John Snow LABS

Applied Generative AI for Data Scientists

April 2025 Training & Certification

Break Until 1:05pm ET

Training Workshop Outline

Medical LLMs	Medical Chatbot	Human in the loop: Generative AI Lab
LLM & RAG with Spark NLP	Multi-Modal Language Models	Information Extraction

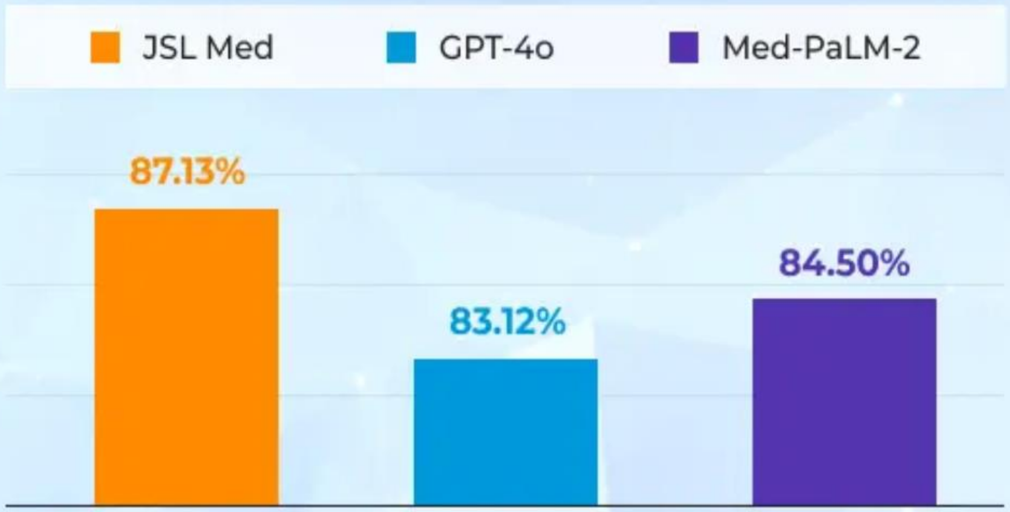
John Snow Labs
Provides State-of-the-Art Medical Language Models

Use a Medical LLM that outperforms GPT-4o on tasks like clinical assessment (**+6%**), research comprehension (**+4.2%**), and clinical case analysis (**+9%**)

In a blind evaluation by practicing medical doctors, the Small Medical LLM was preferred over GPT-4o **45% to 92% more often** on clinical text summarization and information extraction

Designed for privacy and compliance, the Medical LLM runs inside your cloud

Average Performance on OpenMed Benchmarks



Designed for Enterprise Healthcare

John Snow LABS

Keep up with the state of the art

Bi-weekly releases for 8+ years

Run Privately in your infrastructure

Data never leaves your perimeter

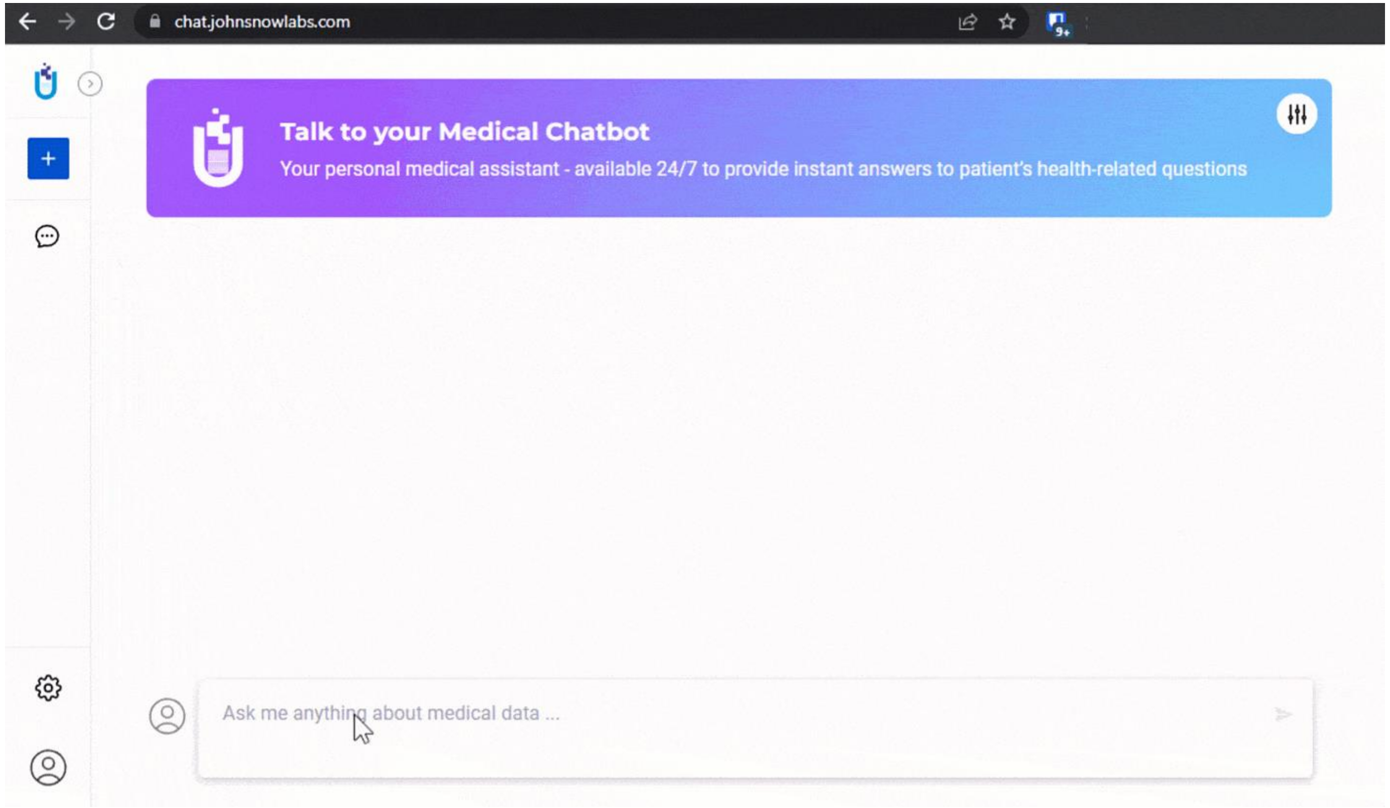
Scale on a budget

Priced per server, not per token

aws Azure databricks snowflake ORACLE CLOUD kubernetes

John Snow Labs' Medical Chatbot

- Delivers Superior Accuracy for Healthcare-Specific Tasks
- Runs privately behind your firewall: No third-party APIs or data sharing
- Updates all medical knowledge daily
- Can consistently reproduce results
- Does not hallucinate, cites its sources
- Explains its answers
- Adds private knowledge bases
- Tunable guardrails and brand voice



John Snow Labs' Medical Chatbot

- ✓ Delivers Superior Accuracy for Healthcare-Specific Tasks → Multi-LLM, Multi-Agent Architecture
- ✓ Runs privately behind your firewall: No third-party APIs or data sharing
- ✓ Updates all medical knowledge daily → Comes with Medical Knowledge Bases
- ✓ Can consistently reproduce results
- ✓ Does not hallucinate, cites its sources → Built-in RAG Backend
- ✓ Explains its answers
- ✓ Adds private knowledge bases → Enterprise Grade Security & Scalability
- ✓ Tunable guardrails and brand voice

Literature Review Agent

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Literature Review

Literature review synthesizes the results of multiple scientific studies to help researchers draw conclusions, identify patterns or to derive a more precise estimate of the overall effect of a treatment or intervention.

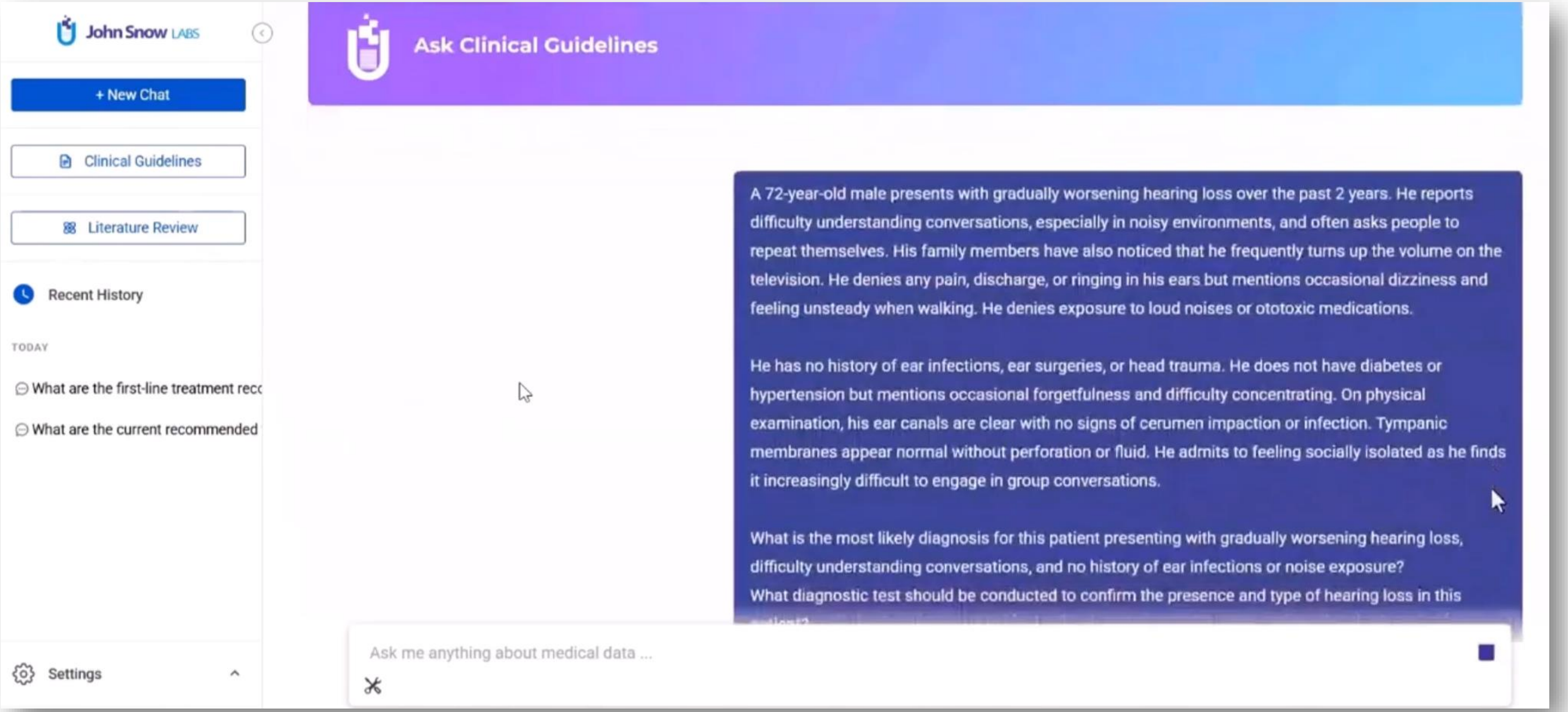
1 Search Criteria — 2 Data Points — 3 Inclusions & Exclusions — 4 Results

Literature Review - Results (98)

Publication Date (Descending) | CSV

ARTICLE	MEDICATIONS	ADE	TESTS	PATIENT AGE	DEMOGRAPHICS	DIAGNOSES	OUTCOMES	INTERVENTION	SYMPTOMS	GENDER
Hypoparathyroidism Revealed by Unsuccessful Anti-epileptic Therapy. Raja Arrab, et al. · Case Reports Cureus 2024 · N/A · PubMed · Full Article	oral valproate	N/A	serum phosphocalcic test	13	female	hypoparathyroidism, epilepsy	corrected diagnosis	oral valproate therapy	cerebral calcifications, metabolic disorders, hypocalcemia	female
Epileptic Seizures in a Pediatric Patient With Vein of Galen Aneurysmal Malformation and Obstructive Hydrocephalus: A Rare Case Report. Kiril Ivanov, et al. · Case Reports Cureus 2024 · N/A · PubMed · Full Article	valproate	N/A	MRI, MR-angiography, ventriculostomy	6	male	Vein of Galen aneurysmal malformation, Obstructive hydrocephalus, Epilepsy	no further seizures	partial transarterial endovascular embolization, ventriculostomy	severe status epilepticus	male
Valproate-induced hyperammonemia, neuroleptic sensitivity, and cerebellar atrophy-A clinical conundrum in the management of bipolar disorder. Samarth S Shetty, et al. · Case Reports Bipolar disorders 2024 · N/A · PubMed	valproate, lithium, electroconvulsive therapy (ECT)	catatonia, seizures, hyperammonemia, essential tremors	N/A	N/A	male, male	bipolar disorder, intellectual development disorder	stability, symptom improvement	electroconvulsive therapy (ECT), tailored medication regimen	catatonia, seizures, hyperammonemia, essential tremors	male
Irregular Tremulous Movements and Infrequent Seizures: A Clinical-Electrophysiological Diagnosis of Benign Adult Familial Myoclonus Epilepsy. Kazuki Imon, et al. · Case Reports Cureus	valproic acid, perampanel	N/A	video EEG, brain MRI, somatosensory evoked potentials (SEP)	31	male	benign adult familial myoclonus epilepsy	significant reduction of symptoms	valproic acid and perampanel	involuntary finger movements, rare seizures	male

Clinical Guidelines Agent

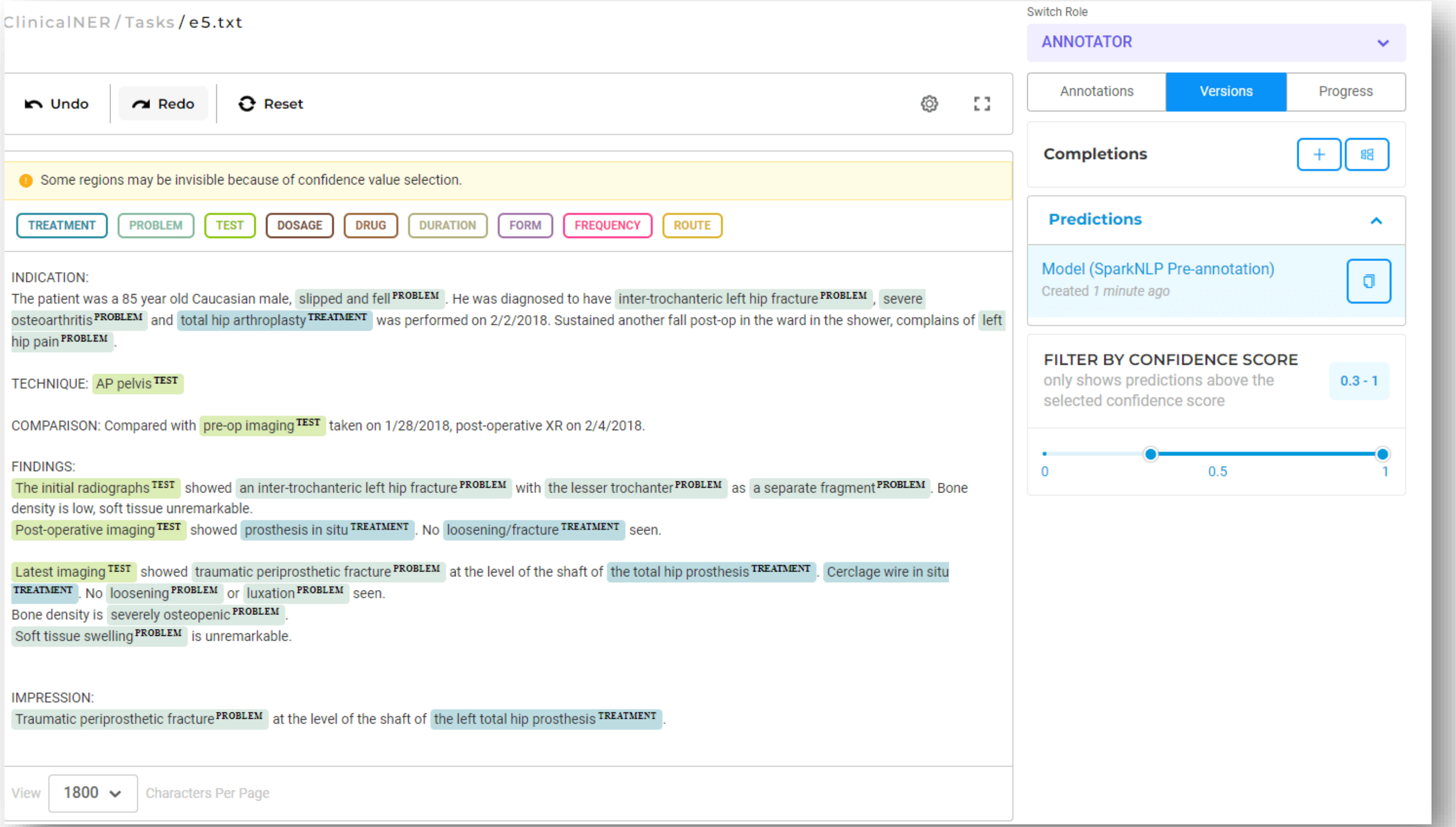


The Generative AI Lab

The No-Code NLP Platform:

- Annotate Text & Images
- AI Assisted Annotation
- Train & Tune Models
- Models, Rules, and Prompts Hub
- Manage Projects & Teams
- Enterprise Security & Privacy

The Generative AI Lab:
Building Small, Task-Specific Language Models



The "Old School" Use Case:

Define the task for a new model

Import documents to Annotate

AI-Assisted Pre-Annotation

Manual work by domain experts

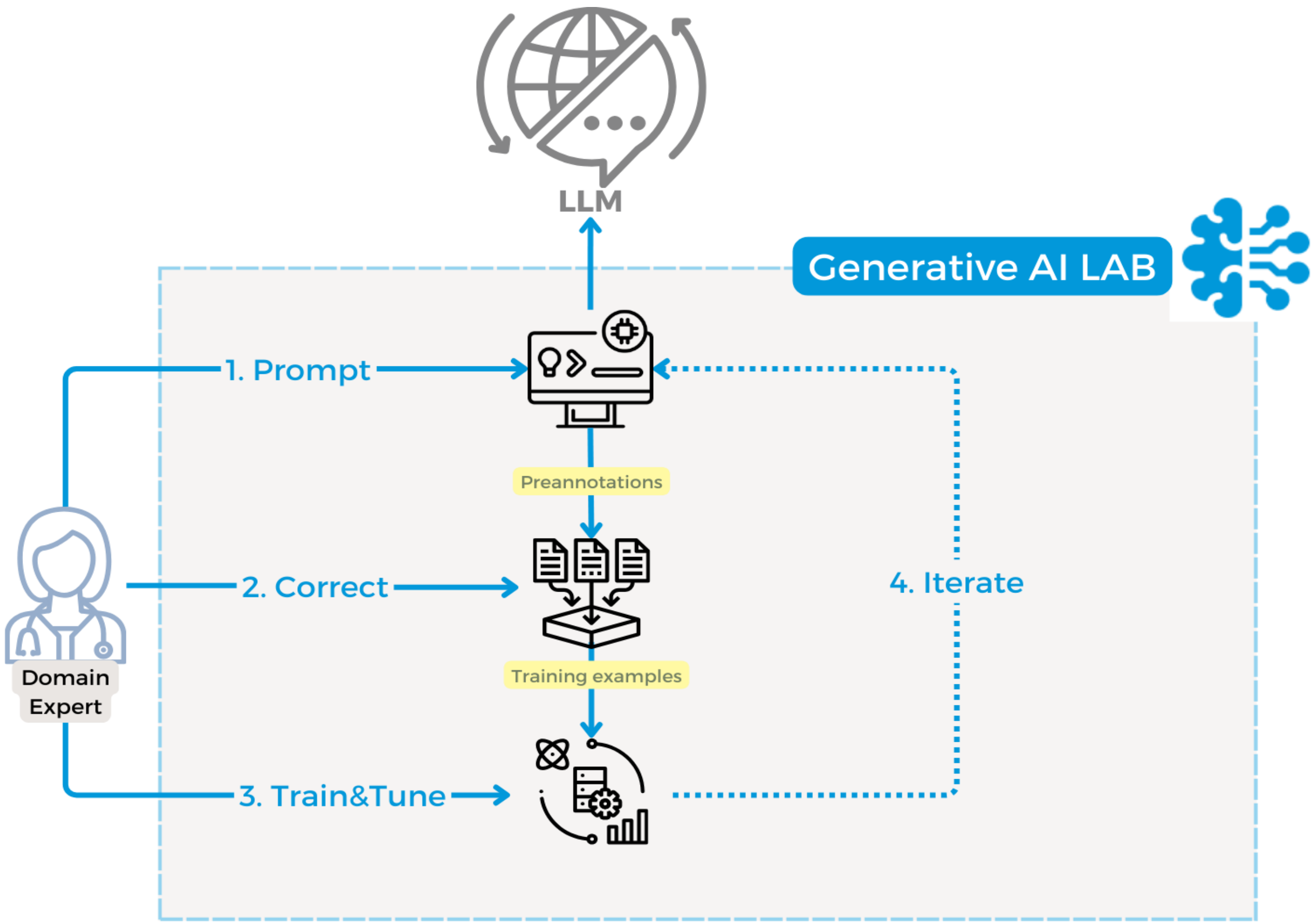
Train or tune a language model

Export the model or the data

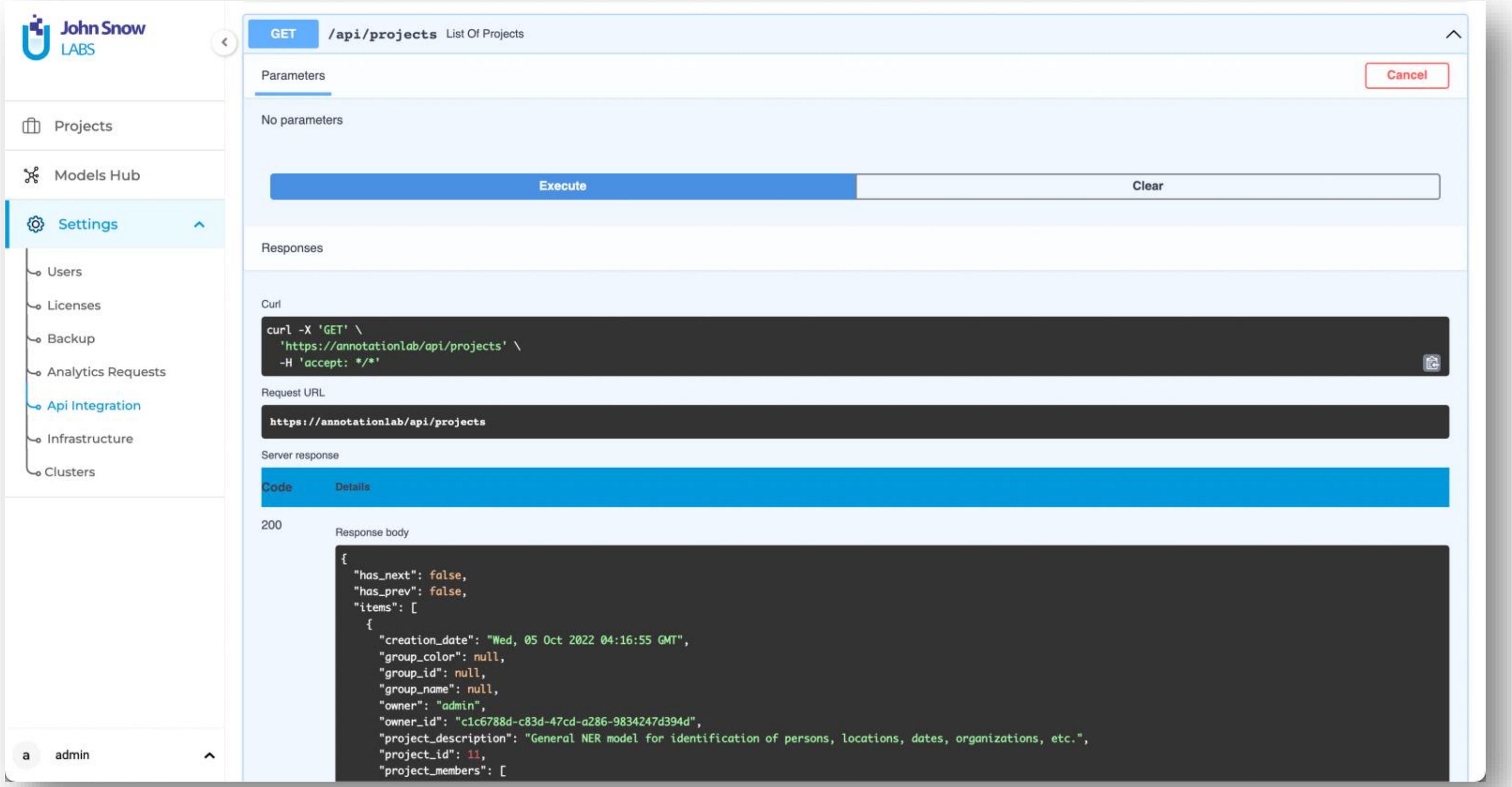
Generative AI Lab Use Cases

1. **Use LLMs to bootstrap task-specific models**
2. **Human-in-the-loop workflows to validate LLMs when regulatory-grade accuracy is required**
3. **Organize and share models, prompts, and rules within one private enterprise hub**

From LLMs to task specific AI Models



Building Enterprise-Grade Human-in-the-Loop Pipelines



Versioning Human & AI Work

Full Audit Trails

Custom Approval Workflows

API Integration

Authentication & Authorization

Private On-Premise Deployment

Scale to Large Teams & Projects

Spark NLP

Open-Source Language Understanding at Scale

140+ million	60% growth	8 years
Downloads on PyPI. "Most Widely Used NLP Library in the Enterprise."	In Spark NLP downloads since the 5.0 release for RAG & LLM pipelines	Straight with frequent releases & upgrades

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Spark NLP

Apache 2.0 license

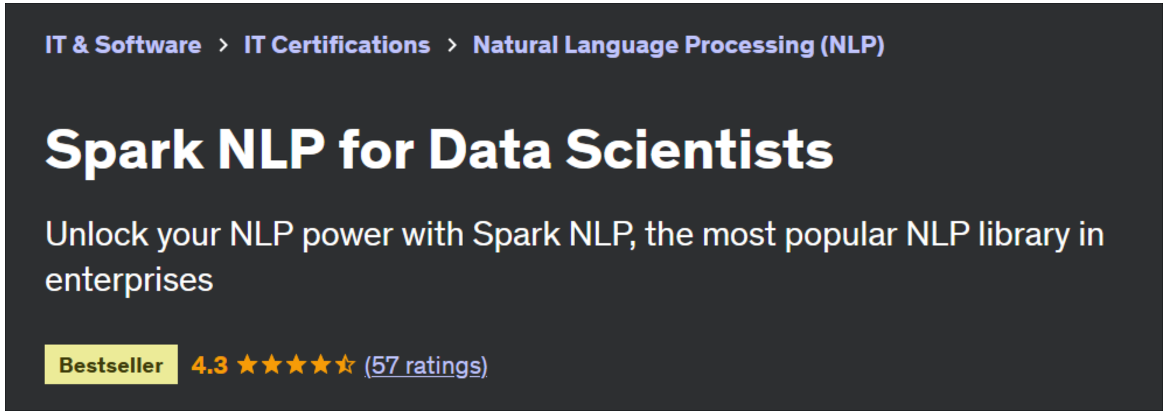
Documentation:
www.sparknlp.org

Community:
spark-nlp.slack.com

Own Curated Model Hub:
www.sparknlp.org/models

Optimized, Tested, Supported Integrations

jupyter
ANACONDA
kubernetes
APACHE Spark
docker
Google colab
CLOUDERA
oneAPI
Cloud Dataproc
intel
databricks
Amazon SageMaker
comet
amazon EMR
mlflow
kaggle
Google Cloud
Microsoft Azure
NVIDIA
Synapse ML
Simple and Distributed Machine Learning



Spark NLP: Built for Scale

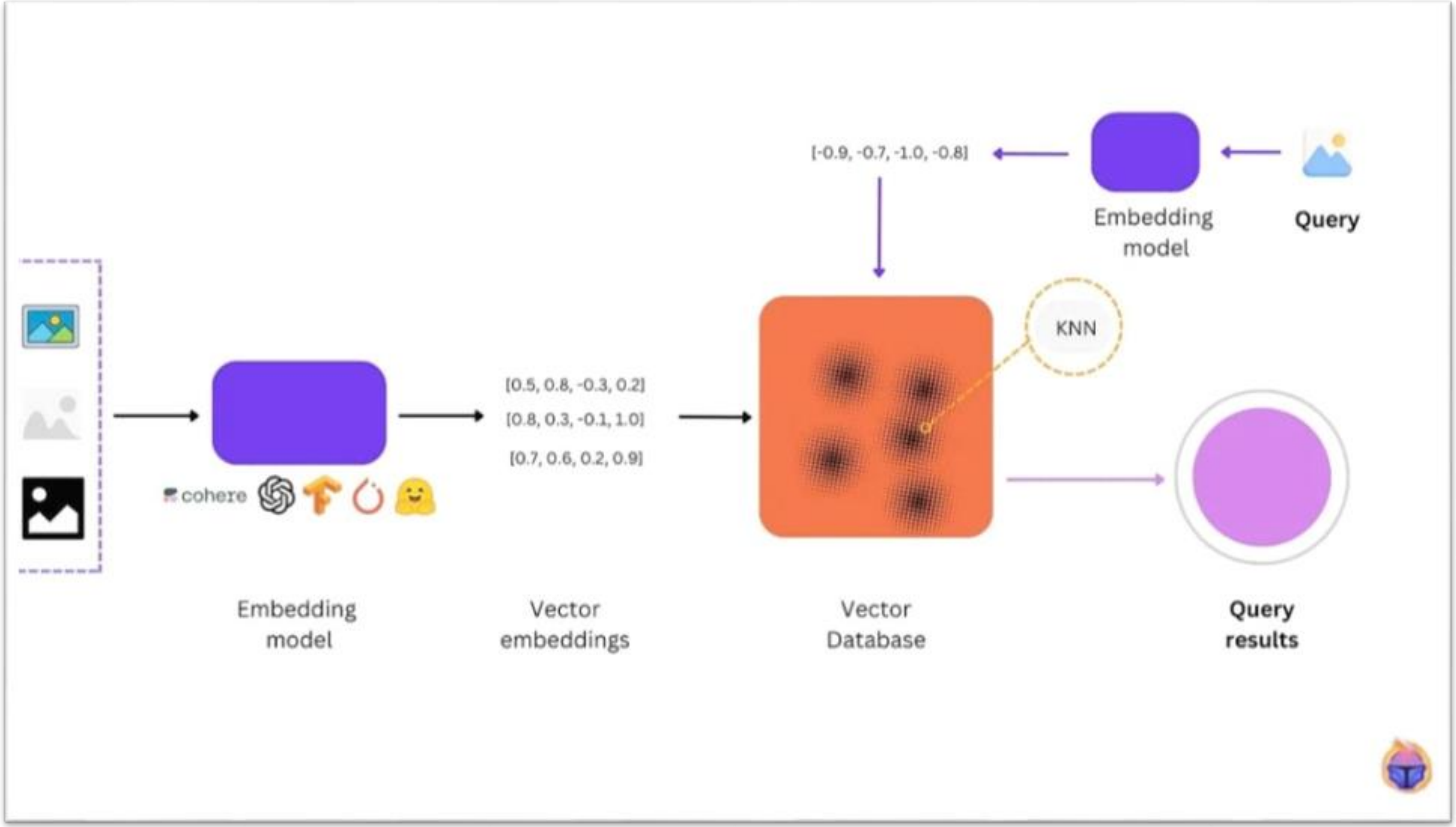
Compose multiple language models into custom pipelines

Natively scalable:
Extends the Spark ML Pipeline

Speed Optimized:
Builds for Intel, Nvidia, Apple

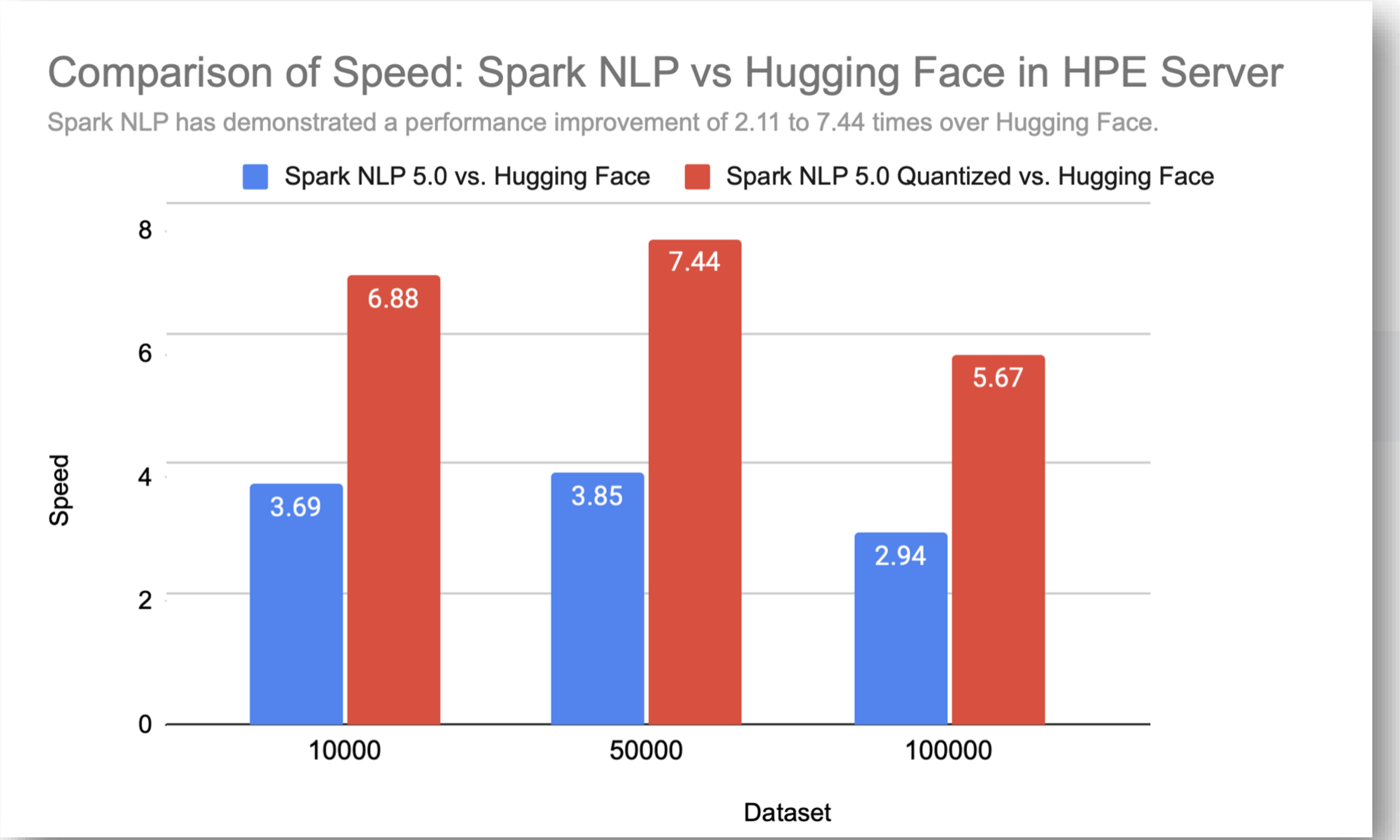
Own optimized codebase

RAG LLM Use Case: Populate a Vector Database



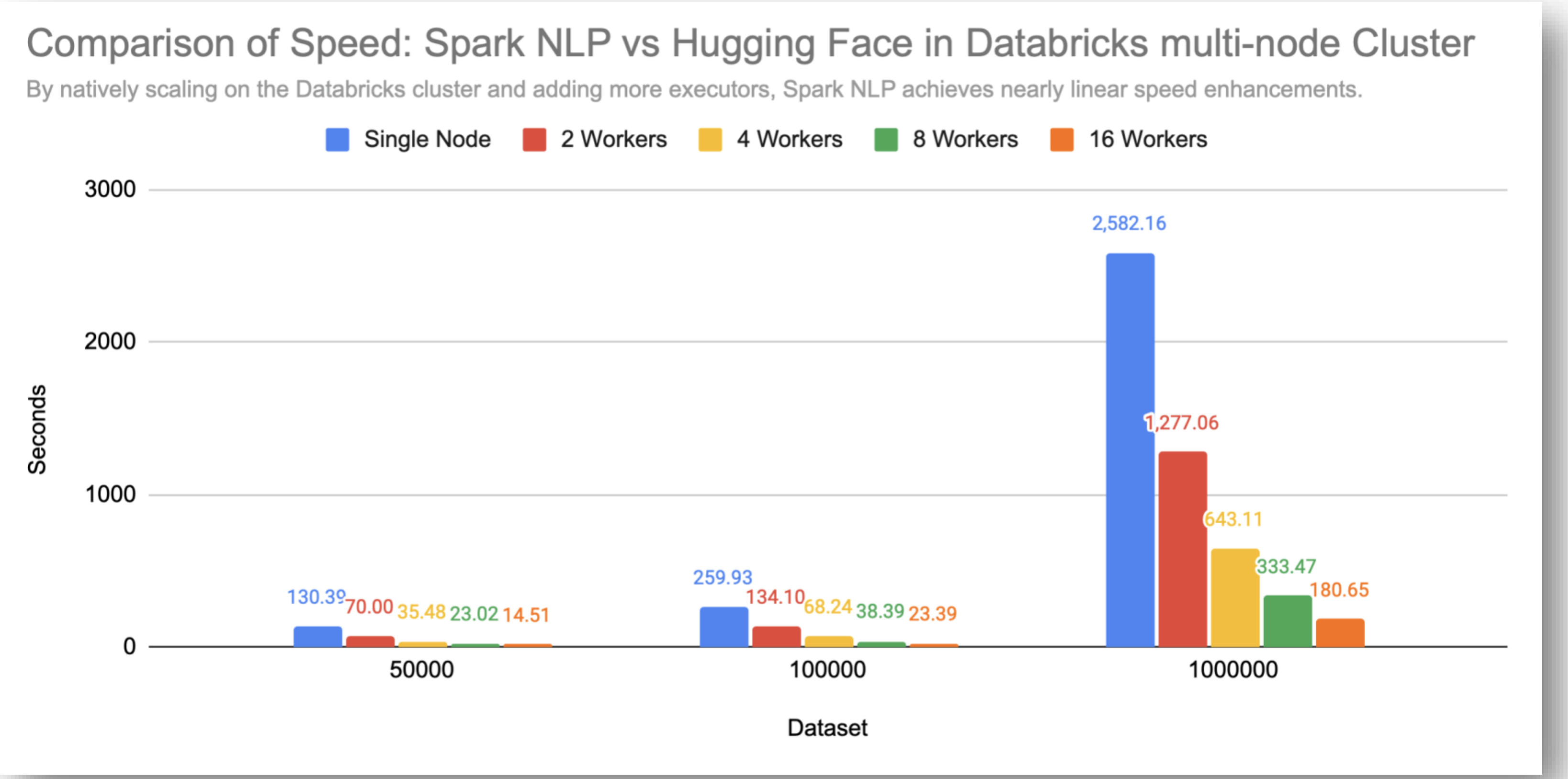
Calculate Embeddings 3x-7x Faster Than Hugging Face on a Single Server

- HPE Server:
  - AMD EPYC 7542 32-Core Processor
  - 80G memory
- Spark NLP based on Onyx Runtime vs. Hugging Face based on PyTorch



Scale Up With Zero Code Changes

- Databricks Single Node Cluster
  - 13.0 ML (includes Apache Spark 3.4.0, Scala 2.12)
  - c6i.8xlarge
  - 32 Cores
  - 64 GB Memory
- By natively scaling on the Databricks cluster and adding more executors, Spark NLP 5 achieves near-linear speedup.



Processing of 1,000,000 records was reduced
from 43 hours to 3 minutes with zero code changes

LLM Inference Use Case:
What if my text processing pipelines needs an LLM?

```
data = spark.createDataFrame([
    ("Is coffee consumption linked to improved cognitive function?",),
    ("What are the implications of quantum computing on data security?",),
    ("Describe the process of photosynthesis in plants.",),
    ("Can renewable energy effectively replace fossil fuels globally by 2040?",),
    ("What is the role of artificial intelligence in healthcare?",),
    ("How does the stock market influence the global economy?",),
    ("Explain the theory behind black holes and event horizons.",),
    ("What are the long-term effects of climate change on coastal ecosystems?",),
    ("Discuss the impact of virtual reality technology on education.",),
    ("What measures can be taken to reduce urban air pollution effectively?",)
], ["text"])
```

Question Answering, Text Generation, Summarization, Translation, Extraction

In Spark NLP, an LLM is just another pipeline step

- Distribute LLM inference on your hardware
- Tens of thousands of curated GGUF models
- Native integration with Llama.cpp
- Optimized builds for:
  - Intel processors
  - Nvidia CUDA GPUs
  - Apple Silicon chips

```
from sparknlp.annotator import *
from sparknlp.base import *

data = (spark.createDataFrame([["""<|start_header_id|>user<|end_header_id|>

Make a coherent and concise summary:\n\n

There are only two movies I would give a 1/10 to, this stinker and "The Man who Fell to
Earth." I remember seeing Protocol at a theater in the early 80s when I was in high
school. ...<|eot_id|>

<|start_header_id|>assistant<|end_header_id|>

"""]]).toDF("text"))

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

gguf_model = (
    AutoGGUFModel.pretrained("Meta-Llama-3.1-8B-Instruct.Q4_K_M")
    .setInputCols("document")
    .setOutputCol("completions")
    .setBatchSize(2)
    .setNPredict(400)
    .setNGpuLayers(99)
    .setTemperature(0.4)
    .setTopK(40)
    .setTopP(0.9)
    .setPenalizeNl(True)
)

pipeline = Pipeline().setStages([
  document_assembler,
  gguf_model
])

results = pipeline.fit(data).transform(data)
results.select("completions").show(truncate=False)
```

Unified Pipelines: Combining Medical LLM & NLP Models

NER with JSL pretrained model for ADE (BioBERT based) → Assertion assignment with model trained on 500+ MD notes. → For each sentence with a positive ADE, add the following pair of sentences → Locally deployed LLM model used to identify the ADE and related drugs if any.

Previous attachment

Example of True Negative relation:

- She continues to tolerate treatment with crizotinib well. She does have continued diarrhea with 4 to 5/day and some shortness of breath.

Example of True Positive relation:

- Pt was started on Alectinib in October; developed worsening bradycardia with HR decreasing to the mid 30's.

Based on annotation on 140 sampled sentence groups, the evaluation resulted a F1 score of 0.93
(recall: 0.95, precision 0.91)

AI-Enhanced Oncology Data: Unlocking Insights from EHRs with NLP and LLMs

Scott Newman – Senior VP, Life Sciences at MiBA
Zach Liu – Senior Research Scientist at MiBA

Visual NLP

Form understanding	Object Character Recognition	Table detection & extraction	Noisy image enhancement
Visual document classification	Visual entity recognition	Signature detection	Image de-identification

Read	Enhance		Recognize	Extract	Generate
Text or PDF	Binarizer	Adaptive scaler	Regions	Text from Images (OCR)	Extracted text & layout (HOCR)
Scanned PDF	Adaptive Tresholding	Noise Scorer	Tables	Data from Tables (CV)	Structured data tables
DOCX	Erosion	Remove objects	Signatures	Named Entities from Forms	Highlighted named entities
Image	Skew corrections	Morphology opening	Dates	De-identification	De-identified text, PDF, or DICOM
DICOM	Scaler	Cropper	Brands	Visual Document Classification	Bounding boxes & coordinates

300+ live demos & Python notebooks:

nlp.johnsnowlabs.com/demos

Peer-reviewed papers:

johnsnowlabs.com/peer-reviewed-papers/

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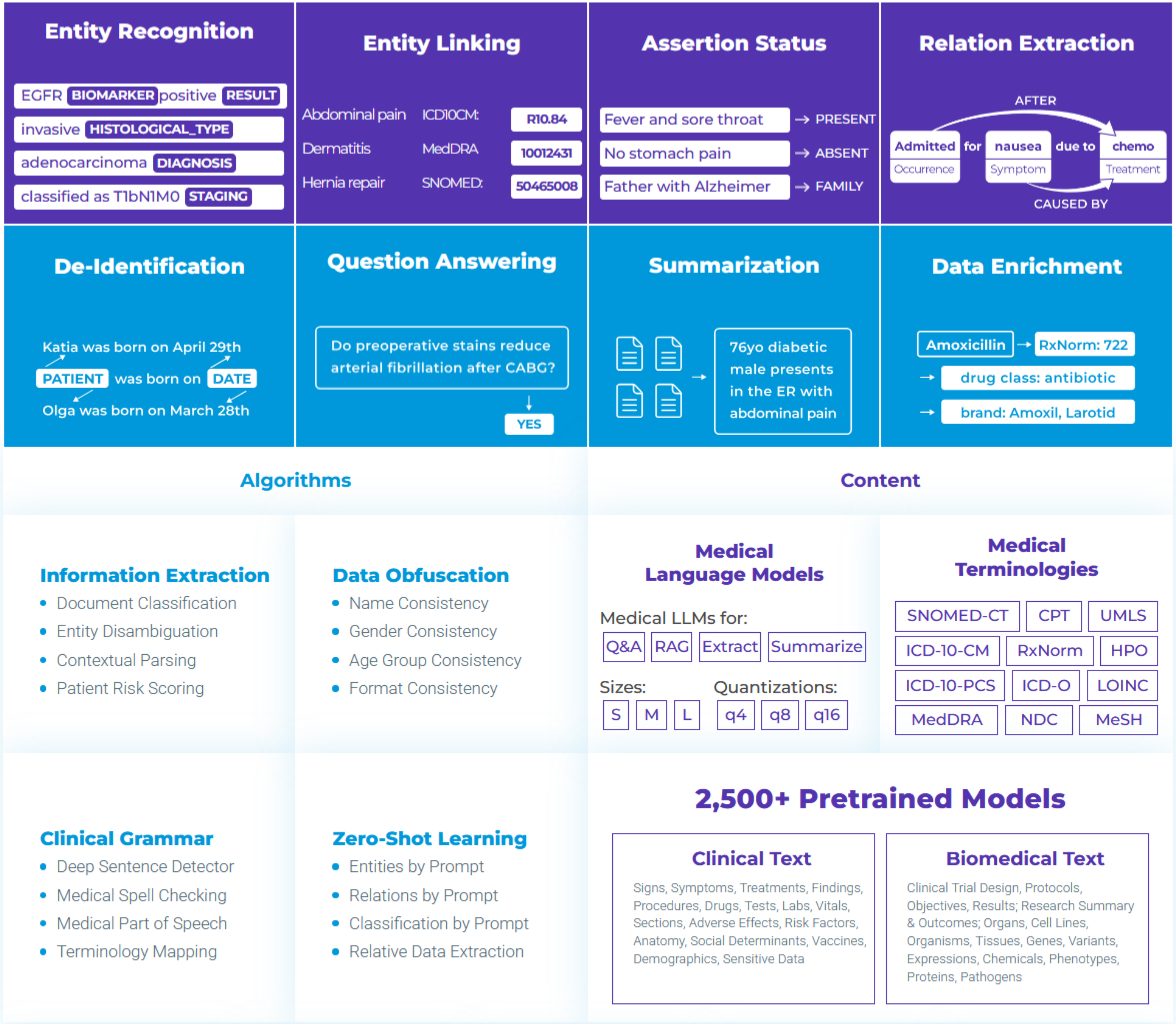


Healthcare NLP

3 tasks where LLMs underperform:

Information Extraction

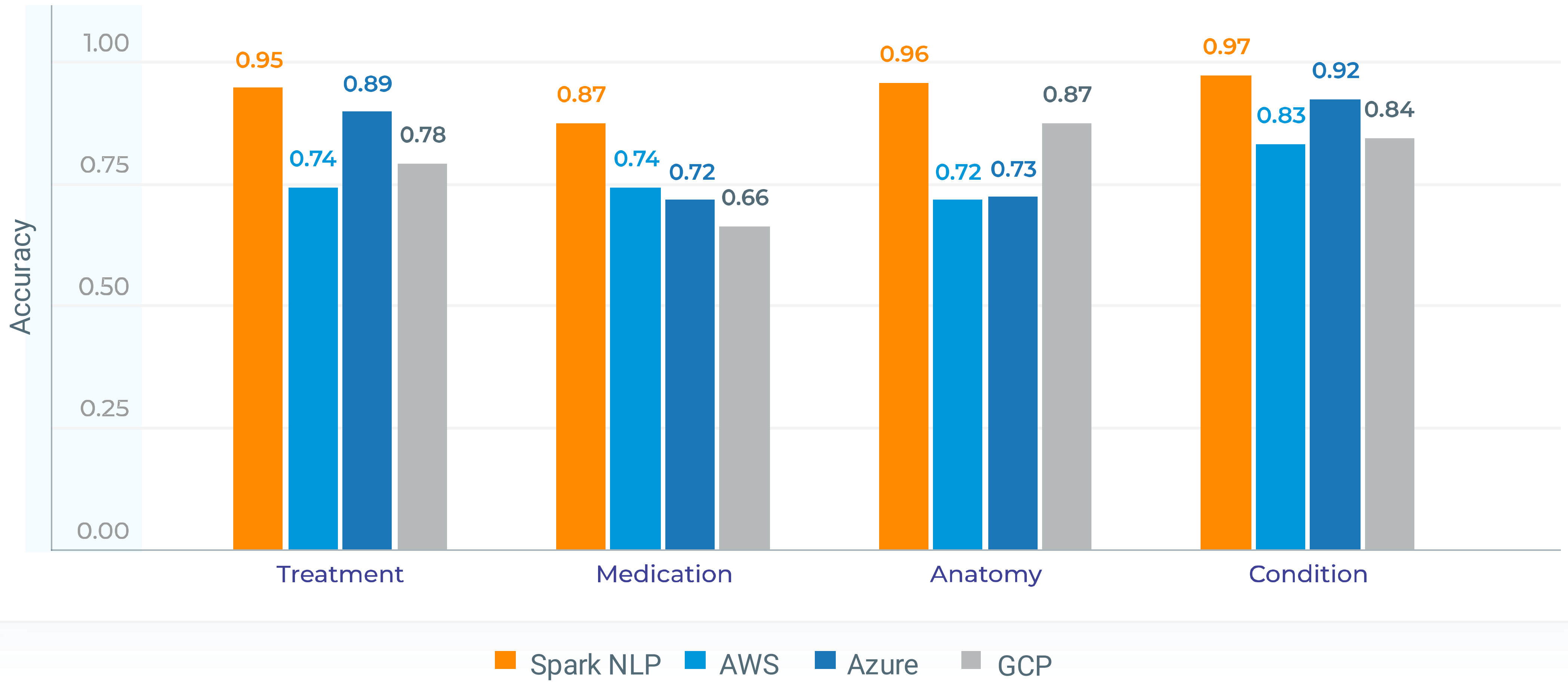
De-Identification

Mapping Terms to Codes

April 2022

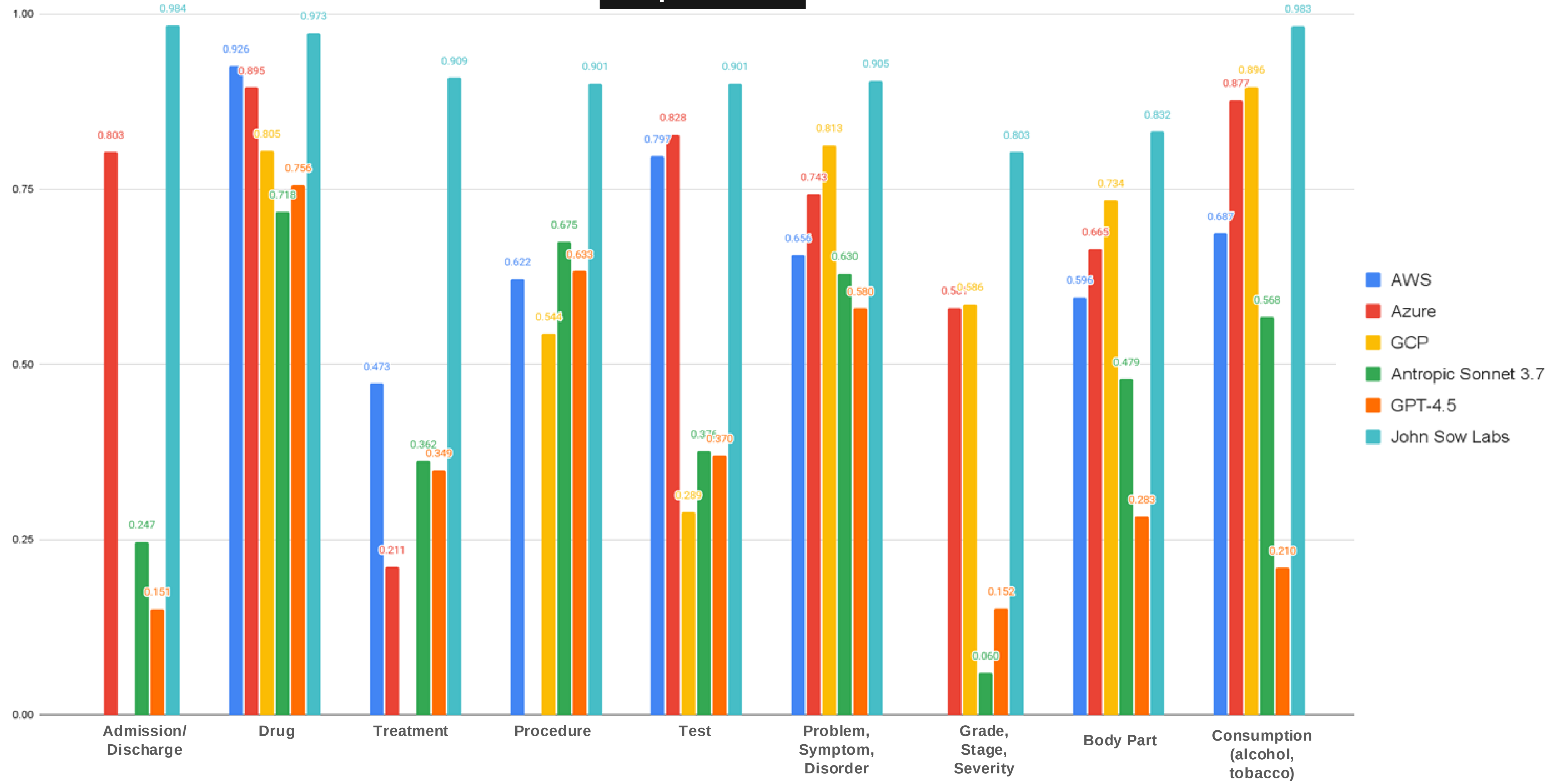
4-6x Fewer Errors than AWS, Azure, & GCP

www.johnsnowlabs.com/comparison-of-key-medical-nlp-benchmarks-spark-nlp-vs-aws-google-cloud-and-azure/



John Snow Labs vs Cloud & Frontier Models on Entity Recognition

April 2025



Clinical Text De-Identification of PHI Data

Healthcare NLP, Azure, Amazon, GPT-4o, and Claude 3.7 Sonnet PHI Recognition and Benchmark Comparison (Sample size: 45172 PHI entities).

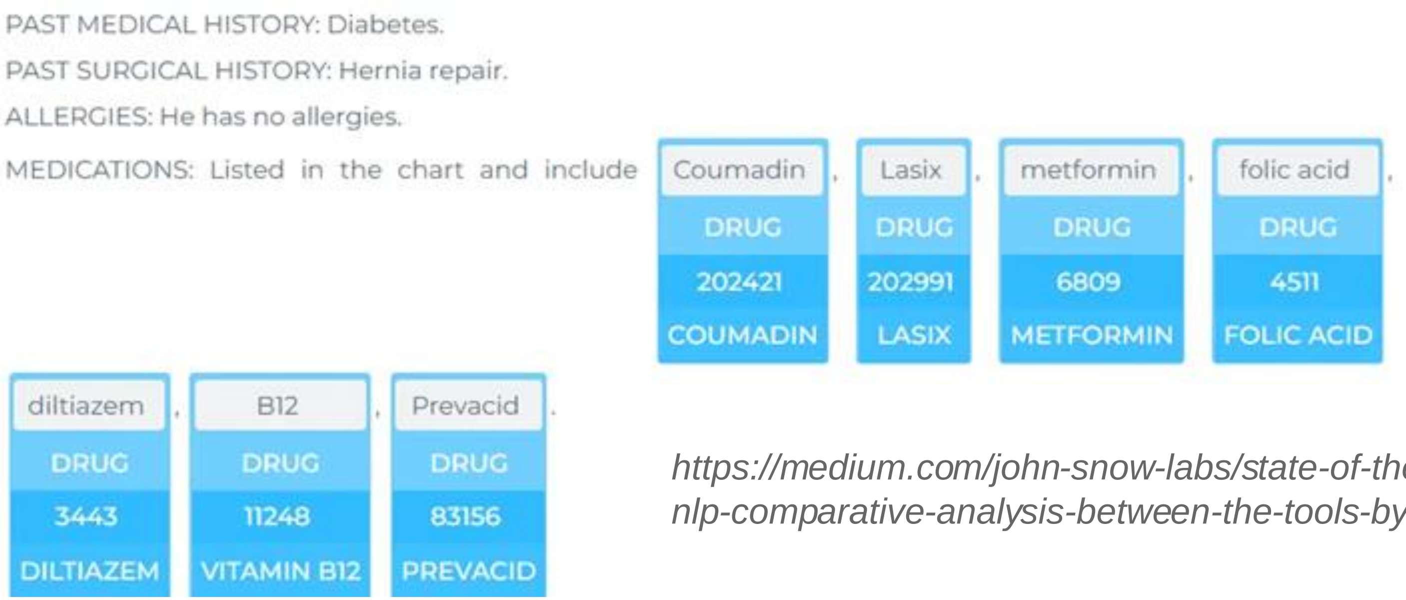
Metric / Entity	Healthcare NLP			Azure			Amazon			GPT-4o			Claude 3.7 Sonnet		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
AGE	0.96	1.00	**0.98**	0.94	0.45	0.61	1.00	0.41	0.58	0.87	0.50	0.64	0.73	0.55	0.63
CONTACT	0.96	0.97	**0.97**	0.73	0.88	0.80	0.78	0.72	0.75	0.67	0.53	0.59	0.74	0.43	0.54
DATE	0.97	0.99	**0.98**	0.91	0.99	0.95	0.90	0.97	0.93	0.79	0.72	0.75	0.84	0.83	0.83
IDNUM	0.98	0.94	**0.96**	0.78	0.93	0.85	0.95	0.86	0.91	0.70	0.92	0.80	0.70	0.95	0.80
LOCATION	0.93	0.92	**0.93**	0.89	0.87	0.88	0.52	0.74	0.61	0.82	0.72	0.76	0.79	0.87	0.83
NAME	0.92	0.94	**0.93**	0.92	0.89	0.90	0.85	0.76	0.80	0.79	0.82	0.80	0.82	0.86	0.84
O	1.00	1.00	**1.00**	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Macro Avg	0.96	0.97	**0.96**	0.88	0.86	0.85	0.86	0.78	0.80	0.80	0.74	0.76	0.80	0.78	0.78
Non-PHI	1.00	1.00	**1.00**	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
PHI	0.96	0.97	**0.96**	0.91	0.92	0.91	0.81	0.85	0.83	0.81	0.77	0.79	0.81	0.84	0.83
Macro Avg	0.98	0.98	**0.98**	0.95	0.96	0.95	0.90	0.92	0.91	0.90	0.88	0.89	0.90	0.92	0.91
cost per 1M doc	**$2,418**			$13,125			$14,525			$21,400			$23,330		

[Submitted on 21 Mar 2025 (v1), last revised 31 Mar 2025 (this version, v2)]

Can Zero-Shot Commercial APIs Deliver Regulatory-Grade Clinical Text DeIdentification?

Veysel Kocaman, Muhammed Santas, Yigit Gul, Mehmet Butgul, David Talby

RxNorm Entity Resolution Benchmarks



https://medium.com/john-snow-labs/state-of-the-art-rxnorm-code-mapping-with-nlp-comparative-analysis-between-the-tools-by-john-snow-794b353dc38e

	Top-3 Accuracy	Top-5 Accuracy	Cost
Healthcare NLP	82.7%	84.6%	$4,500
Amazon Comprehend Medical	55.8%	56.2%	$24,250
GPT-4 (Turbo)	8.9%	8.9%	$44,000
GPT-4o	8.9%	8.9%	$22,000

Medical Language Models Workshop Outline

Clinical Data Abstraction	Patient Risk Adjustment	Summarization and Q&A
Text De-Identification	DICOM De-Identification	Terminology Server

How to Get The Most from This Training

1. Try the libraries and tools hands-on
2. Ask questions
3. Learn how the tools apply to use cases: www.johnsnowlabs.com/customers

Thank you!