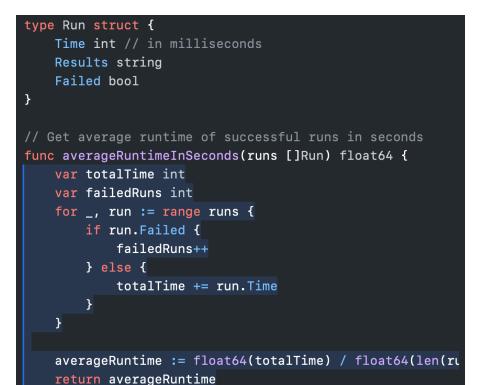
Natural Language Meets Query Processing

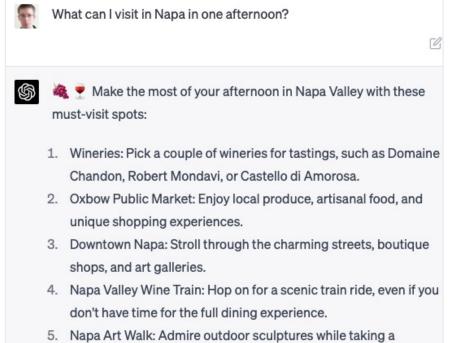
Matei Zaharia



NLP is Advancing Fast







leisurely walk.

+ getting democratized via smaller models (Llama, Alpaca, Dolly, Vicuna, Koala, ...)

NLP will Simplify Analytics

Cmd 1	
1 2	%chat what are the top five teams that received sev0s outside of working hours in past two weeks?
То	find the top five teams that received sev0s outside of working hours in the past two weeks, we can use the following query in Spark SQL:
SEI	LECT TeamName, COUNT(*) AS Sev0Count
	DM q4_hackathon.main.pagerduty_incidents
	ERE Timestamp NOT BETWEEN '09:00:00' AND '17:00:00'
AND	<pre>> Severity = 'sev0'</pre>
ANI	D Timestamp >= CURRENT_TIMESTAMP - INTERVAL 2 WEEKS
GRO	OUP BY TeamName
	DER BY Sev0Count DESC
	MIT 5
-	
	is query first filters the incidents to only include those with a severity of 'sev0' that occurred outside of working hours (defined as betw∉ idents per team. Finally, it orders the teams by the number of incidents and returns the top five teams.
Com	mand took 43.64 seconds by kyle.rong+e2@databricks.com at 12/10/2022, 3:40:04 PM on Kyle hackathon
Cmd 2	
1	%sql
2	
3	SELECT TeamName, COUNT(*) AS Sev0Count
4	FROM q4_hackathon.main.pagerduty_incidents
5	WHERE Timestamp NOT BETWEEN '09:00:00' AND '17:00:00'
6	AND Severity = 'sev0'
7	AND Timestamp >= CURRENT_TIMESTAMP - INTERVAL 2 WEEKS
8	GROUP BY TeamName
9	ORDER BY Sev0Count DESC
10	LIMIT 5

But Modern NLP still has Problems



B

How large are elephant eggs?

Wrong

Elephants have the largest eggs of any land animal. A single elephant egg can weigh as much as 2 pounds (about 0.9 kilograms), and is about the size of a grapefruit. However, despite their large size, elephant eggs are much smaller in proportion to the size of the mother than the eggs of most other animals. For example, a human egg is about the size of a small pea in relation to the mother's body size, whereas an elephant egg is more like a golf ball in relation to the size of an adult elephant.



Who are the current World Cup champions?

Out-of-date



The current World Cup champions are France. They won the 2018 FIFA World Cup, which was held in Russia. Expensive

High latency and error rates on text-davinci-003

Resolved - This incident has been resolved.

Jan 10, 11:04 PST

Jan 10, 2023

Investigating - We are experiencing error rates of around 20%

And It's Hard to Fix



Why did Ion Stoica win the Turing Award?



Ion Stoica has not won the Turing Award as of my knowledge cutoff date of September 2021, and there has been no announcement of him winning the award since then. The Turing Award is one of the most prestigious awards in computer science, awarded annually by the Association for Computing Machinery (ACM) to individuals who have made significant contributions to the field of computing.

ß

It is possible that Ion Stoica may be considered for the award in the future if he makes significant contributions to the field of computing. However, at the time of my knowledge cutoff date, he has not yet received the award.

And It's Hard to Fix



Why did Matei Zaharia win the Turing Award?



Matei Zaharia won the 2021 ACM A.M. Turing Award, also known as the Nobel Prize of Computing, for his foundational contributions to large-scale data processing. He was recognized for his work on Apache Spark, an open-source cluster computing system that has become one of the most widely used data processing platforms in the world.

C

Large-Scale NLP Today

Huge DNNs that store "knowledge" in their weights



Problems:

- Limited interpretability
- Hard to update model's knowledge
- Expensive training and inference

From a Systems Point of View

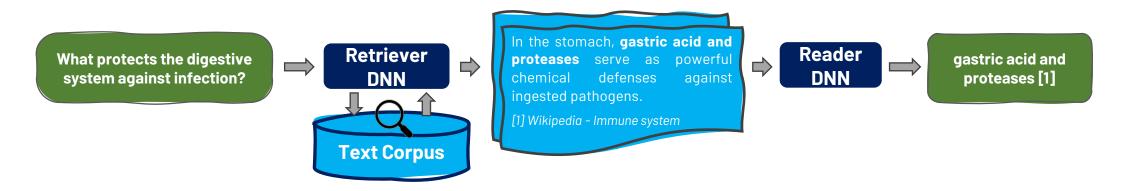
Accessing all weights to run a task seems very inefficient

Like a linear scan through our "knowledge"

Retrieval-Based NLP

Examples: REALM, DPR, RAG, RETRO, ColBERT, DSP

Separate "language processing" from "knowledge"



tinyurl.com/rnlp21

Benefits:

- Easier to interpret and "program"
- Can update knowledge in milliseconds by updating a doc
- 100-1000x faster inference

Our Results with Retrieval Models



With Omar Khattab, Keshav Santhanam, Chris Potts

SOTA performance on multiple NLP tasks at lower compute cost

- Information retrieval: CoIBERT (SIGIR'20) can match BERT-based retrievers at 100–1000x lower cost
- Question answering: ColBERT-QA (TACL'21) improves EM scores for TriviaQA and Natural Questions by 3-12 points
- Multi-hop reasoning: Baleen (NeurIPS'21) improves score on HoVer from 15 to 57 and runs 10x faster; DSP offers general programming model

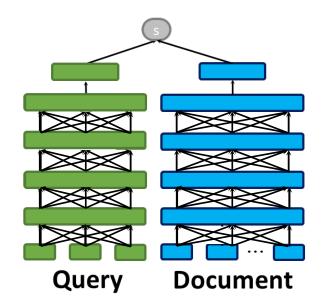
How Did We Get These Results?

Improvements in retrieval: "late interaction" approach that keeps the modeling benefits of Transformers while enabling efficient retrieval

Supervision for retrieval-based models: teaching models how to search for relevant documents given only the final answer for a task

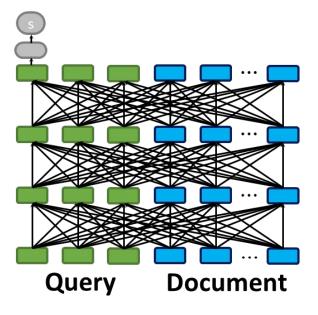
Data systems insights: improved indexes and query plans

Previous Neural Retrieval Approaches



(a) Encoding similarity e.g. run BERT separately on query & doc

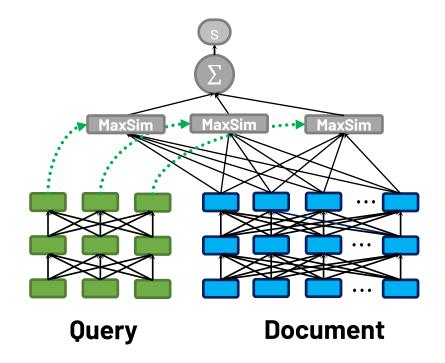
- \checkmark Cheap search computation
- × Coarse-grained representations



(b) All-to-all interaction e.g. BERT on query || doc

- ✓ Joint contextualization of terms
- imes Expensive to compute on all docs

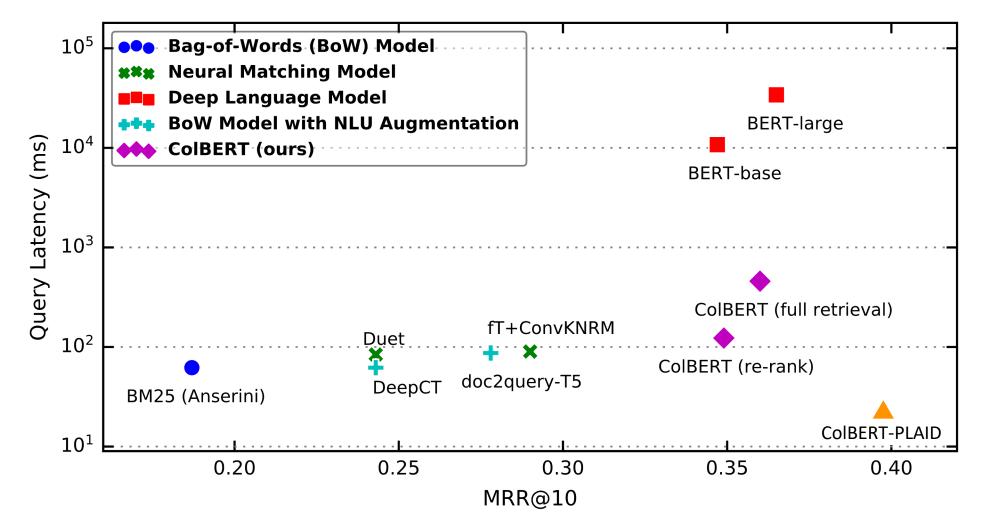
ColBERT's Approach: Late Interaction



Independent encoding using all but the last layers of BERT

✓ Fine-grained representations
 ✓ Joint contextualization of terms
 ✓ Scalable search computation

Retrieval Results on MS MARCO



SIGIR 2020, CIKM'22

Example of ColBERT Matching

when did the transformers cartoon series come out?

[...] the animated [...] The Transformers [...] [...] It was released [...] on August 8, 1986

when did the transformers cartoon series come out?

[...] the animated [...] The **Transformers** [...] [...] It was released [...] on August 8, 1986

when did the transformers **<u>cartoon</u>** series come out?

[...] the **animated** [...] The Transformers [...] [...] It was released [...] on August 8, 1986

Question Answering with ColBERT-QA

"Where does the Volga river end?"

→ Caspian Sea

Challenge: QA Retrievers are Hard to Supervise

The training data for QA has the form

Question where does the volga river end, **Answer** Caspian Sea

But each **retriever** training example needs to be of the form

Question, Positive Passage(s), Negative Passage(s)

And we train the retriever to give higher scores to the positives

Challenge: QA Retrievers are Hard to Supervise

The training data for QA has the form

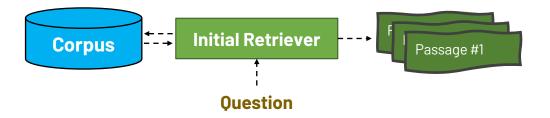
Question where does the volga river end, **Answer** Caspian Sea

But each **retriever** training example needs to be of the form

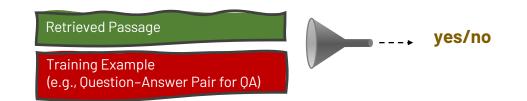
Question, Positive Passage(s), Negative Passage(s)

And we t How do we collect positives and negatives? ves.

RGS: Relevance-Guided Supervision

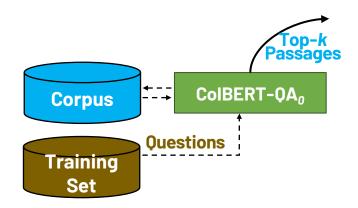


A weak initial retriever – e.g., BM25 or ColBERT trained for standard IR



A task-aware heuristic for "useful" passages: for OpenQA, "does answer appear in passage?"

 Initial Retriever: Find the top-1000 passages per training question



Q: where does the volga river end A: caspian sea

Q: who won world cup 2016 A: real madrid

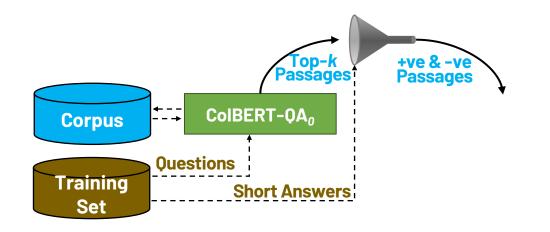
Q: where does the volga river end

- 1. Volga Township lies in Clayton County (Iowa), named after the Volga River.
- 2. The Akhtuba river flows toward the Volga Delta and <u>Caspian Sea</u>.
- **3.** The Volga is an Executive car from the Soviet Union to replace GAZ Pobeda.
- **10.** The <u>Caspian Sea</u> is home to a wide range of species, known for caviar and oil industries.

...

...

2. Weak Heuristic: Identify the highest-ranked passages that pass the filter (contain the answer string) as weak positives



Q: where does the volga river end A: caspian sea

Q: who won world cup 2016 A: real madrid

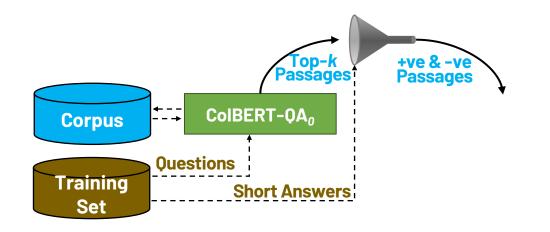
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. . .

. . .

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Q: where does the volga river end A: caspian sea

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Q: where does the volga river end

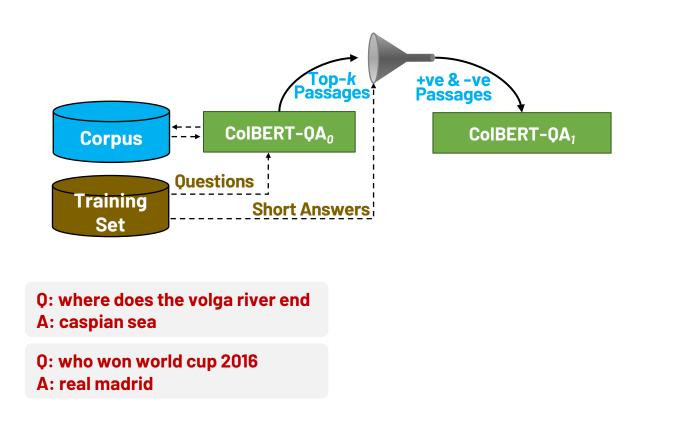
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- **3.** The Volga is an Executive car from the Soviet Union to replace GAZ Pobeda.
- **10.** The <u>Caspian Sea</u> is home to a wide range of species, known for caviar and oil industries.

...

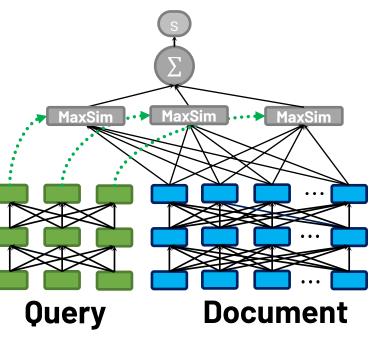
. . .

3. Inner-Loop Training: Collect and cache triples of the form

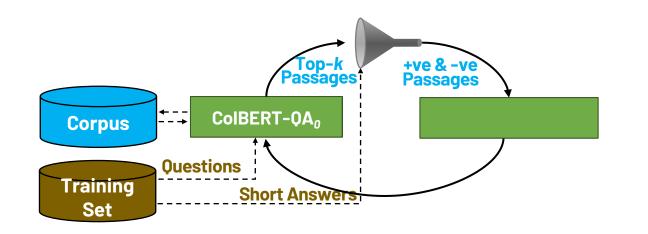
(Question, Weak Positive Passage, Sampled Negative Passage)



and train with them!



4. Outer-Loop Refresh: Encode the corpus with the new retriever, and retrieve the top-k passages once more.



Q: where does the volga river end A: caspian sea

Q: who won world cup 2016 A: real madrid

Q: where does the volga river end

- 1. Volga River discharges into the <u>Caspian Sea</u> below Astrakhan at below sea level.
- 2. The Volga River flows through central Russia and into the <u>Caspian Sea</u>.

Results for Question Answering

	End-to-End QA Exact Match (EM)								
Model	Natural Questions	TriviaQA	SQuAD						
BM25 + BERT	32.6	52.4	38.1/53.0						
REALM	40.4	-	-						
DPR	41.5	57.9	36.7						
RAG	44.5	56.1	-						
CoIBERT-QA (3 rounds)	47.8	70.1	54.7 / 58.7						
T5-11B (24x more params)	34.8								
GPT-3 (400x more params)	29.9								

 Q_0 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame.

Is this claim true or false?

- Q_0 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame.
- Q_1 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame. **Red Flaherty**: He umpired in World Series 1955, 1958, 1965, and 1970.

- Q_0 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame.
- Q_1 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame. **Red Flaherty**: He umpired in World Series 1955, 1958, 1965, and 1970.
- Q2 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame. Red Flaherty: He umpired in World Series 1955, 1958, 1965, and 1970. 1965
 World Series: It is remembered for MVP Sandy Koufax.

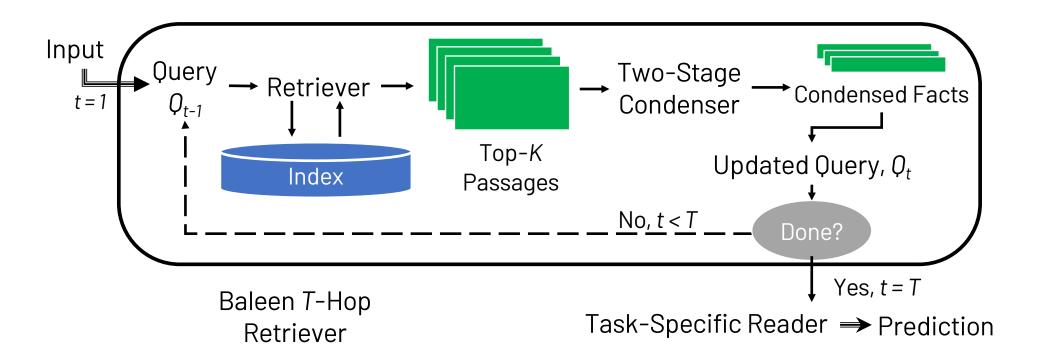
- Q_0 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame.
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- Q2 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame. Red Flaherty: He umpired in World Series 1955, 1958, 1965, and 1970. 1965
 World Series: It is remembered for MVP Sandy Koufax.
- Q3 The MVP of [a] game Red Flaherty umpired was elected to the Baseball Hall of Fame. Red Flaherty: He umpired in World Series 1955, 1958, 1965, and 1970. 1965 World Series: It is remembered for MVP Sandy Koufax. Sandy Koufax: He was elected to the Baseball Hall of Fame.

→ True!

Multi-Hop Reasoning Challenges

- 1. Multi-hop queries have multiple information needs
- 2. Retrieval errors in each hop propagate to subsequent hops
- **3**. Don't have supervision on which passages to retrieve and which order (like our QA situation, but worse!)

Baleen Overview



Results for Multi-Hop Reasoning

	Model	Code	Fa Extra		HoVer Score
			EM	F ₁	Acc
1 May 24, 2021	Baleen Anonymous Anonymous		39.78	80.41	57.53
2 Oct 13, 2020	Baseline Model (single model) UNC Chapel Hill & Verisk Analytics (Jiang, Bordia, et al. 2020)	E	4.5	49.5	15.32

How Do We Program Complex NLP Apps?

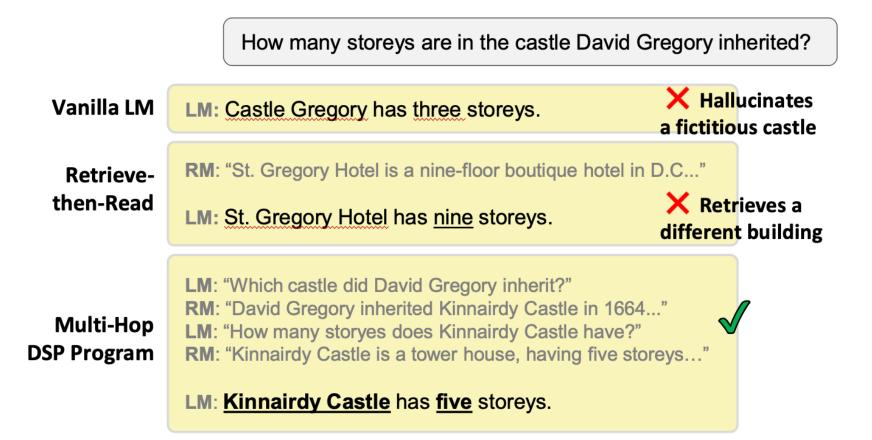
ColBERT-QA, Baleen, etc are nice, but required a PhD student to write

Our new project is a high-level programming model for NLP apps: **Demonstrate-Search-Predict (DSP)**

Key ideas:

- Start with pretrained foundation models (e.g. ColBERT, GPT-4)
- Write pipelines of operators that exchange plain text
- 3 kinds of operators: Demonstrate (find task examples), Search (over examples or knowledge), Predict
- "Compile" a pipeline to get faster and more accurate models!

DSP Example: Multi-Hop QA



DSP Model: LMs and retrieval models (RMs) exchange text in sophisticated pipelines

LMs and RMs both consume (and generate or retrieve) natural language text.

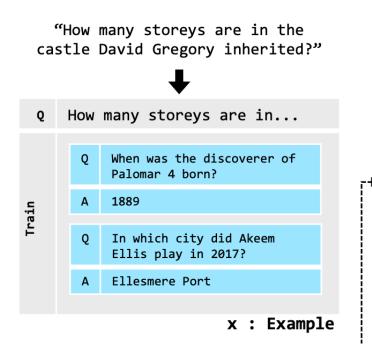
Instead of focusing on carefully engineering prompts, let's **write a program** whose leaves are **declarative** generate or retrieve calls.

e.g., write_search_query(context, question) -> query

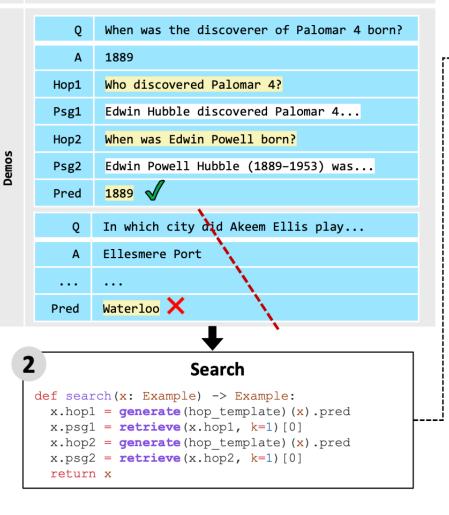
The **framework runtime** will decide how to effectively map this to a model call (e.g., a few-shot prompt or finetuning a new model)

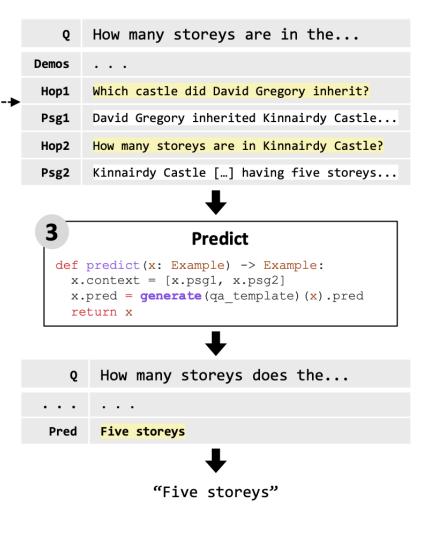


DSP Example: Multi-Hop QA



Q How many storeys are in the castle...





DSP Compiler

Take a DSP program + unlabeled inputs and compile it:

Compiler automatically explores:

- Using smaller foundation models for each step (e.g., T5, LLaMa, Ada)
- Fine-tuning the models for each step
- Picking the best demonstrations for each step

Result: Similar quality at 1/10th the cost

The Evolution of Programming NLP Apps?

Paradigm	Examples	Frameworks
Training bespoke architectures	BiLSTMs with attention, etc.	TensorFlow, PyTorch
Fine-tuning pretrained Transformers	BERT, ELECTRA, etc.	HuggingFace
Prompting instruction-tuned LLMs	GPT-3, Flan-T5, etc.	OpenAl/Cohere, LangChain (with tool use)
Programming FM pipelines	Socratic Models, RARR, DSP programs, etc.	DSP



The example in the first figure is handled by Bing Chat. Maybe it is more important to generate good keywords from input question? Web search engines today can already do it for you.

low m	any storeys a	are in the ca	astle Dav	ARCH	🗩 СНАТ				
astle G	regory has th	nree storeys	6.	27	Hov	v many storeys are	in the castle I		
	ory Hotel is a r			avid Greg	ory inherited				
Grego	ory Hotel has	nine store	/S.	y Castle s	storeys				
hich ca	stle did David	Gregory inh	orit?"	you					
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nnaird	y Castle has	s <u>five</u> store	/S.	n 2. en.	wikipedia.org	3. wikiwand.com	4. arxiv.org		
12:34 A 1 Like	\M · Feb 21, 2	023 · 131 Vie	9WS						
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Conclusion

LLMs will just be one building block in powerful NLP applications

Learn more about our work:

- Retrieval-based NLP: <u>tinyurl.com/rnlp21</u>
- DSP: <u>github.com/stanfordnlp/dsp</u>
- Dolly open LLM: <u>github.com/databrickslabs/dolly</u>

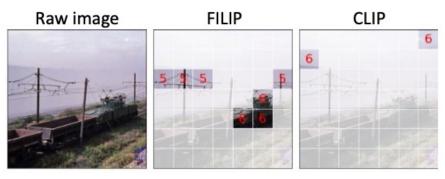
Work Based on ColBERT

Cross-lingual QA IBM.											
XOR-TyDi Cross-lingual Open-Retrieval Question Answering											
Rank	Rank Model										
1 February 11, 2022	Single model CHIMAERAS B Anonymous	70.3	63.0								
2 January 7, 2022	Contrastive Context-aware Pretraining Model (CCP) Anonymous	63.0	54.8								
3 August 26, 2021	Single Encoder Retriever (Sentri) Huawei Noah's Ark lab	61.0	52.7								
4	Single Encoder Retriever (Sentri,	60.7	55.5								

Text generation Stanford

KILT Organized by: KILT Starts on: Dec 31, 2018 4:00:00 PM Ends on: May 31, 2099 4:59:59 PM								
Rank \$	Participant team 💲	R-Prec (↑) ≑	Recall@5 (↑) ≑	ROUGE- L(↑) ≑	F1 (↑) ≑	KILT-RL (↑) ≑	KILT-F1 (↑) ≑	Last submission at \$
1	Stanford NLP (Hindsight)	56.08	74.27	17.06	19.19	11.92	13.39	3 months ago
2	2 Re2G (Re2G)		79.98	16.76	18.90	11.39	12.98	5 months ago
3	IBM_research_AI (KGI)	55.37	78.45	16.36	18.57	10.36	11.79	6 months ago

Image + text embedding **₩ ниа**wei



	Flickr30K							MSCOCO					
	im	age-to-	-text	tex	t-to-in	nage	im	age-to	-text	text-to-image			
	R@1	R@5	R@10	R@1 R@5 R@10			R@1	R@5	R@10	R@1	R@5	R@10	
Unicoder-VL	64.3	85.8	92.3	48.4	76.0	85.2	_	_	_	_	_	_	
ImageBERT	70.7	90.2	94.0	54.3	79.6	87.5	44.0	71.2	80.4	32.3	59.0	70.2	
UNITER	83.6	95.7	97.7	68.7	89.2	93.9	_	_	_	_	_	_	
CLIP	88.0	98.7	99.4	68.7	90.6	95.2	58.4	81.5	88.1	37.8	62.4	72.2	
ALIGN	88.6	98.7	99.7	75.7	93.8	96.8	58.6	83.0	89.7	45.6	69.8	78.6	
FILIP	89.8	99.2	99.8	75.0	93.4	96.3	61.3	84.3	90.4	45.9	70.6	79.3	

(d) Electric locomotive (5,6)

Baleen Results by # of Required Hops

	S	Sentenc	e EM		S	Verification			
Model / # of Hops	All	2	3	4	All	2	3	4	Accuracy
TF-IDF + BERT*	4.8/4.5	13.6	1.9	0.2	50.6/49.5	57.2	49.8	45.0	73.7
Baleen 1-hop	19.7	40.9	15.4	4.3	72.3	77.5	72.4	66.4	-
Baleen 2-hop	37.0	46.9	35.7	28.4	80.8	81.2	81.8	78.7	-
Baleen 3-hop	38.9	47.1	37.0	33.2	81.4	81.2	82.3	80.0	-
Baleen 4-hop	39.2 /39.8	47.3	37.7	33.3	81.5 /80.4	81.2	82.5	80.0	84.5 /84.9
Oracle + BERT ^{\star}	19.9	25.0	18.4	17.1	71.9	68.3	71.5	76.4	81.2
Human*	56.0	75.0	73.5	42.1	88.7	86.5	93.1	87.3	88.0

Compressing ColBERT

ColBERT vectors cluster very well, aligning with intuition for objective

Encodings with about **20 bytes** per vector preserve 99% of quality

And work robustly in and out of domain

github.com/stanford-futuredata/CoIBERT