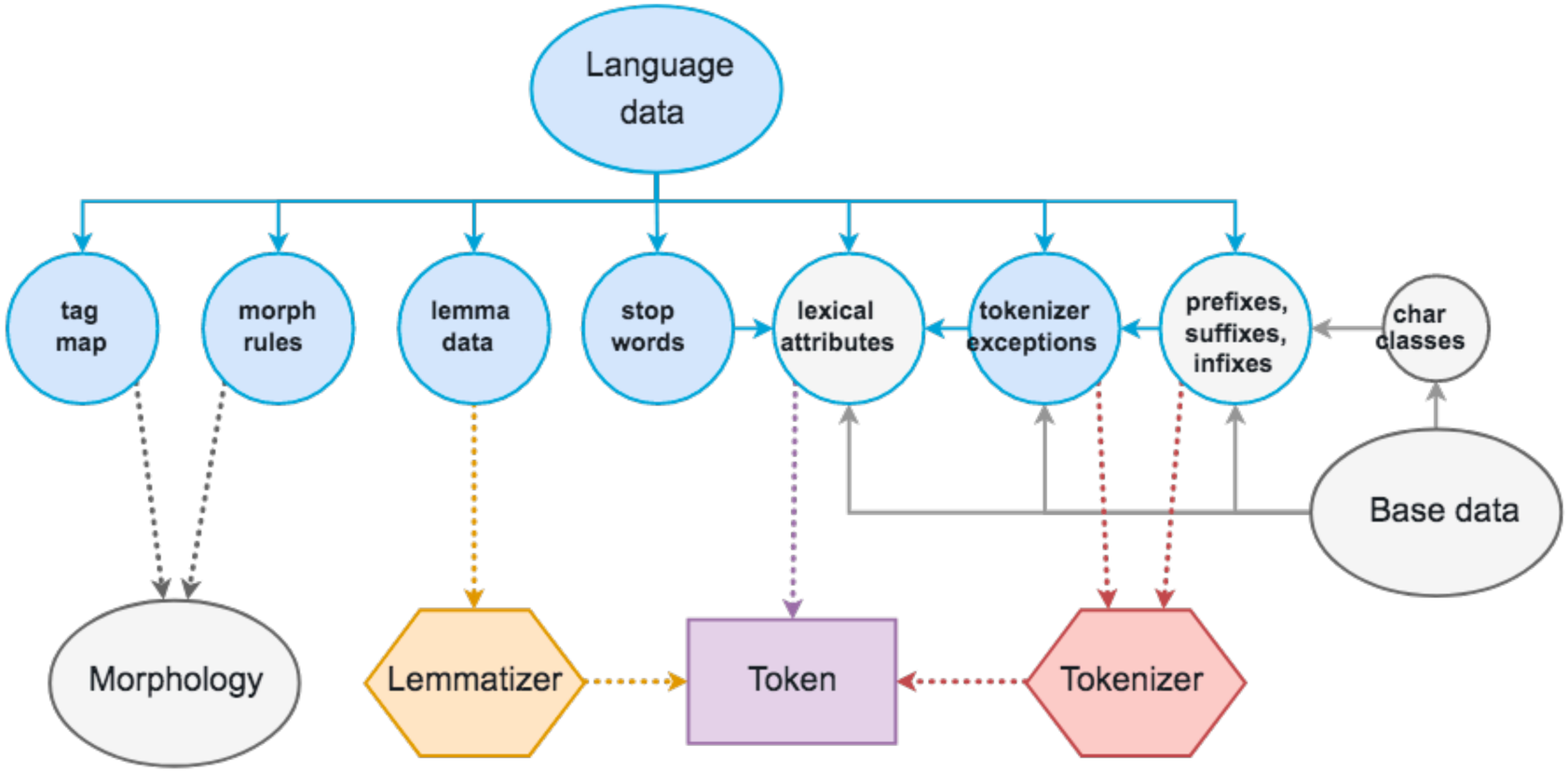
Let's explore more of **spaCy**… still using that same **notebook** in **Google Colab**, go to the section titled **"Acquiring Text"**



part 04:
understanding text

spaCy

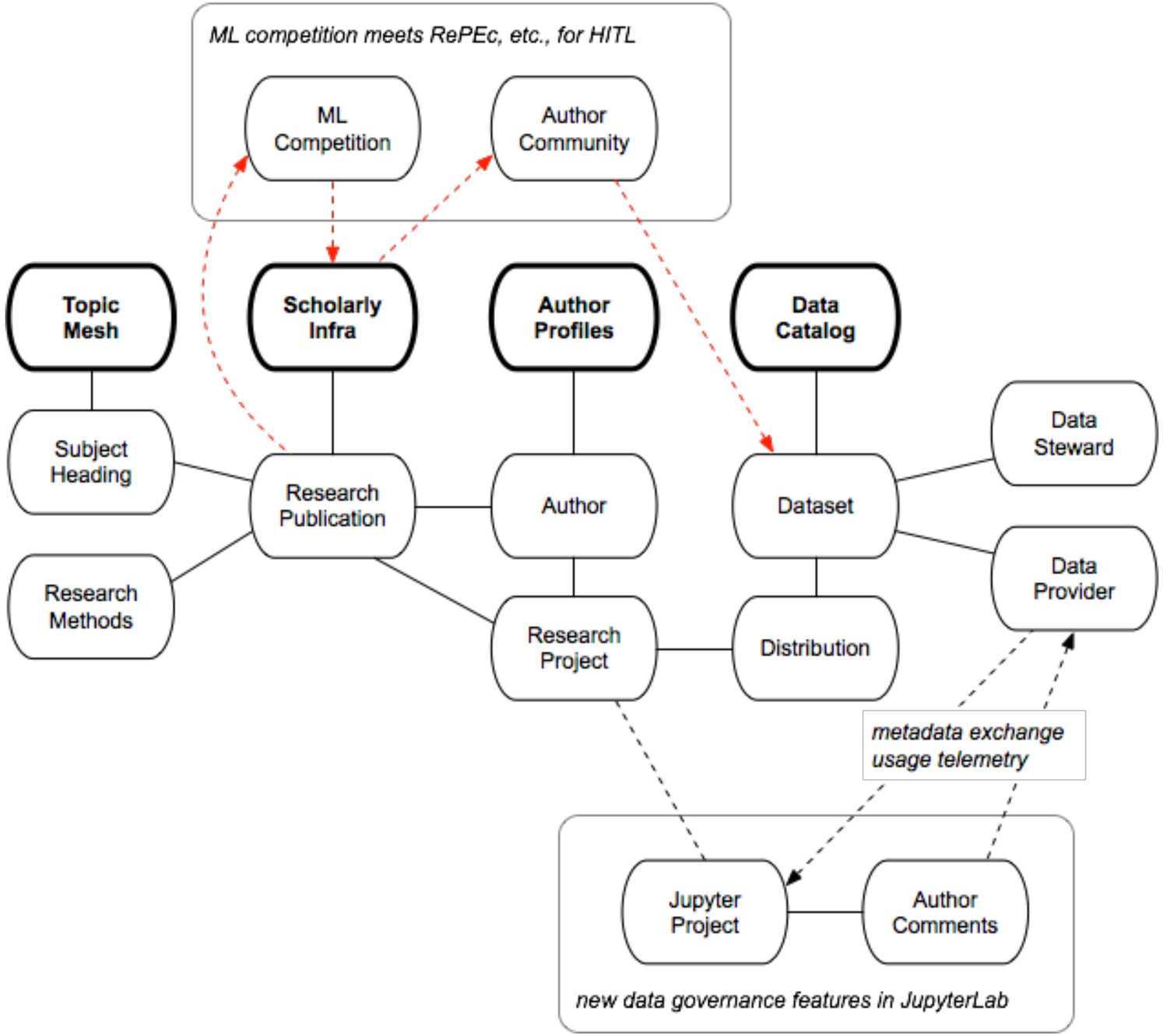
Let's explore more of **spaCy**… still using that same **notebook** in **Google Colab**, go to the section titled **"Natural Language Understanding"**



Knowledge Graph

the **vocabulary** used in the graph integrates W3C metadata standards: **DCAT**, **PAV**, **CITO**, **FaBiO**, **FOAF**, **DCMI**, etc.

initial problem of **entity linking**: leverage ML models to infer dataset attribution, i.e., link from research publications to a **known set of datasets**



Serialized Formats: TTL, JSON-LD

rc.ttl

Raw

```
@base <https://github.com/Coleridge-Initiative/adrf-onto/wiki/Vocabulary> .

@prefix cito:   <http://purl.org/spar/cito/> .
@prefix dct:    <http://purl.org/dc/terms/> .
@prefix foaf:   <http://xmlns.com/foaf/0.1/> .
@prefix rdf:    <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix xsd:    <http://www.w3.org/2001/XMLSchema#> .

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  dct:publisher "J Family Med Prim Care" ;
  dct:title "Subclinical hypothyroidism and the risk of hypercholesterolemia" ;
  dct:identifier "10.1370/afm.79" ;
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.

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  dct:publisher "Centers for Disease Control and Prevention" ;
  dct:title "National Health and Nutrition Examination Survey" ;
  dct:alternative "NHANES" ;
  dct:alternative "NHANES I" ;
  dct:alternative "NHANES II" ;
  dct:alternative "NHANES III" ;
.
```

ML Competitions

- **RCC 2018-2019** finalists Allen AI, KAIST, GESIS, Paderborn; participating teams contributed to an upcoming book: *Rich Search and Discovery for Research Datasets: Building the next generation of scholarly infrastructure*
- **RC leaderboard** ongoing competition on GitHub; open corpus, open access PDFs; teams collaborate via GH issues on corpus data quality, etc.
- initial baseline at ~78% precision for entity linking of datasets

Current SOTA

source	precision	entry	code	paper	corpus	submitted	notes
LARC @philipskokoh	0.7836	ipynb	repo	RCC_1	v0.1.5	2019-09-26	RCLC baseline experiment using RCC_1 approach
KAIST @HaritzPuerto	0.6319	ipynb	repo	RCC_1	v0.1.5	2019-11-01	model trained a different dataset using DocumentQA and Ultra-Fine Entity Typing -- NB: this approach is able to identify new datasets

Related Conferences

AKBC (UC Irvine)

Knowledge Graph Conference (Columbia U, NYC)

Connected Data London (London)

spaCy IRL (Berlin)

Extracting Text from PDF Files

In addition to using **Beautiful Soup** to extract text from HTML, another common need is to extract text from PDF files.

We'll show how to use **PDFx** by **Chris Hager** to handle this kind of work. Use the **notebook** in **Google Colab** to run an example.

Other popular libraries for PDF text extraction include:

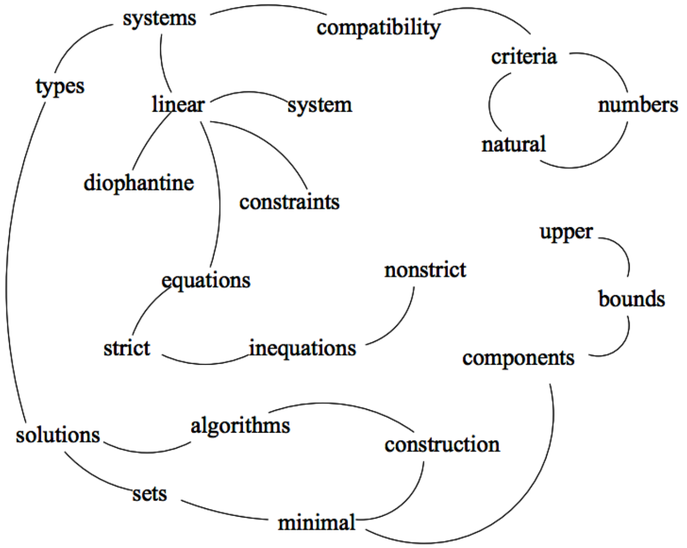
- **https://pypi.org/project/PyPDF2/**
- **https://github.com/euske/pdfminer**
- **https://tika.apache.org/**

Optional Exercise

See the GitHub repo for this course for details about a **programming challenge** as an optional exercise:

- based on spaCy
- language-independent
- relatively fast, low-cost graph algorithm
- extracts keyphrases from a text document

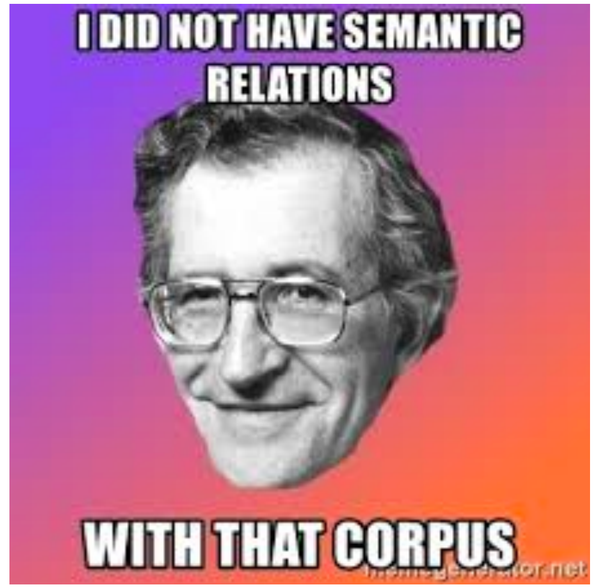
Compatibility of systems of linear constraints over the set of natural numbers. Criteria of compatibility of a system of linear Diophantine equations, strict inequations, and nonstrict inequations are considered. Upper bounds for components of a minimal set of solutions and algorithms of construction of minimal generating sets of solutions for all types of systems are given. These criteria and the corresponding algorithms for constructing a minimal supporting set of solutions can be used in solving all the considered types systems and systems of mixed types.



Optional Exercise – answers

PyTextRank is a Python implementation of TextRank as a **spaCy extension**, used to:

- extract the top-ranked phrases from text documents
- infer links from unstructured text into structured data
- run extractive summarization of text documents



See also:

"TextRank: Bringing Order into Text"
Rada Mihalcea, **Paul Tarau**
Empirical Methods in Natural Language Processing (2004)

"Single and Multiple Document Summarization with Graph-based Ranking Algorithms"
Rada Mihalcea
Microsoft Research @ YouTube (2016-09-05)

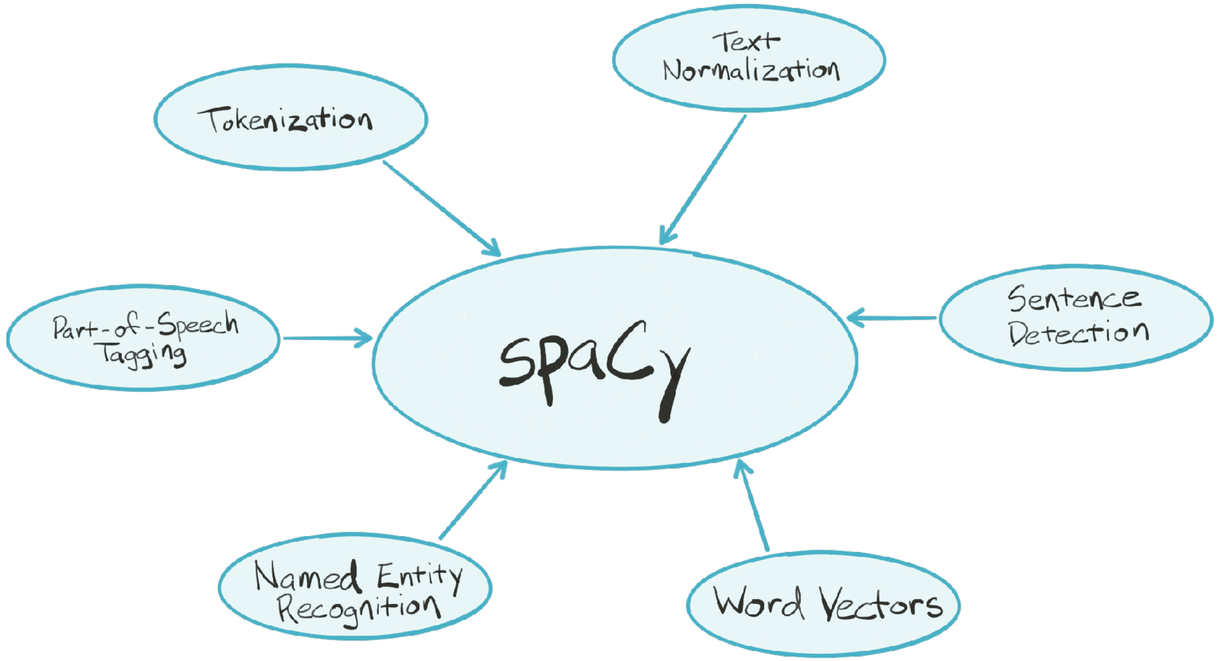
part 05:
examples

Examples

“A New State of the Art for Named Entity Recognition”
John Bohannon, Primer AI

“Modern NLP in Python”
Patrick Harrison, S&P Global Market Intelligence

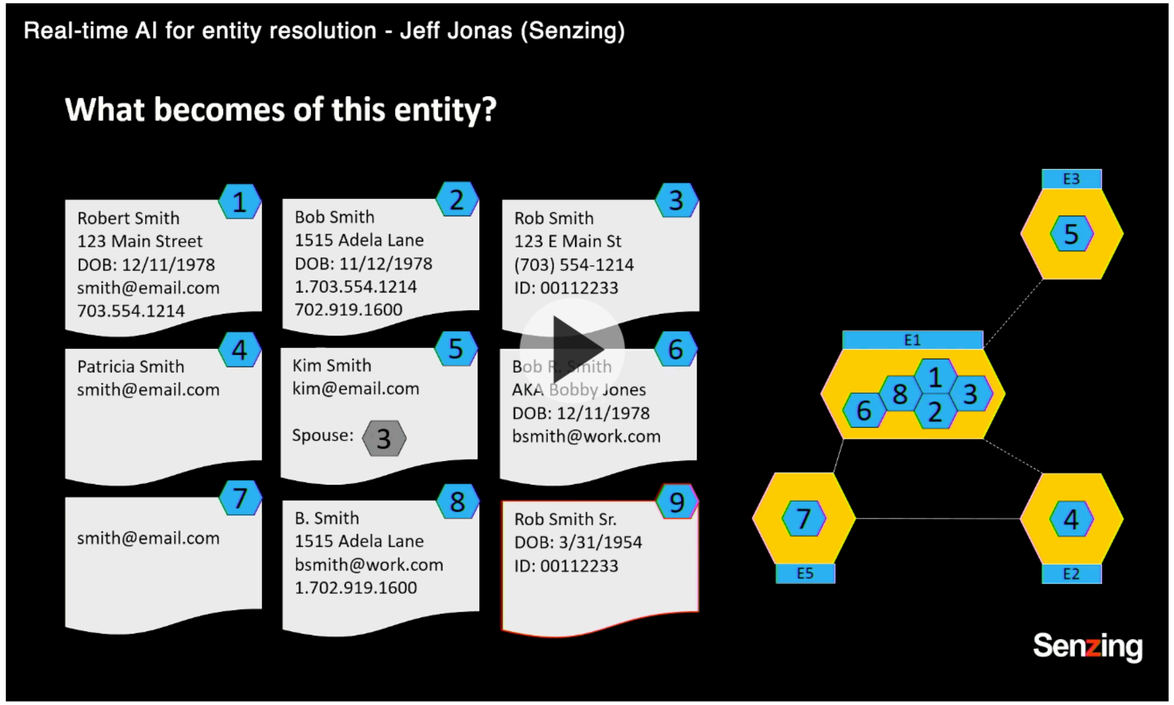
- large corpus data mining
- knowledge graph construction



Examples

One of the leading commercial vendor for *named entity resolution* is from **Senzing**, led by **Jeff Jonas**

- **“Real-time AI for entity resolution”**
- **“Real-time entity resolution made possible”**



Examples

Long short-term memory (LSTM) is an approach that allows recurrent neural networks to learn over many time steps. These can be used for time-series analysis, and also for learning sequences of data, such as in streams of voice or text.

Imagine feeding many scripts (semi-structured text) from a particular film genre through an LSTM, then generating new output.

For example that's what **Ross Goodwin** does…

Using LSTM to generate film scripts

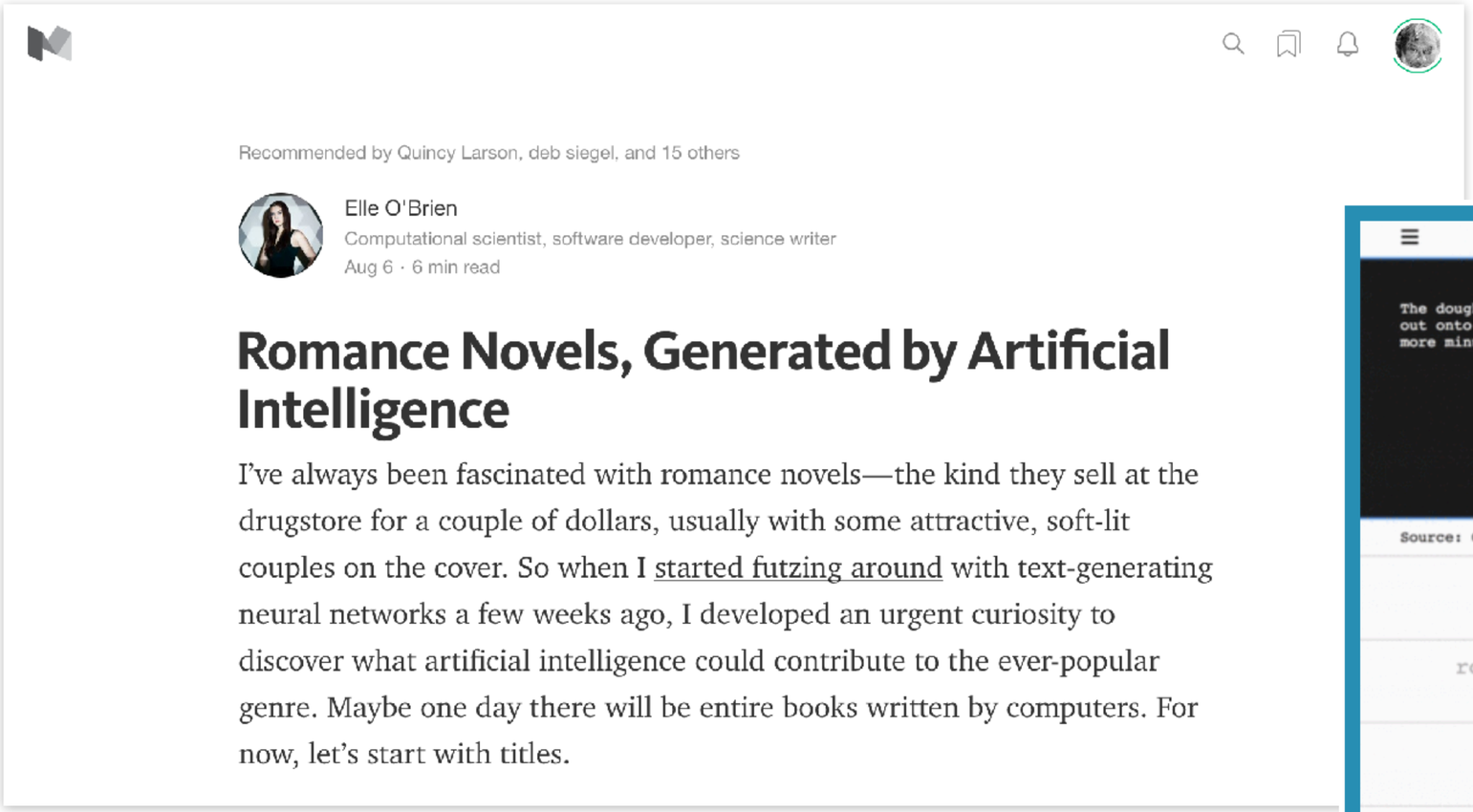
Sunspring
youtu.be/LY7x2Ihqjmc

by **Benjamin AI**

It's No Game
goo.gl/Waw5Px

Examples

Botnik Studios with Voicebox, etc.

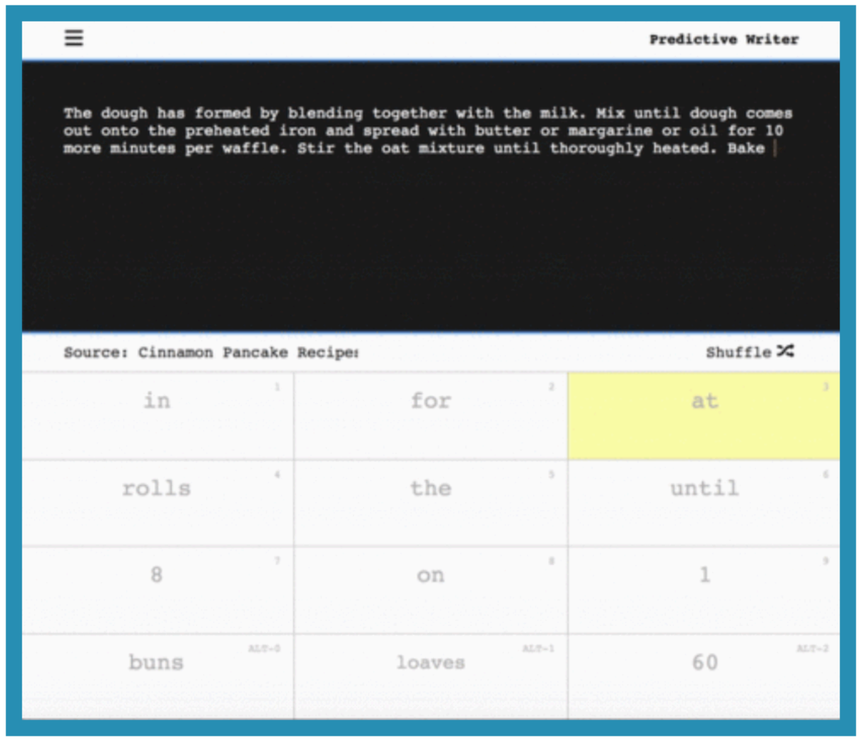


Recommended by Quincy Larson, deb siegel, and 15 others

Elle O'Brien
Computational scientist, software developer, science writer
Aug 6 · 6 min read

Romance Novels, Generated by Artificial Intelligence

I've always been fascinated with romance novels—the kind they sell at the drugstore for a couple of dollars, usually with some attractive, soft-lit couples on the cover. So when I started futzing around with text-generating neural networks a few weeks ago, I developed an urgent curiosity to discover what artificial intelligence could contribute to the ever-popular genre. Maybe one day there will be entire books written by computers. For now, let's start with titles.



part 06:
transformers

Embedded Language Models

ELMo: *Deep Contextualized Word Representations*

BERT: *State-of-the-Art Pre-training for Natural Language Processing*

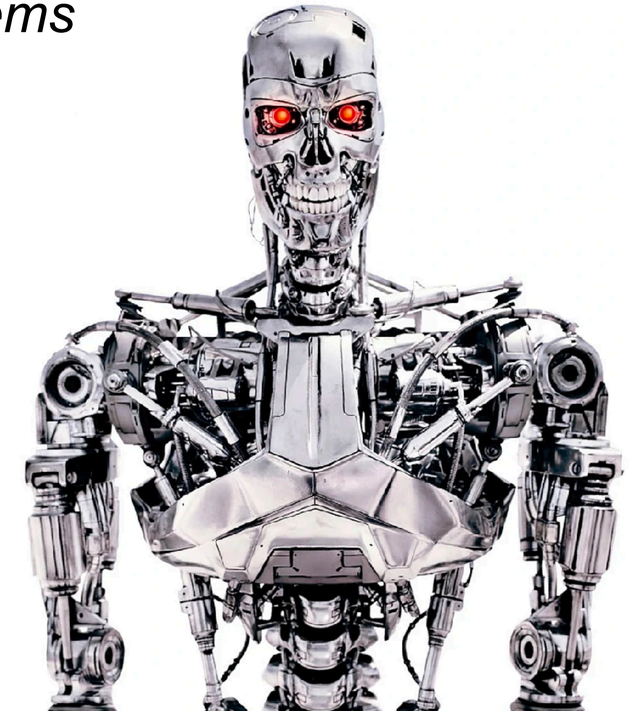
ERNIE: *Enhanced Representation through kNowledge IntEgration*

XLNet: *Generalized Autoregressive Pretraining for Language Understanding*

GPT-2: *Language Models are Unsupervised Multitask Learners*

RoBERTa: *An optimized method for pretraining self-supervised NLP systems*

DistilBERT: *Knowledge distillation during the pre-training phase*



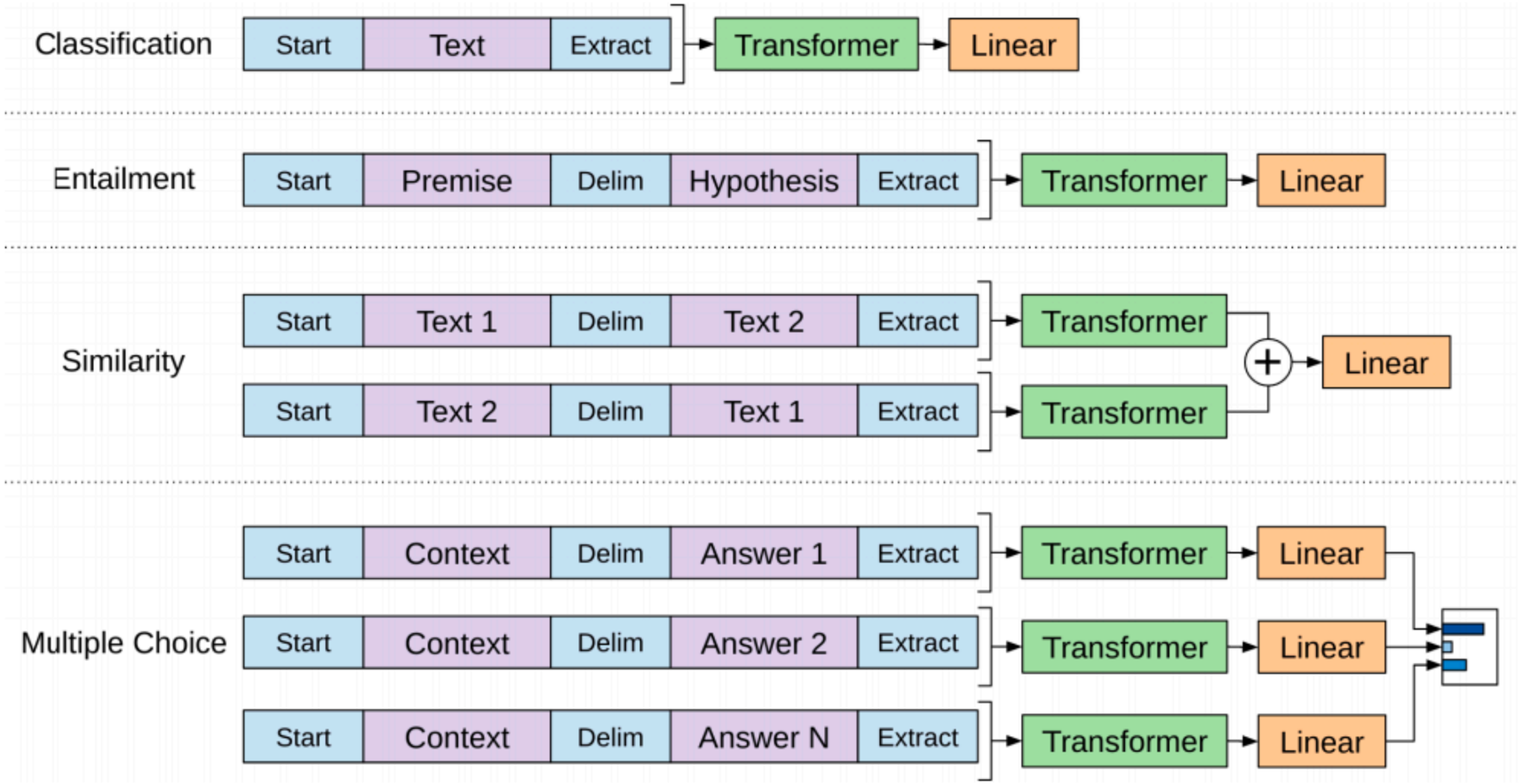
Transformers

word embeddings	Word2Vec, GloVe, etc.	• use a vector (a list of numbers) to represent words in a way that captures semantic or meaning-related relationships • pre-trained on vast amounts of text data • creates a kind of linear algebra for computing semantics
language modeling	ELMo	• contextualized word-embeddings • gained its language understanding from being trained to predict the next word in a sequence of words • a model can learn from vast amounts of text data without needing labels
transfer learning	ULM-FiT	• introduced a process to effectively fine-tune that language model for various tasks • NLP finally had a way to do transfer learning probably as well as Computer Vision could
masked language model	BERT	• a transformer-based model where the language model looks both forward and backwards • openAI transformer had provided a fine-tunable pre-trained model, but it wasn't bi-directional like ELMo
unsupervised multitask learners	GPT-2	• both unsupervised learning and supervised learning • subword representation, obtained by Byte Pair Encoding (BPE)
model compression	distilBERT	• a compression technique in which a small model is trained to reproduce the behavior of a larger model • about 50% as many parameters as BERT, retaining 95% of its performances on the language understanding benchmark GLUE

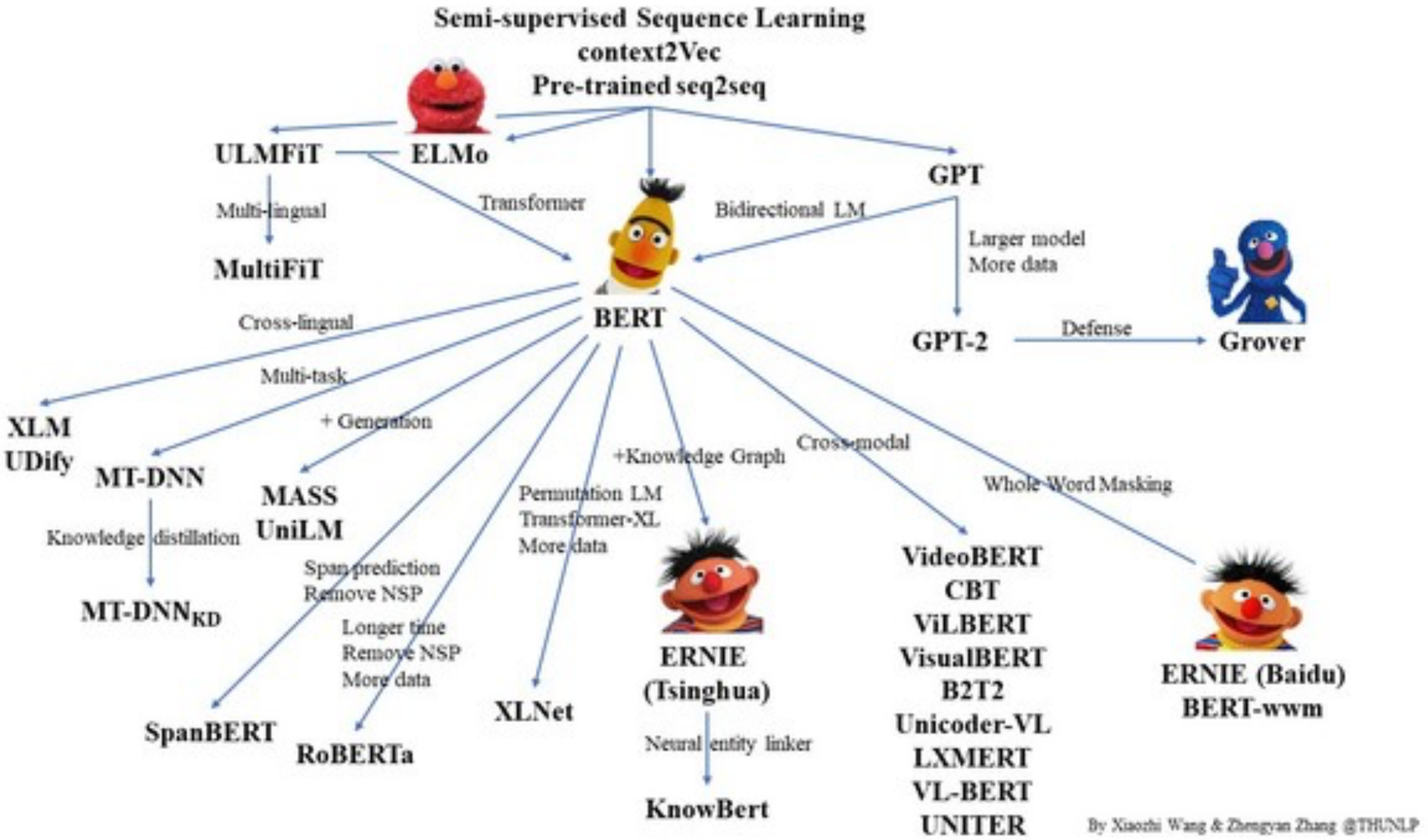
Transformers

“The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning)”

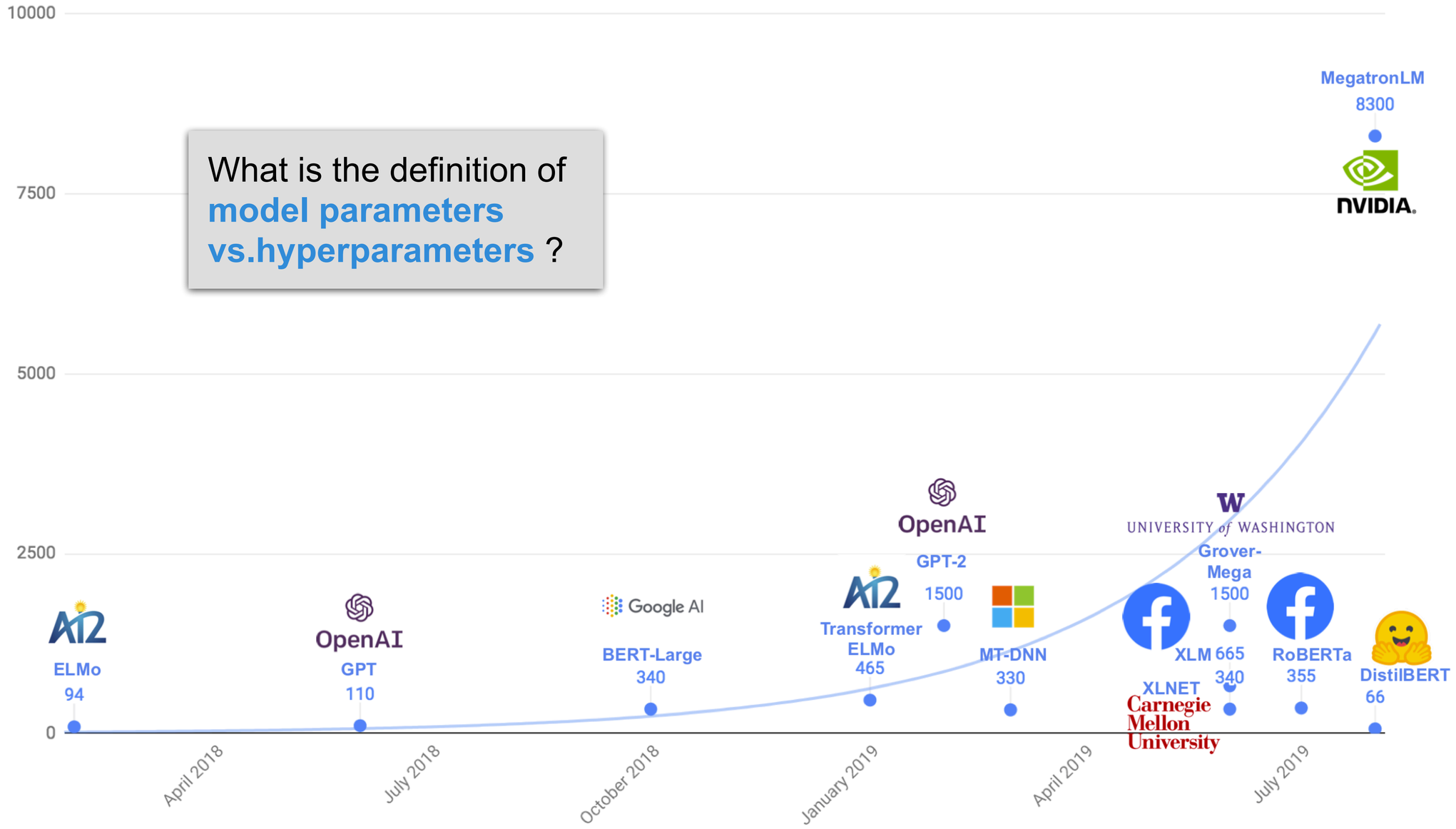
Jay Alammar



Transformers



Transformers – growth of parameters



Distillation

“DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter”

“Hugging Face Implements SOTA Transformer Architectures for PyTorch and TensorFlow 2.0”

“EIE: Efficient Inference Engine on Compressed Deep Neural Network”

https://huggingface.co/transformers/

“…it is possible to reduce the size of a BERT model by 40%, while retaining 97% of its language understanding capabilities and being 60% faster…”

spaCy transformers

“spaCy meets Transformers: Fine-tune BERT, XLNet and GPT-2”
Matthew Honnibal, **Ines Montani**

- **notebook** (load in Google Colab)

Leaderboards

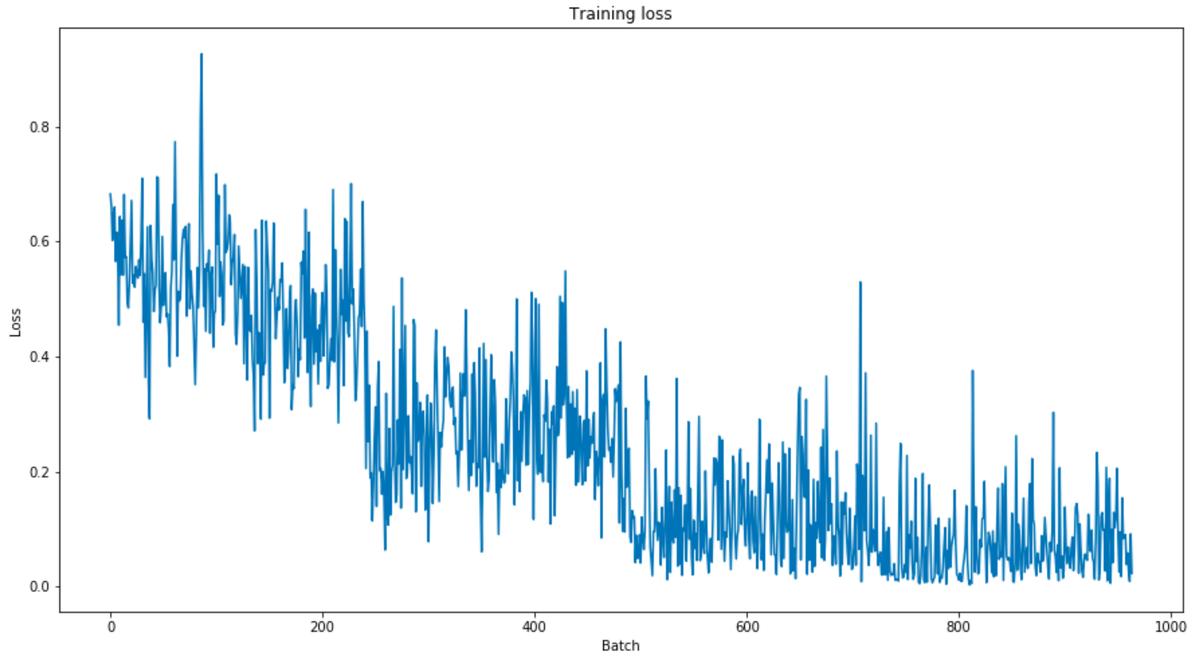
- GLUE leaderboard
- NLP-Progress
- Papers With Code state-of-the-art (SOTA)

BERT Fine-Tuning

“BERT Fine-Tuning Tutorial with PyTorch”

Chris McCormick

- **notebook** (load in Google Colab)
- **download** (add through your Google Drive)
- **leaderboard** (compare results)

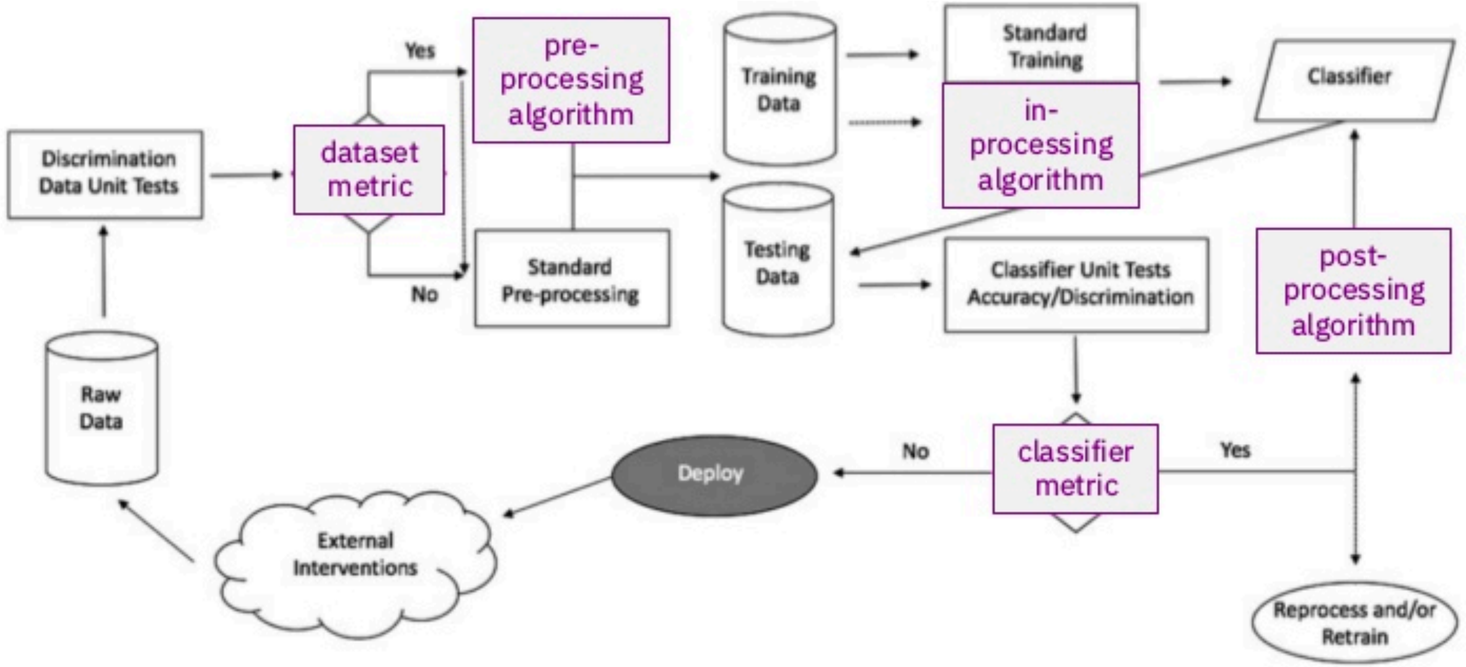


part 07:
ethics and compliance

AIF360: Fairness and Bias

AI Fairness 360 Open Source Toolkit

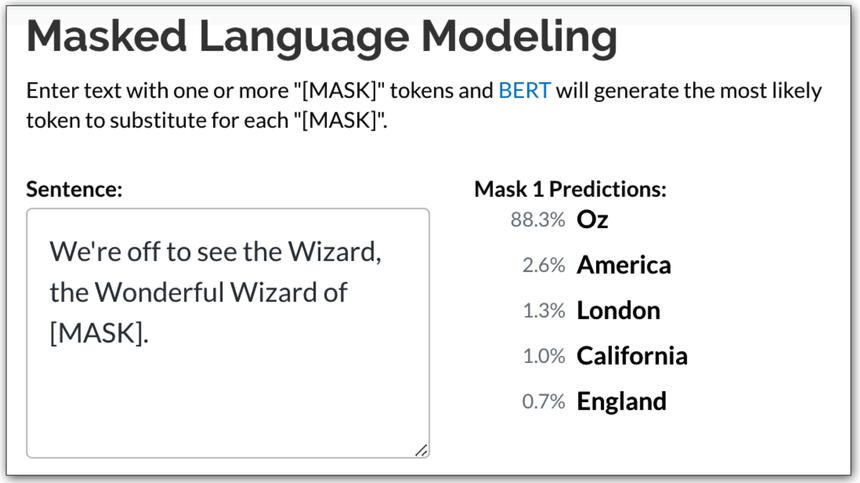
- "OSCON, 2019: Removing Unfair Bias"
  part 1, part 2
  Ana Echeverri, **Trisha Mahoney**
- **"AIF360 - Trusted and Fair AI"**
  Animesh Singh
- **online demo**

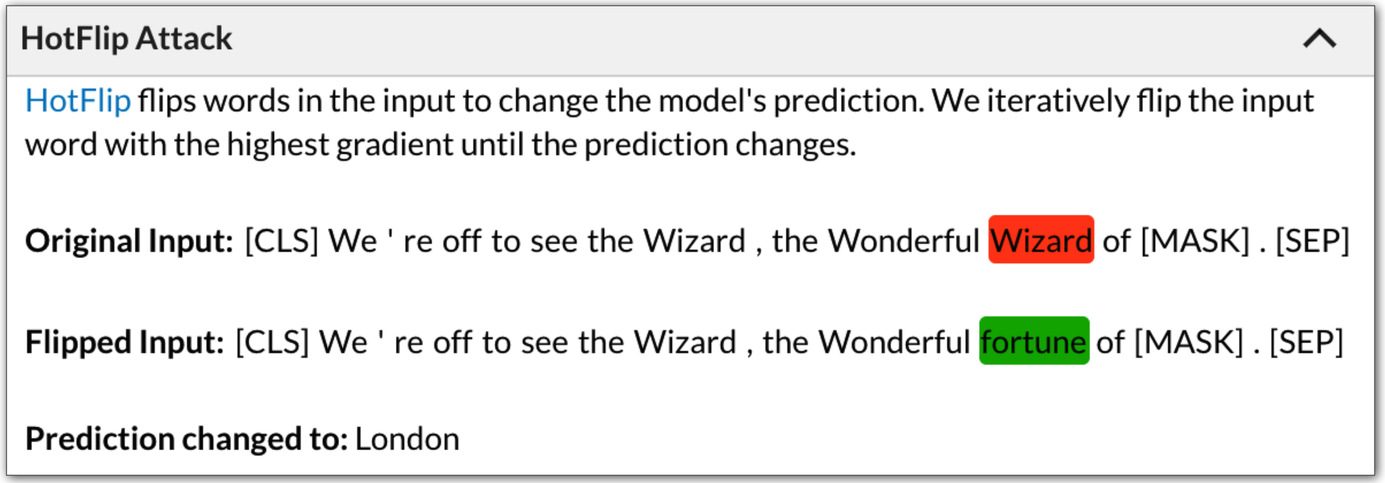


AllenNLP Interpret

AllenNLP Interpret:
A Framework for Explaining Predictions of NLP Models

- **interactive demo**: masked language model (BERT)
- **paper**
- **demo code**



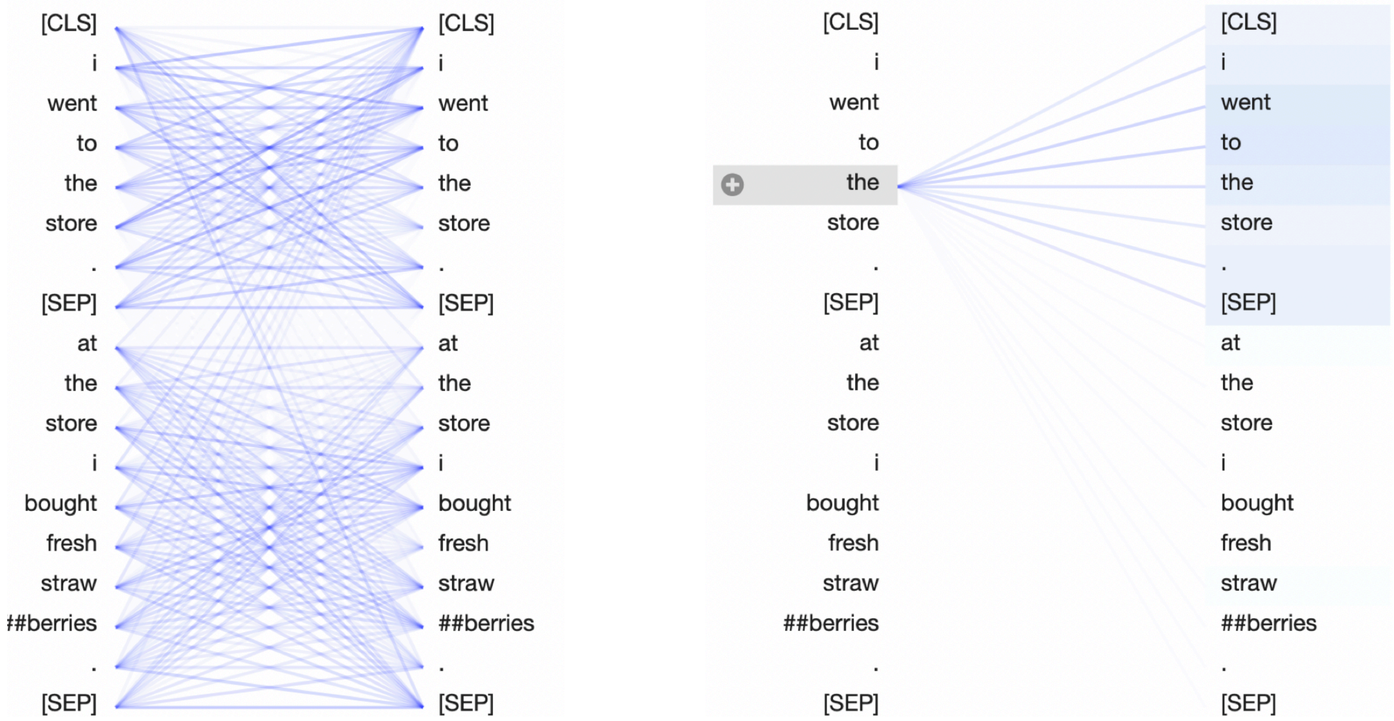


Visualizing BERT

BertViz, Jesse Vig

Visualize BERT's self-attention layers on text classification tasks

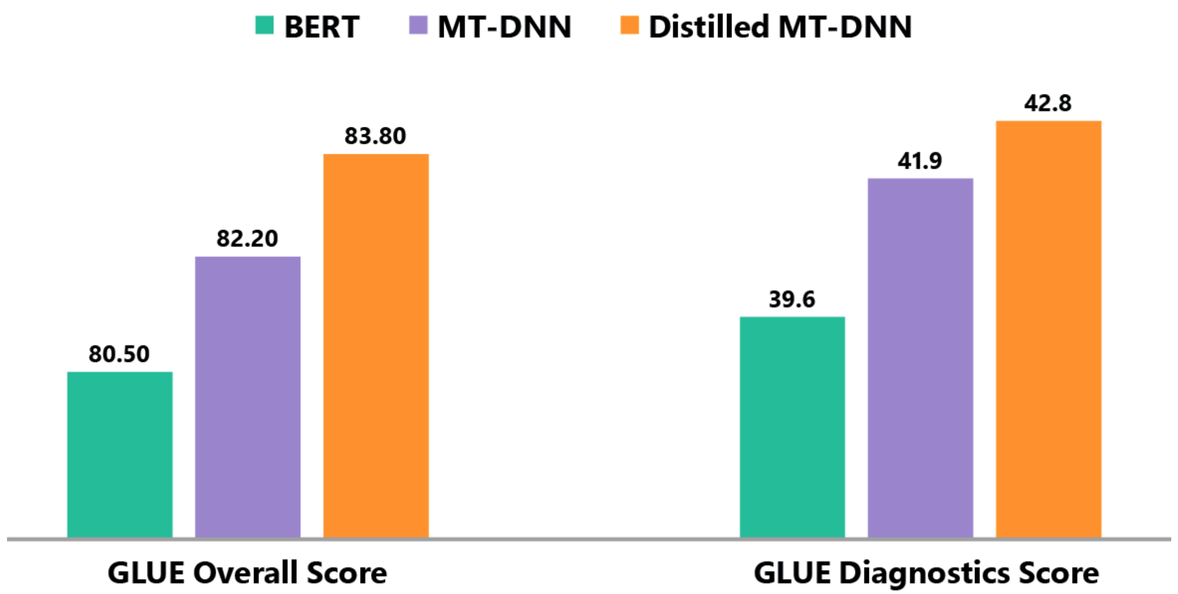
AI Explainability 360 Open Source Toolkit



MT-DNN: Explainability for BERT

Multi-Task Deep Neural Networks for Natural Language Understanding

- “Robust Language Representation Learning via Multi-task Knowledge Distillation”
- “Improving Multi-Task Deep Neural Networks via Knowledge Distillation for Natural Language Understanding”
- code repo



part 08:
hardware

Hardware in perspective

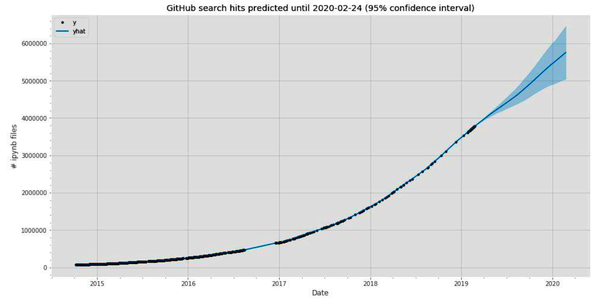
An **emerging trend** disrupts the past 15-20 years of software engineering practice:

hardware > software > process

Hardware is now evolving more rapidly than software, which is evolving more rapidly than effective process

Moore's Law is all but dead, although ironically many inefficiencies had been based on it

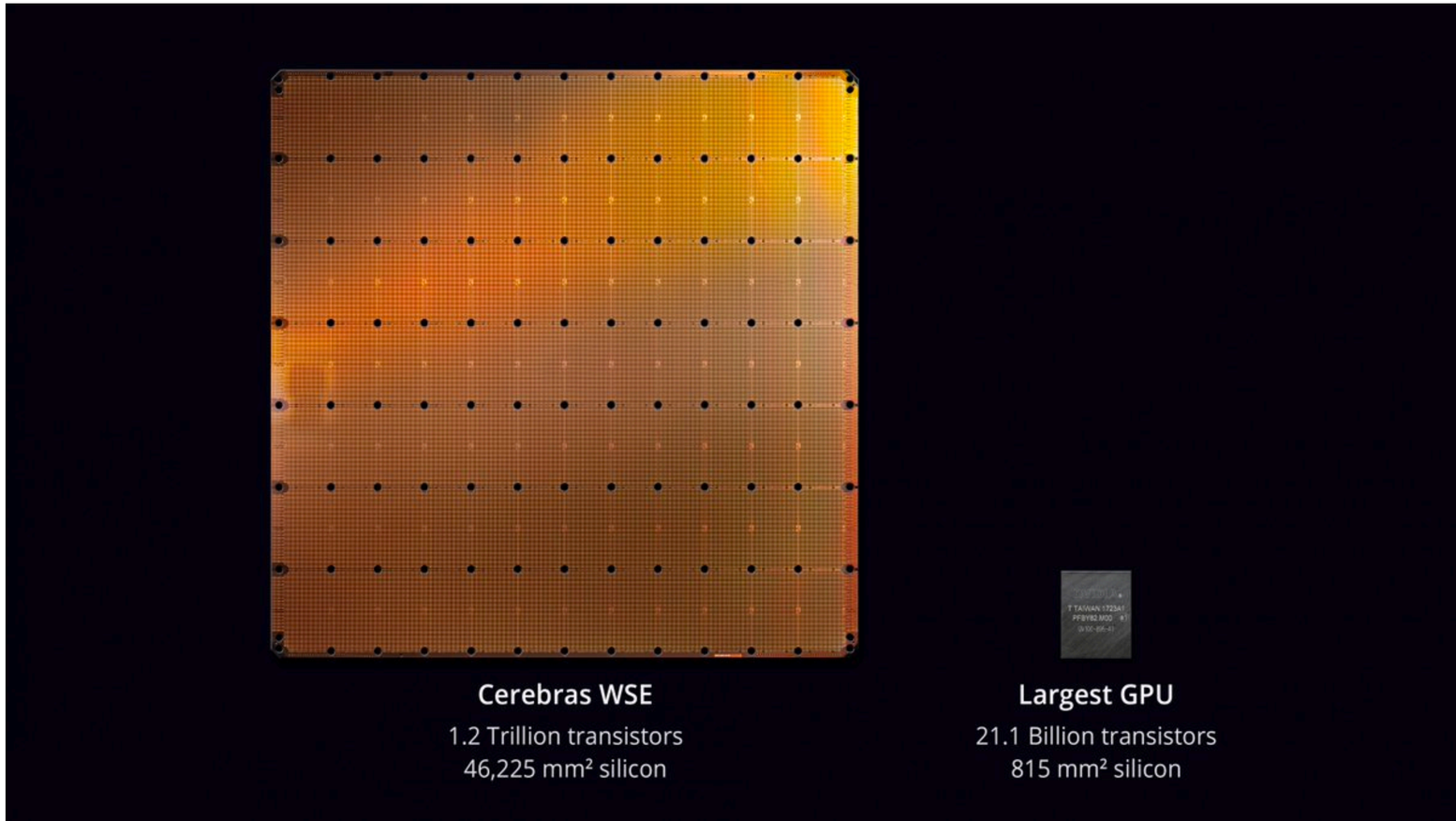
Project Jupyter, **Apache Arrow**, **NumPyWren** and the related **Ray** are emblematic for data infrastructure transformation in enterprise



ASICs the size of iPads, for ML

processor redesign:

- 10^2 more compute units
- 10^3 faster compute
- 10^5 faster memory



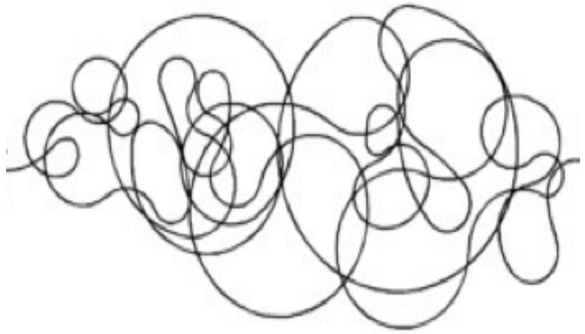
Cluster topologies, by generation

1. MPI was too complex for reuse and scale of communities across both academia and industry (since 1992)

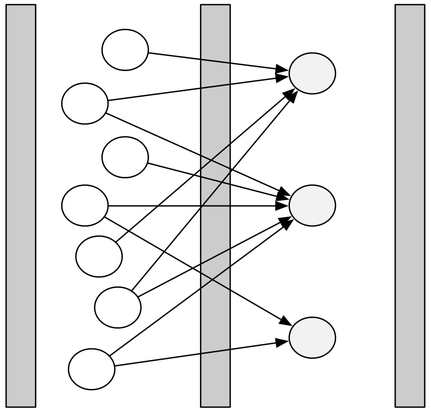
2. Batch, i.e., Hadoop, Spark, and their communities scaled (2006-2016); however their topologies were often too overdetermined for the more valuable use cases in ML – meanwhile, hardware assumptions changed significantly

3. More flexible compute topologies became prioritized:
   - **“Taming Latency Variability and Scaling Deep Learning”** **Jeff Dean** Google (2013-11-10) *pre-Tensorflow*
   - UC Berkeley RISE Lab: **Ray** and related work, now turning out to be even more general purpose than TF

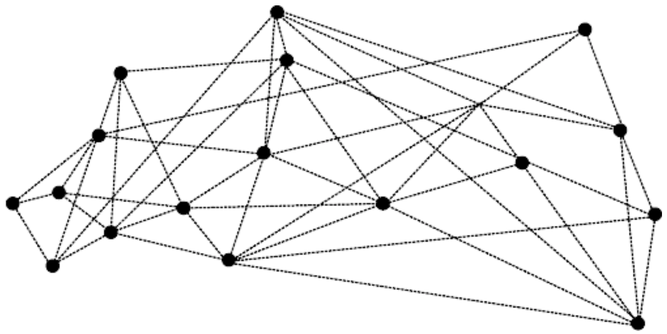
Cluster topologies, by generation



1990s



mid-2000s



current

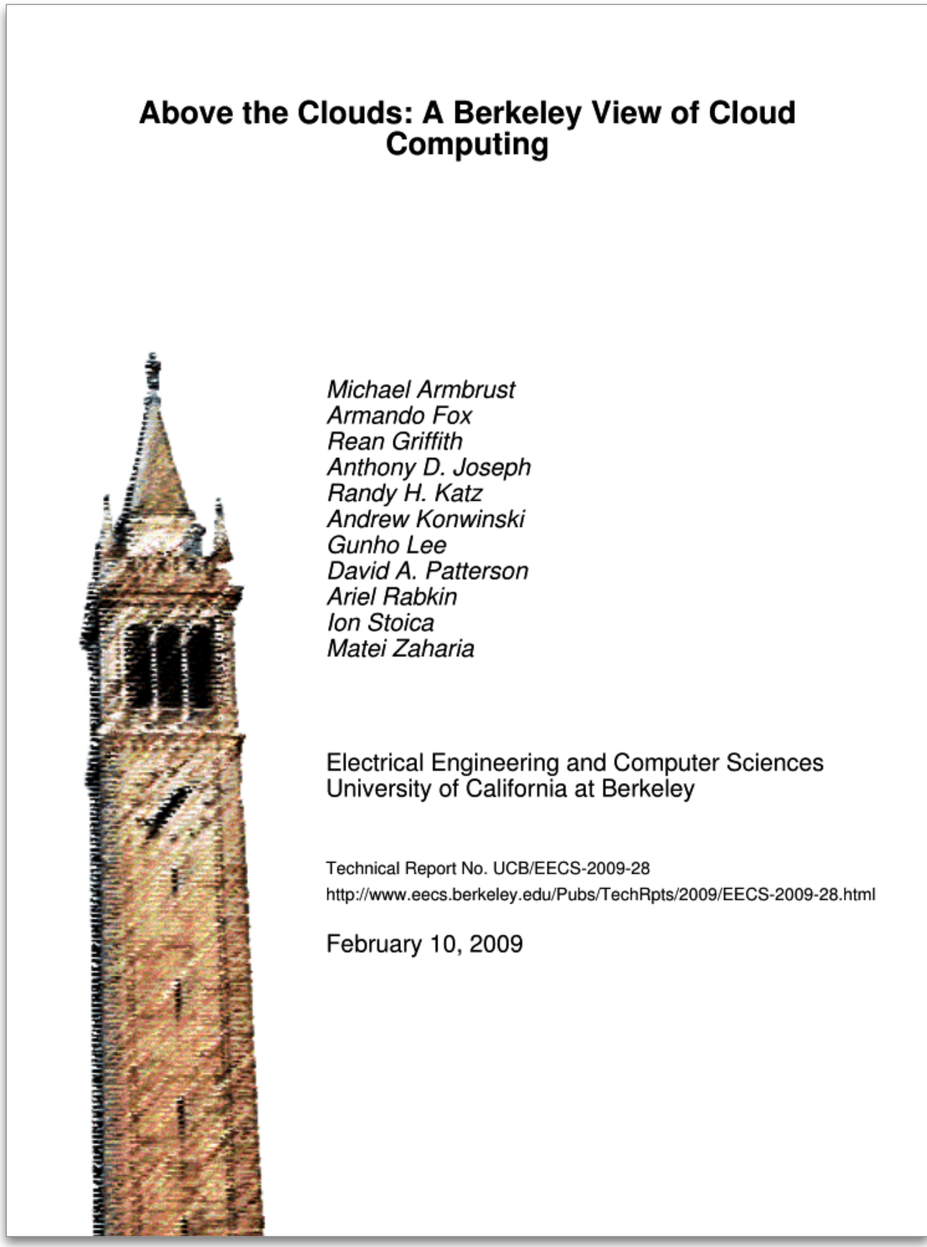
Opinion: one problem with software/hardware interface for distributed systems is that it's taken *decades* to prioritize the need for handling **graphs/tensors** directly in popular, accessible open source libraries, without having some **commercial database vendor** intermediate.

Evolution of cloud patterns

UC Berkeley published a **2009 report** about early use cases for cloud computing, which foresaw the shape of industry deployments over much of the next decade, and led directly to **Apache Mesos** and **Apache Spark**

It's fascinating to study the **contrasts** between that 2009 report and its 2019 follow-up.

(minor footnote: **vimeo.com/3616394**)

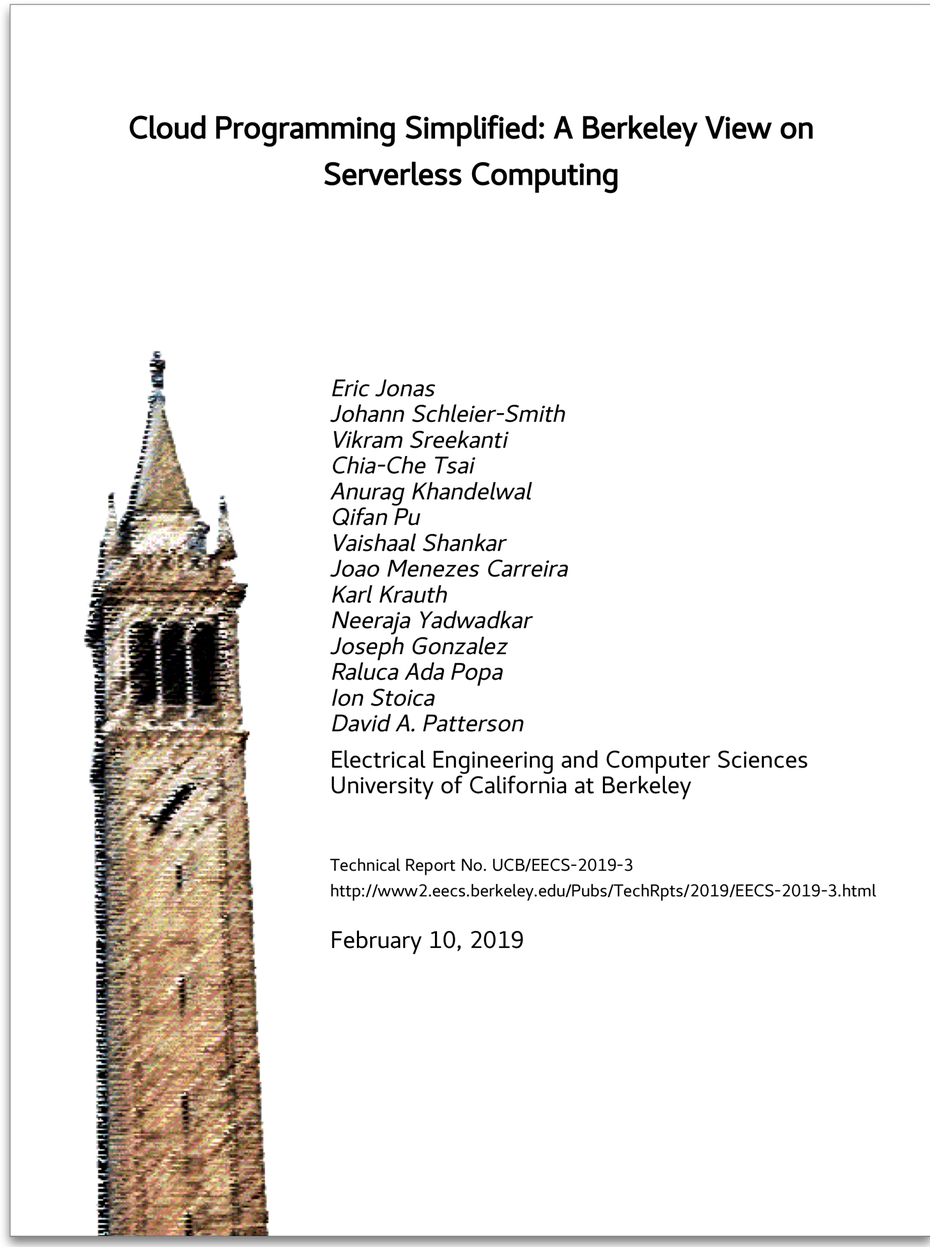


2009

Evolution of cloud patterns

Early patterns of cloud use mirrored the **virtualization** familiar to enterprise firms in their existing on-prem architectures, mostly as a convenience – *for migration*

More **contemporary patterns** force restructuring – *for efficiency and security* – **decoupling computation and storage**



Cloud Programming Simplified: A Berkeley View on Serverless Computing

Eric Jonas
Johann Schleier-Smith
Vikram Sreekanti
Chia-Che Tsai
Anurag Khandelwal
Qifan Pu
Vaishaal Shankar
Joao Menezes Carreira
Karl Krauth
Neeraja Yadwadkar
Joseph Gonzalez
Raluca Ada Popa
Ion Stoica
David A. Patterson

Electrical Engineering and Computer Sciences
University of California at Berkeley

Technical Report No. UCB/EECS-2019-3
http://www2.eecs.berkeley.edu/Pubs/TechRpts/2019/EECS-2019-3.html

February 10, 2019

2019

Key takeaways from “A Berkeley View”

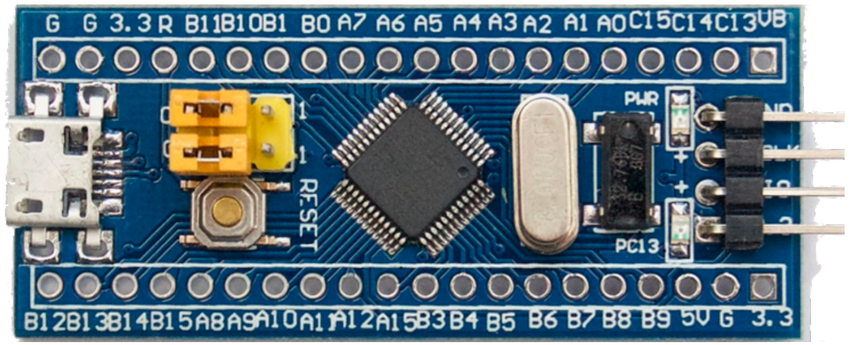
- physics + cloud economics imply less “framework” layers
- service offerings **migrate up** the tech stack
- issues with **data gravity**, increased **vendor lock-in**

Impact of edge devices and low-power ML

- **Episode 3**, *Domino*: massive latent hardware (2018-11-07)
- **Alasdair Allan**, Babilim Light Industries: **The intelligent edge and the demise of big data?** (2019-05-02)
- **Pete Warden**, Google: **TensorFlow.js on low-power devices** (2018-10-10)

edge inference:

- multi-modal perception (e.g., CV + speech)
- no battery, PV on ambient light
- low price per unit



part 09:
energy and policy concerns

Problem: AI-based Climate Change

The current process of training **deep learning** models generates exceptionally large quantities of atmospheric carbon and heat…

Computer Science > Computation and Language

Energy and Policy Considerations for Deep Learning in NLP

Emma Strubell, Ananya Ganesh, Andrew McCallum

(Submitted on 5 Jun 2019)

Recent progress in hardware and methodology for training neural networks has ushered in a new generation of large n
abundant data. These models have obtained notable gains in accuracy across many NLP tasks. However, these accuracy
on the availability of exceptionally large computational resources that necessitate similarly substantial energy consump
models are costly to train and develop, both financially, due to the cost of hardware and electricity or cloud compute ti
environmentally, due to the carbon footprint required to fuel modern tensor processing hardware. In this paper we brin
attention of NLP researchers by quantifying the approximate financial and environmental costs of training a variety of r
neural network models for NLP. Based on these findings, we propose actionable recommendations to reduce costs and
research and practice.

Comments: In the 57th Annual Meeting of the Association for Computational Linguistics (ACL). Florence, Italy. July 2019
Subjects: **Computation and Language (cs.CL)**
Cite as: **arXiv:1906.02243 [cs.CL]**
(or **arXiv:1906.02243v1 [cs.CL]** for this version)

Carbon Emissions

Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

NLP model emits ~5x car (incl. fuel)

arxiv.org/abs/1906.02243

Consumer	Renew.	Gas	Coal	Nuc.
China	22%	3%	65%	4%
Germany	40%	7%	38%	13%
United States	17%	35%	27%	19%
Amazon-AWS	17%	24%	30%	26%
Google	56%	14%	15%	10%
Microsoft	32%	23%	31%	10%

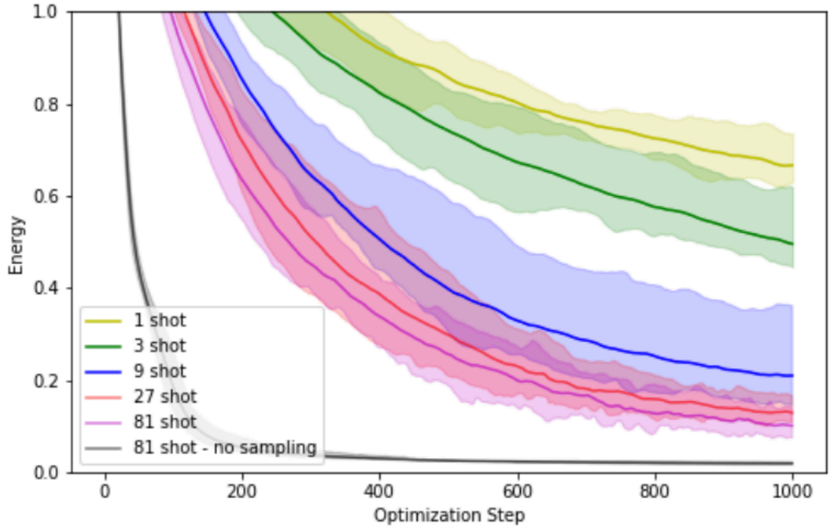
Table 2: Percent energy sourced from: Renewable (e.g. hydro, solar, wind), natural gas, coal and nuclear for the top 3 cloud compute providers (Cook et al., 2017), compared to the United States,[4] China[5] and Germany (Burger, 2019).

But the Algorithms…

However, most of the computation required to train deep learning models relies on variants of **stochastic gradient descent**.

Fortunately these algorithms can be performed with *superlinear* (read: nearly exponential) performance increase on quantum vectorization devices.

https://arxiv.org/abs/1910.01155



Algorithm 3 n-shot QSGD with Hamiltonian sampling

Given $U(\boldsymbol{\theta})$ satisfying a K-term parameter shift rule, with $\boldsymbol{\theta} \in \mathbb{R}^d$, and $\mathcal{L}(\boldsymbol{\theta}) = \langle H \rangle_{\boldsymbol{\theta}}$ where $H = \sum_{j=1}^{M} H_j$
Set initial circuit parameters $\boldsymbol{\theta}^{(0)}$ and learning rate α
$t \leftarrow 0$
while $t < T$ **do** ▷ Iterate through optimization steps
  for all $1 \leq i \leq d$ **do** ▷ Iterate through circuit parameters
    Sample $j \in \{1, \ldots, M\}$ with $\text{prob}(j) = 1/M$ ▷ Sample a Hamiltonian term
    for all $1 \leq k \leq K$ **do** ▷ Iterate through parameter shift terms
      Evaluate $\tilde{h}_j^{(n)}(\boldsymbol{\theta}_{k,i}^{(t)})$ ▷ Construct estimator for $\langle h_j \rangle_{\boldsymbol{\theta}_{k,i}^{(t)}}$ via n measurements
    end for
    $g_i(\boldsymbol{\theta}^{(t)}) \leftarrow \sum_{k=1}^{K} M \gamma_{k,i} \tilde{h}_j^{(n)}(\boldsymbol{\theta}_{k,i}^{(t)})$ ▷ Construct estimator for $\partial \langle H \rangle_{\boldsymbol{\theta}^{(t)}} / \partial \theta_i$
    $\theta_i^{(t+1)} \leftarrow \theta_i^{(t)} - \alpha g_i(\boldsymbol{\theta}^{(t)})$ ▷ Update parameters
  end for
  $t \leftarrow t + 1$
end while

Something something quantum

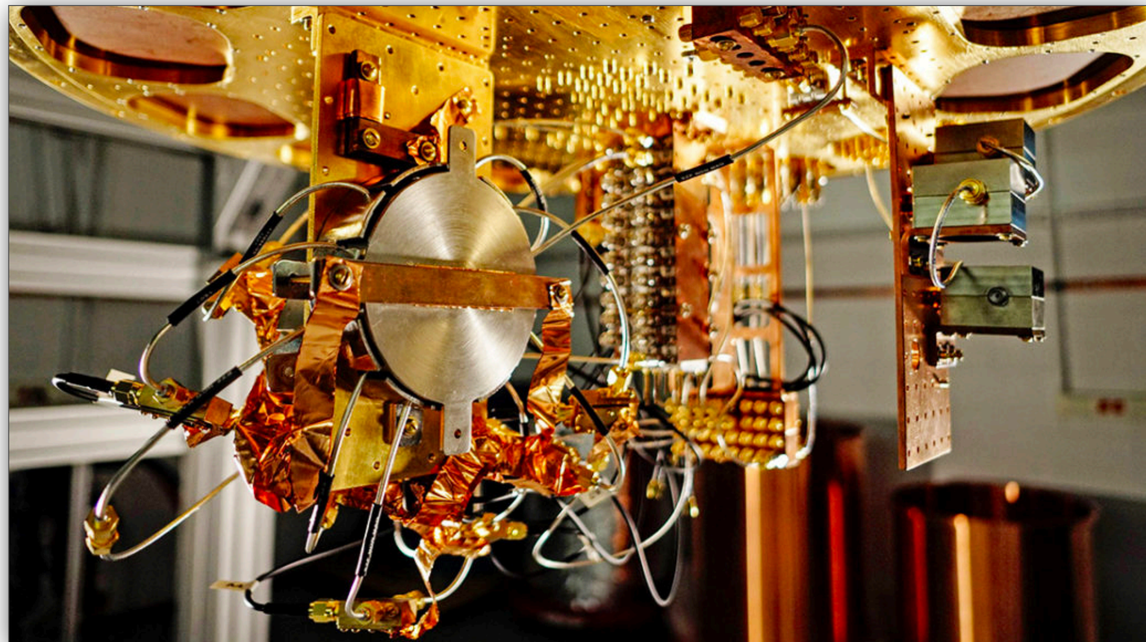
However, **quantum devices** tend to require:

- lots of power
- extreme cooling

Which brings us back to the general problem of cloud computing, etc.

Google: **“quantum supremacy”**

IBM: **“quantum advantage”**

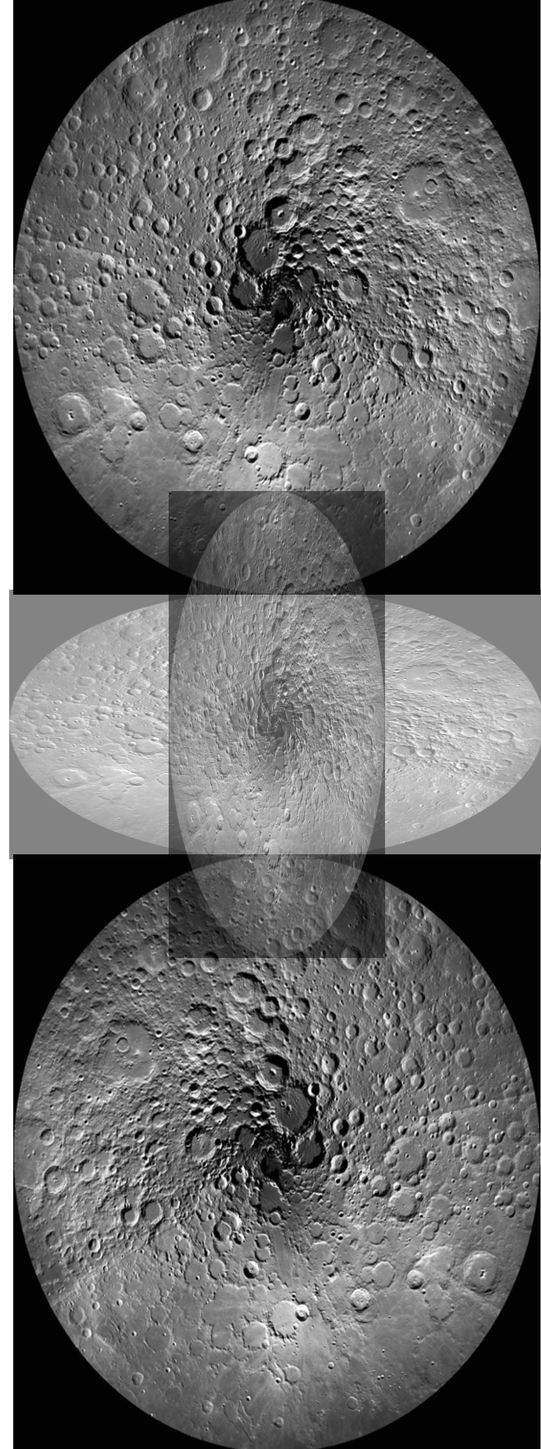


Eus Keus?

Hence, we might consider migrating those extreme cloud computing needs to **The Moon** ?!?

Craters in the South Polar region offer the coldest points in our solar system (inside craters) plus perpetual sunlight (craters rides) for solar power.

Then run heat pumps out under the surface regolith.



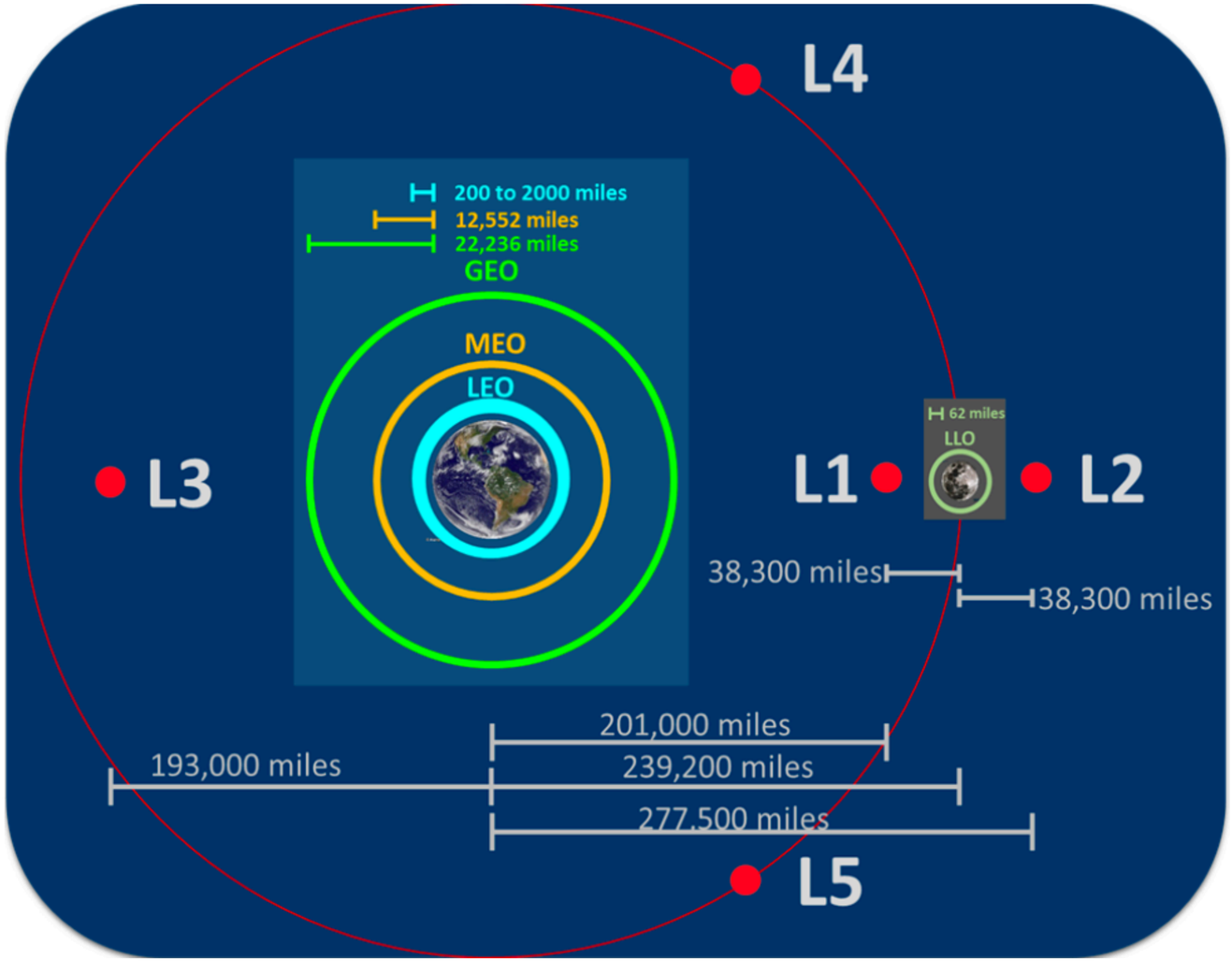
Cislunar System

Big Data to the rescue…

Train ginormous ML models in quantum datacenters located on The Moon using batch operations, serialize them, then transmit back to the Earth – to support transfer learning use cases.

We can place routers on a supply station at the L1 point.

In any case, we'll need to fly a soletta out to Lagrange points soon enough.



Because Fashion Choices

Two words: “moon busses”

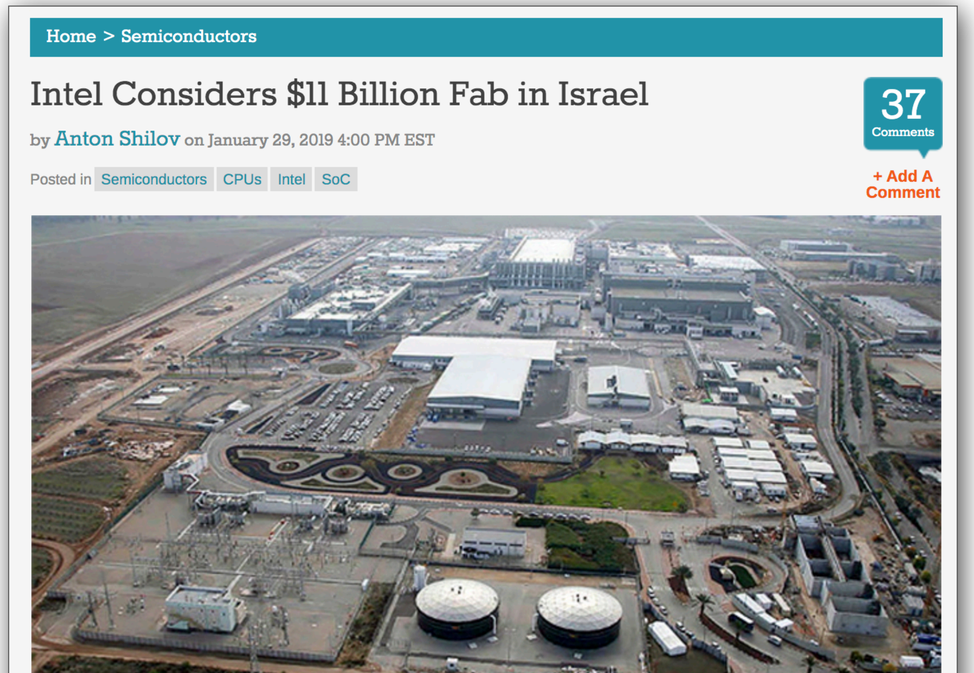
We’d get to wear incredibly cool outfits and hair styles.

Plus we would spend much time Underground, which should be rather familiar to Londoners.

Balancing the Budget

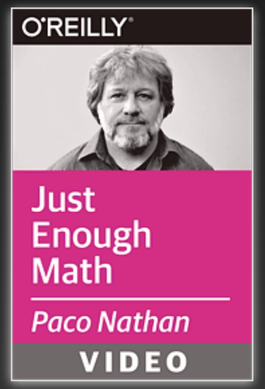
A former CTO of NASA (and devout rocket scientist) estimates the costs for establishing a permanent Lunar Base to be < **$15 billion**.

Frankly, the fabrication plants built by Intel recently in the US and Israel cost approximately that.

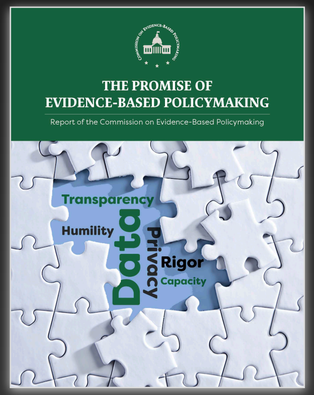


publications, interviews, conference summaries…

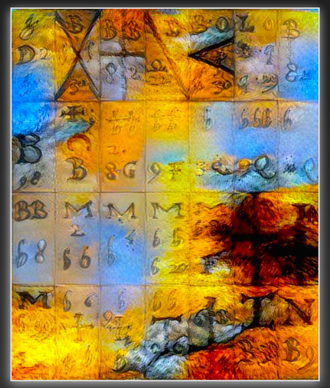
https://derwen.ai/paco
@pacoid



Just Enough Math



Rich Context



Hylbert-Speys

Rev conf

Themes + Confs
per Pacoid

derwen.ai