Tac-Know™
Lab Assistant

A Novel Low-cost LLM Agentic Framework for Tacit Knowledge Capture

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John Conway

David Hessler

[Previously called PythiaAI Lab Assistant]

Tacit knowledge

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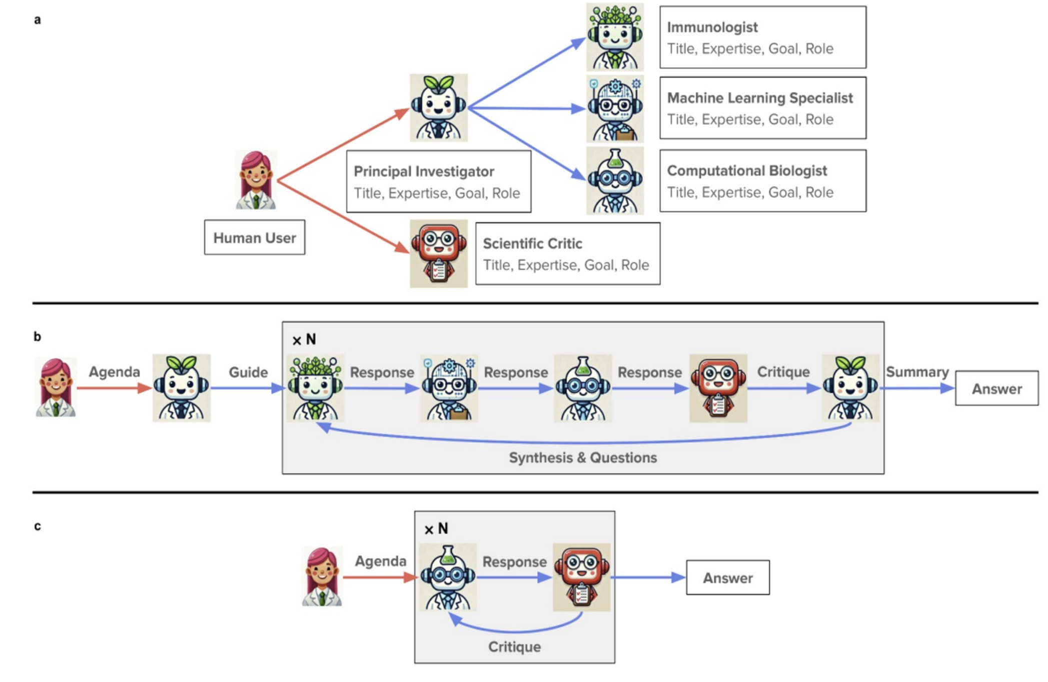
The knowledge we don’t write down

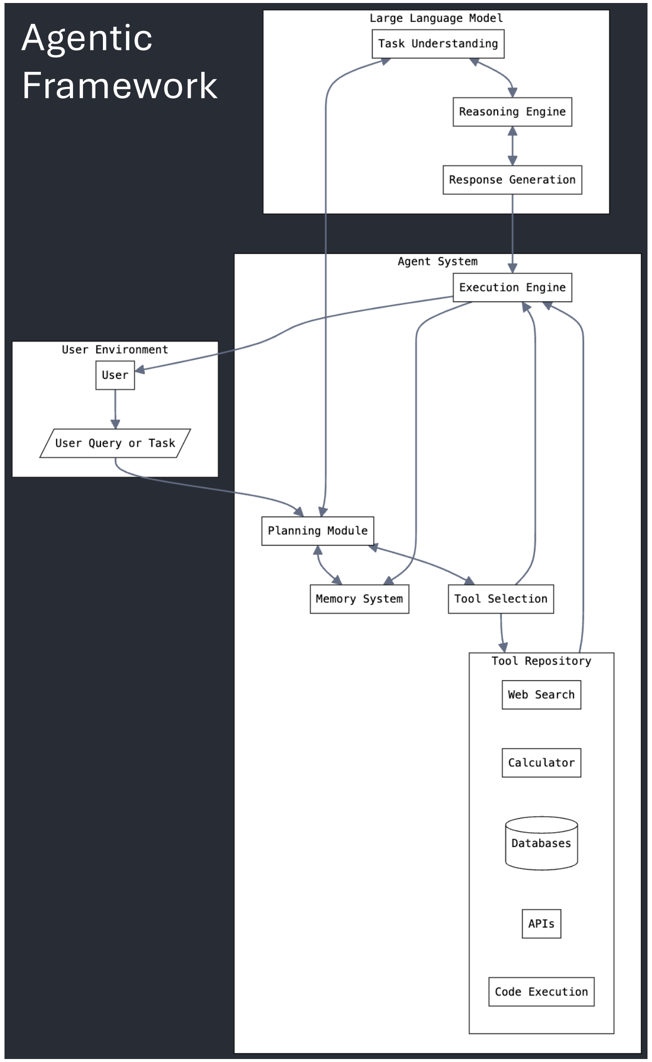
- LLMs and Agents
- LabVoice Digital Assistant
- Tac-Know Lab Assistant

LLMs and Agents

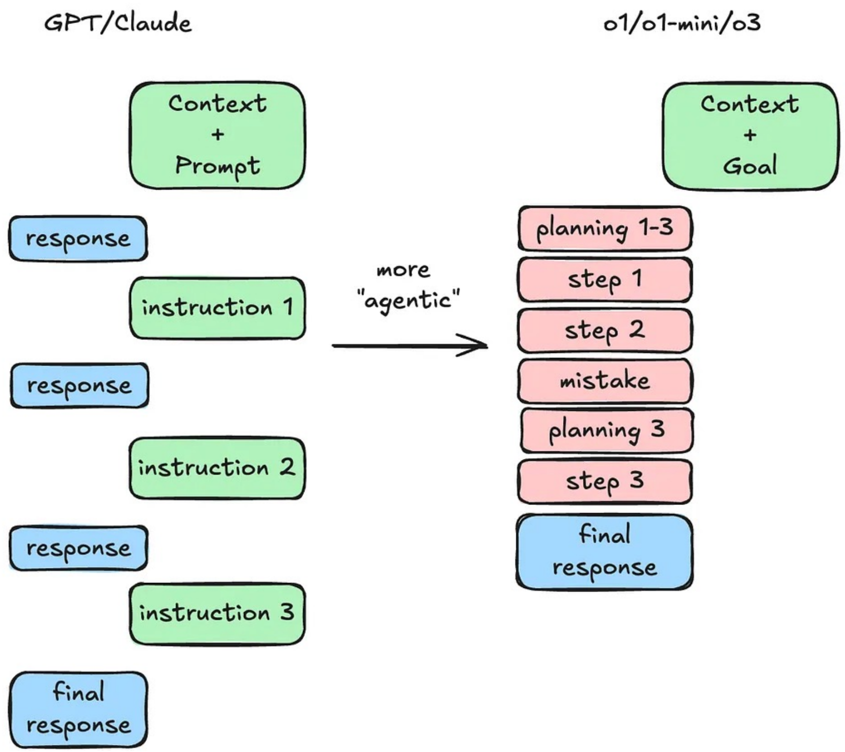
LLM & Agents are cool



The Virtual Lab: AI Agents Design New SARS-CoV-2 Nanobodies with Experimental Validation
https://www.biorxiv.org/content/10.1101/2024.11.11.623004v1

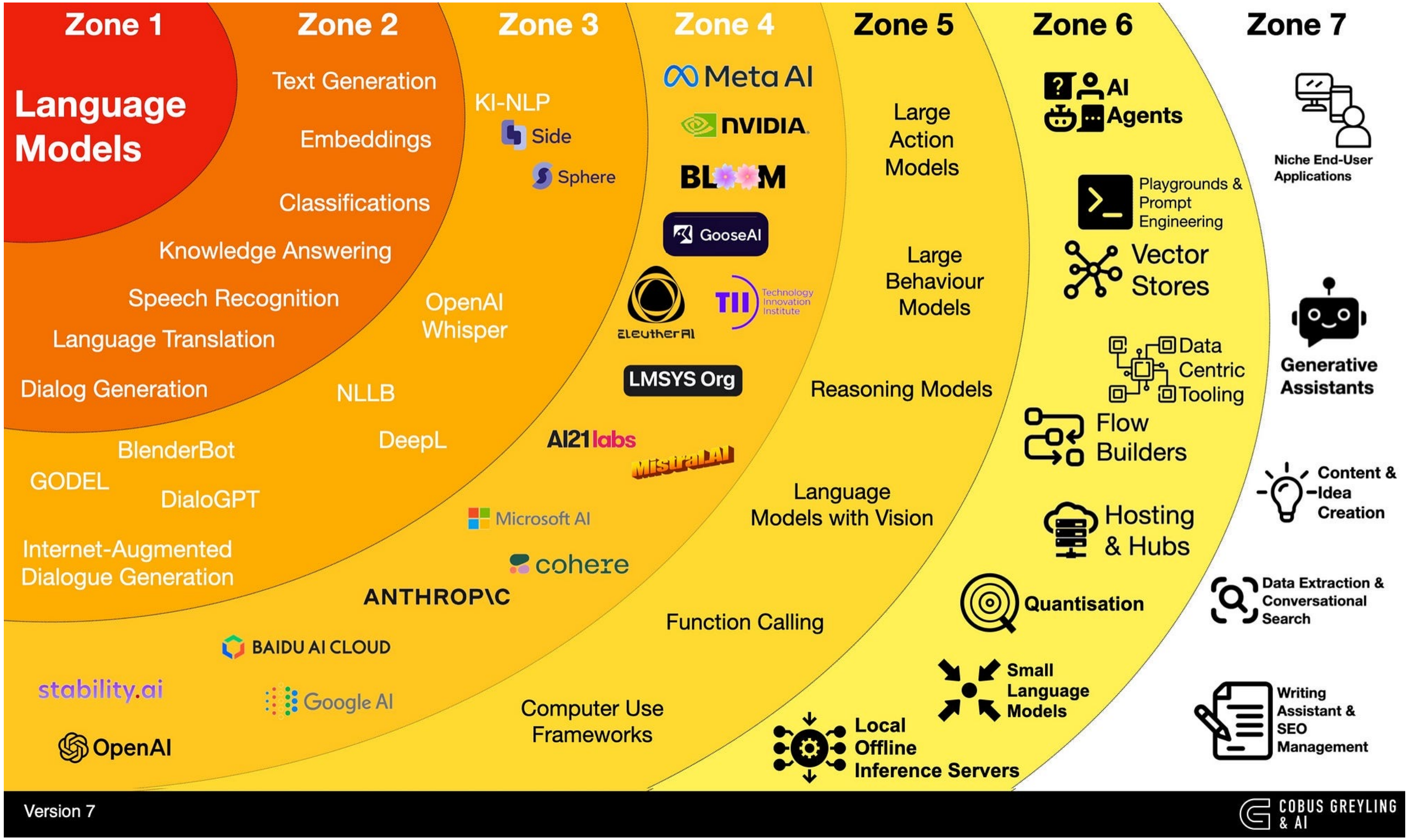


LLM themselves are becoming agentic



https://www.latent.space/p/o1-skill-issue

Lots going on here ...



COMPARISION: Core Characteristics and Relationships

Aspect	Artificial Intelligence (AI)	Natural Language Processing (NLP)	Large Language Models (LLMs)
Definition	The broader field of creating systems that can simulate intelligent behavior	A subfield of AI focused on enabling computers to understand and process human language	Neural network architectures specifically designed to process and generate human language at scale
Scope	Encompasses all forms of machine intelligence, including vision, robotics, expert systems, and decision-making	Focuses specifically on computational linguistics and language-related tasks	Specializes in language understanding and generation using transformer-based architectures
Historical Development	Emerged in the 1950s with early computing; evolved through symbolic AI, expert systems, and machine learning	Developed in the 1960s, initially rule-based, then statistical, now neural-based	Emerged in 2017 with the transformer architecture; rapid evolution through BERT, GPT series, etc.
Key Technologies	Includes machine learning, neural networks, expert systems, genetic algorithms, and robotics	Includes tokenization, parsing, word embeddings, and various ML algorithms	Primarily based on transformer architecture with self-attention mechanisms
Primary Applications	Autonomous systems, game playing, pattern recognition, problem solving, and general intelligence tasks	Language translation, sentiment analysis, text classification, information extraction	Text generation, conversation, code writing, creative tasks, and complex reasoning
Data Requirements	Varies by application; can use structured or unstructured data	Typically requires annotated linguistic data and text corpora	Requires massive amounts of text data for pre-training
Processing Approach	Can be rule-based, statistical, or neural, depending on the application	Combines linguistic rules with statistical and neural methods	Primarily neural, using attention mechanisms and deep learning
Strengths	Versatile problem-solving capabilities across domains	Specialized language understanding and task-specific performance	Powerful language generation and transfer learning abilities
Limitations	May struggle with common-sense reasoning and generalization	Can be brittle and domain-specific	Resource-intensive, potential for bias, lack of true understanding
Relationship to Others	Parent field encompassing both NLP and LLMs	Broader field that includes LLMs as one implementation approach	Specialized implementation that advances both AI and NLP goals

COMPARISON: Key Differentiating Features

Feature	AI	NLP	LLMs
Learning Approach	Multiple paradigms (supervised, unsupervised, reinforcement)	Often task-specific supervised learning	Primarily self-supervised pre-training with optional fine-tuning
Scale	Varies by application	Typically moderate-scale models	Extremely large-scale models with billions/trillions of parameters
Resource Requirements	Varies widely	Moderate computing resources	Substantial computing resources for training and inference
Interpretability	Varies by method; some highly interpretable	Often provides linguistic interpretability	Generally black-box with limited interpretability
Real-world Integration	Widely deployed in specific applications	Common in specialized language tasks	Increasingly deployed as general-purpose tools

Pragmatic guidelines to building LLM systems

LLM systems are made up of LLM models (for example, OpenAI and Claude) and software frameworks (for example, Autogen Studio, HuggingFace smolagents, Pydantic AI, Langgraph). Both these technology types are evolving rapidly, with multiple offerings.

Any system you select needs to be adaptable to technology changes, for example if an effective drug discovery LLM model is offered as open-source next year.

In addition to a rapidly evolving technology landscape, it is important to understand the changing balance between commercial and open-source offerings.

As with other industries, these words of wisdom stand (relatively) true: “**Wait a year, and someone will offer it for free!**” It is important to be agile and respond to changes in this balance.

Your LLM system may need to support both research-intensive activities, such as extracting new insights from large amounts of (.pdf) research publications, and workflow-driven tasks, such as designing a lab experiment.

These are different problems that need to be solved with different approaches. A useful tip here is to **design your system with a human performing the proposed LLM functions, and then swap the LLM technology in for the human once the design is ready.**

Pragmatic guidelines to building LLM systems (con't)

Model Options

PRINCIPLE: Use affordable models if you can. Life sciences info is heavily-typed, and your efforts should be on prompts and prompt chains to get the most out of the workflow.

- Full function APIs: GPT4o / o1 and Claude 3.5 Sonnet are the go-to places, but can be expensive.
- Lesser function APIs: OpenAI and Anthropic offer older models at cheaper costs, but my preference is to go to open-source models through low-cost services such as GROQ CLOUD. For example, Llama3.3:70b is a great model.
- Local models: Ollama is great.   It offers numerous native models as well as running GGUF files available on HuggingFace. There is a lot you can do with smaller models, e.g. Phi4 (14b) and Llama3.1 (8b).

Agentic Frameworks

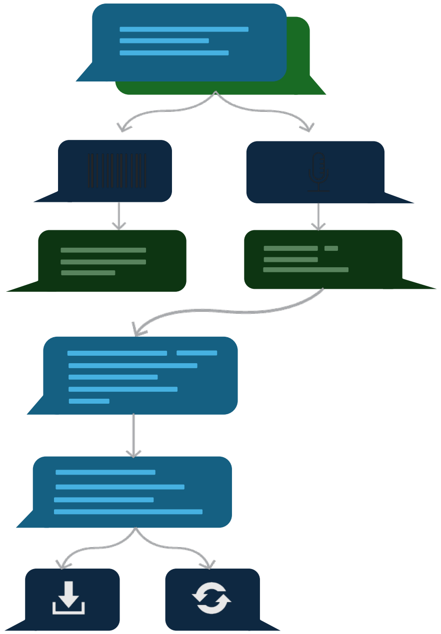
PRINCIPLE: Be wary of black-box frameworks with 100ks of code in them. You need to know (roughly) what is going on, otherwise everything breaks when you try and scale.

- Cloud providers offer them and there are several open-source. For example, within Bedrock in AWS.
- My favorite is Pydantic-AI as it is open-source, light-weight, and a natural extension of Pydantic (which many of us already use in our coding). Also, it support numerous model providers.


LabVoice
Digital Assistant
For more info: https://tinyurl.com/slas2025labvoice

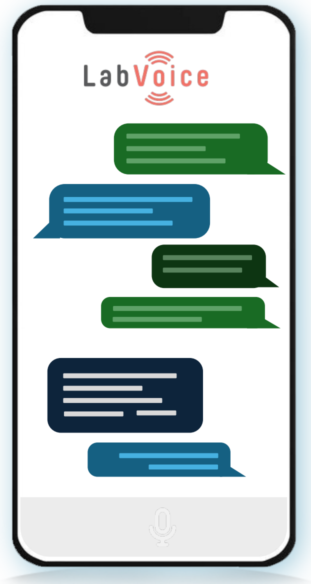
An AI-Powered Platform to Optimize Lab Processes

Model



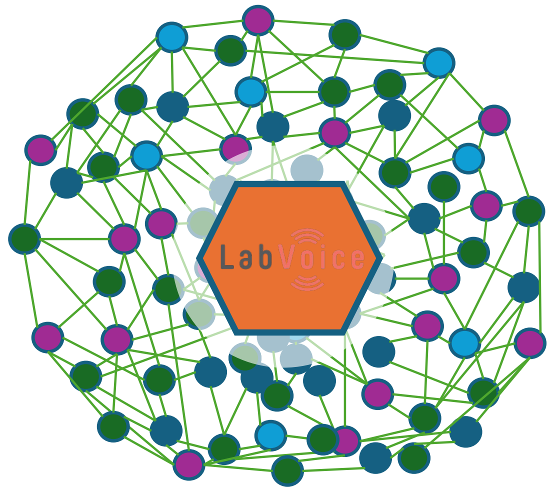
Model your lab workflows with a no-code visual designer

Execute



A scientific digital assistant to guide processes & collect data

Optimize



Metrics to improve & enhance lab processes

Breadth of Uses

LabVoice

Lab Animal Science

- Animal Injection Records
- Cage Checks
- Necropsy Reports
- Tumor Measurements
- Dosing Records
- in vivo Software Integration
- RapID Tag Scanning
- Birth Check
- PK Dosing
- Animal Measurements
- Census
- Time-in-Motion Studies

Sample & Compound Management

- Sample Lookup
- Manual Sample Picking
- Inventory Integrations
- Sample Accessioning
- Robotics/Instr. Voice Control
- Manifest/Order Check
- ELN Sample Characterization
- Container Data Lookup
- Create Container
- Dissolution & Transfers

Routine Labwork

- Assay Results Collection
- ELN Material Weighing
- Pipetting
- Dilution Calculations
- Analytical Testing
- Direct Excel / ELN Entry
- ELN Experiment Creation
- Solution/Buffer Prep
- Cell Counting
- Cell Transduction
- Ordering Supplies
- pH Sampling

Lab Ops

- Maintenance Instructions
- Instrument Calibration
- Check Equip QC Status
- Ordering Supplies
- Spill Reporting & Documentation


TAC-KNOW
Lab Assistant

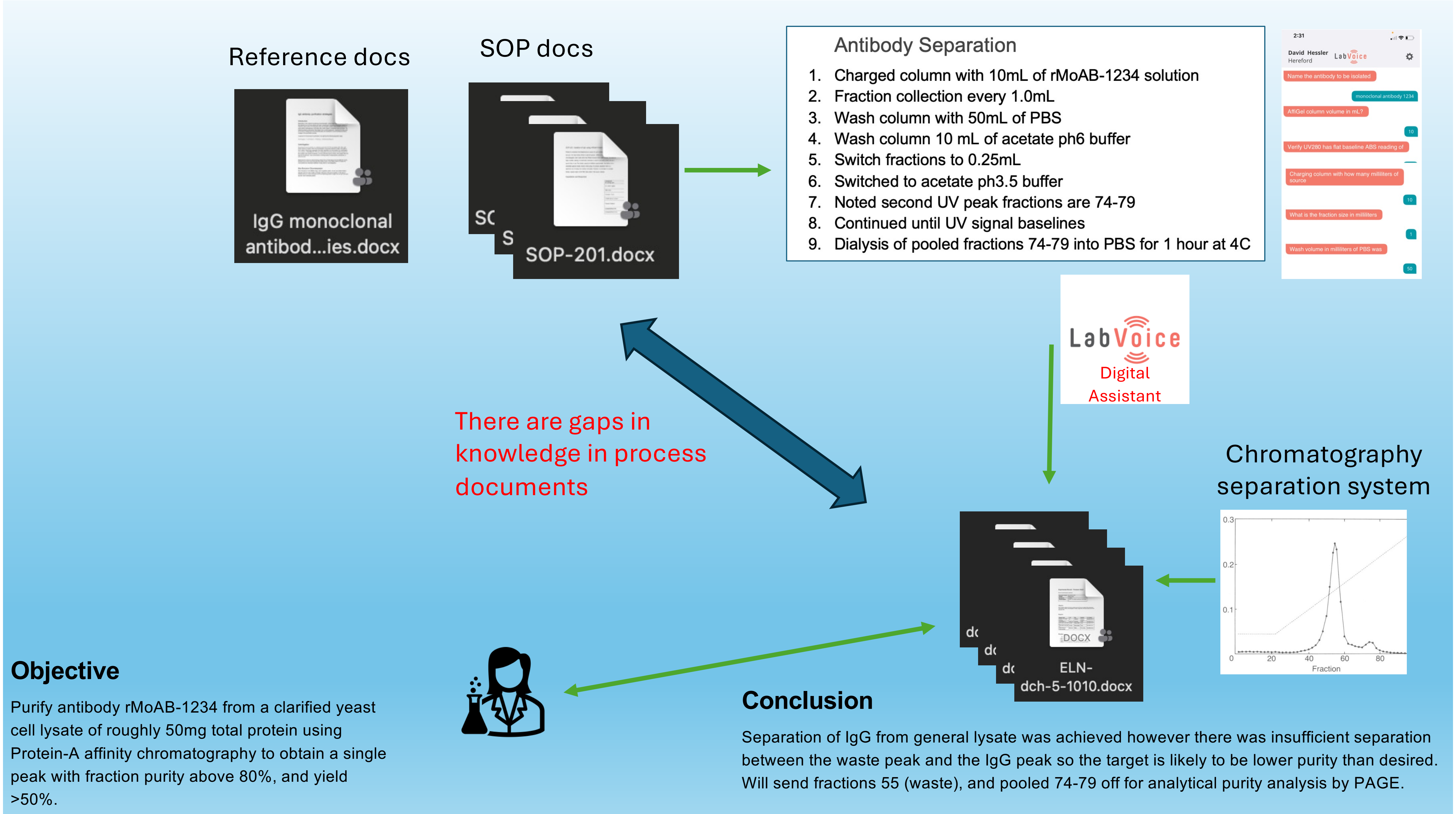
Requirements

GOAL

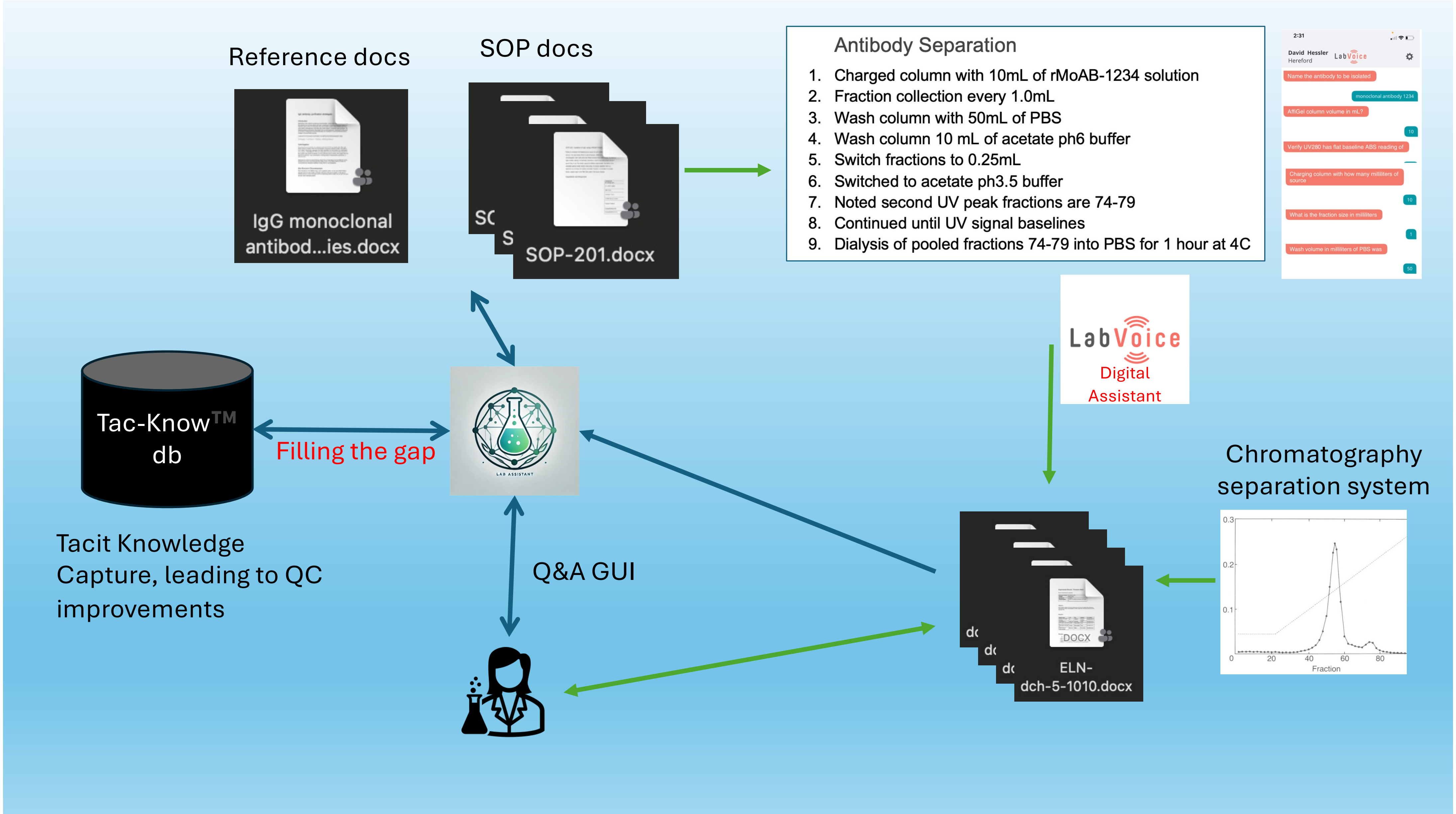
- To capture institutional know-how easily and without stress.

System features

- Frictionless interaction with users - voice, image, hands-free.
- Capturing and sharing tacit knowledge with junior and senior scientists.
- Intelligent discovery and management of tacit knowledge.
- Integrates seamlessly into current ELN and lab system environments.



Reference docs
IgG monoclonal antibod...ies.docx
SOP docs
SOP-201.docx
Antibody Separation
1. Charged column with 10mL of rMoAB-1234 solution
2. Fraction collection every 1.0mL
3. Wash column with 50mL of PBS
4. Wash column 10 mL of acetate ph6 buffer
5. Switch fractions to 0.25mL
6. Switched to acetate ph3.5 buffer
7. Noted second UV peak fractions are 74-79
8. Continued until UV signal baselines
9. Dialysis of pooled fractions 74-79 into PBS for 1 hour at 4C
2:31
David Hessler
Hereford
LabVoice
Name the antibody to be isolated
monoclonal antibody 1234
AffiGel column volume in mL?
10
Verify UV280 has flat baseline ABS reading of
Charging column with how many milliliters of source
10
What is the fraction size in milliliters
1
Wash volume in milliliters of PBS was
50
LabVoice
Digital Assistant
There are gaps in knowledge in process documents
Chromatography separation system
0.3
0.2
0.1
0
20
40
60
80
Fraction
DOCX
ELN-dch-5-1010.docx
Objective
Purify antibody rMoAB-1234 from a clarified yeast cell lysate of roughly 50mg total protein using Protein-A affinity chromatography to obtain a single peak with fraction purity above 80%, and yield >50%.
Conclusion
Separation of IgG from general lysate was achieved however there was insufficient separation between the waste peak and the IgG peak so the target is likely to be lower purity than desired. Will send fractions 55 (waste), and pooled 74-79 off for analytical purity analysis by PAGE.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David Hessler
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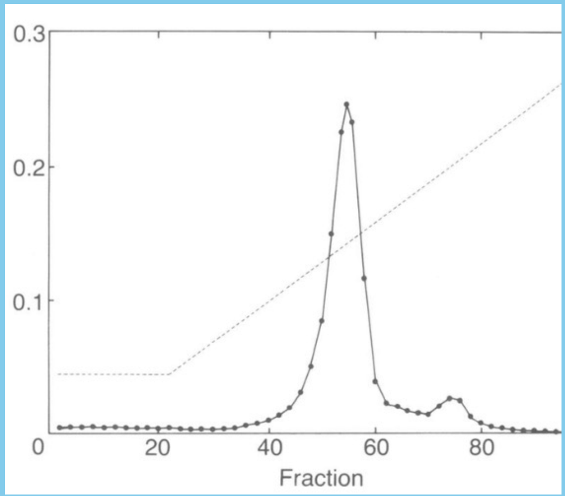
Name the antibody to be isolated
monoclonal antibody 1234
AffiGel column volume in mL?
Verify UV280 has flat baseline ABS reading of
Charging column with how many milliliters of source
What is the fraction size in milliliters
Wash volume in milliliters of PBS was
LabVoice
Digital Assistant
Tac-Know™ db
Filling the gap
LAB ASSISTANT
Tacit Knowledge Capture, leading to QC improvements
Q&A GUI
Chromatography separation system
0.3
0.2
0.1
0
20
40
60
80
Fraction
DOCX
ELN-dch-5-1010.docx

ELN



Conclusion

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Tac-Know db

=== Tacit Knowledge Entry ===
Date: 2025-01-07 13:37:10
Type: Lab Process Recommendation
Context: IgG Purification
Source: Expert System Analysis

Based on the laboratory conclusion, it appears that the separation of IgG from the general lysate was achieved, but there was insufficient separation between the waste peak and the IgG peak, resulting in a lower purity than desired.

To address this issue, I recommend re-evaluating the washing and elution steps in the Affinity Chromatography (LC Protein-A) process. According to the reference document, "Washing the column with PBS, and then extracting waste at pH 6, must be done with care. The UV280 detector will show when the column is truly clear of eluted proteins. Assuming that a given number of column volumes of wash will work is a mistake: use the effluent detector to indicate when a stage is complete." (Reference: IgG antibody purification strategies)

Specifically, I suggest re-washing the column with 2X column volumes of PBS or until UV280 detection baseline is achieved, as stated in SOP-201: Isolation of IgG using AffiGel Protein-A. Additionally, the pH 6 acetate buffer washing step should be repeated until the UV280 detector indicates a stable baseline, ensuring that the column is truly clear of eluted proteins.

Furthermore, the reference document highlights the importance of running the column slowly enough to allow binding time for the IgG. Therefore, I recommend verifying that the column flow rate is set at no faster than 10% column volume per minute, as specified in the reference document.

If the issue persists, consider implementing additional polishing steps, such as Ion Exchange Chromatography (LC using DEAE media) or Precipitation, as described in the reference document. These methods can provide additional purification and help achieve the desired purity levels.

Lastly, it is essential to ensure that the analytical purity analysis by PAGE is conducted correctly to verify the purity of the IgG fractions. This will help determine the effectiveness of the revised purification strategy and identify any further adjustments that may be necessary.

Reducing variability and hallucinations

Challenges

- LLMs use inference to guess results. This means that not 2 unstructured answers will be the same. This isn't always a bad thing!
- They are also known for providing unreal responses. This is because they are "guessing the next word", which can take the answer into strange spaces.

Guidelines

- A RAG-based system helps define the knowledge-space.
- Careful prompting allows for refined requests and sanity-checks.
- Also, multi-prompting approaches can be powerful.

PLEASE JOIN OUR COMMUNITY:

hitchhikersai.org

Welcome to HitchhikersAI

A non-profit impact community, accelerating the adoption of AI/ML and data in drug discovery & development.

DON'T PANIC!
THE ANSWER IS 42

HitchhikersAI aims to fix the disconnect between AI/ML and data and their practical application in early drug discovery by offering targeted non-profit consulting to biotech companies.

This involves helping scientists clearly define their research questions (killer questions) and designing customized plans that integrate educational resources, computational tools, and curated data to effectively use AI/ML technologies in their research.

The community is growing and currently consists of 300+ bench scientists, data scientists, mathematicians, business owners, executives, academics etc.

THANK YOU

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