Summarization of BLAST Results Utilizing LLMs

Dr. Daniel Standage

Grace Frizzell

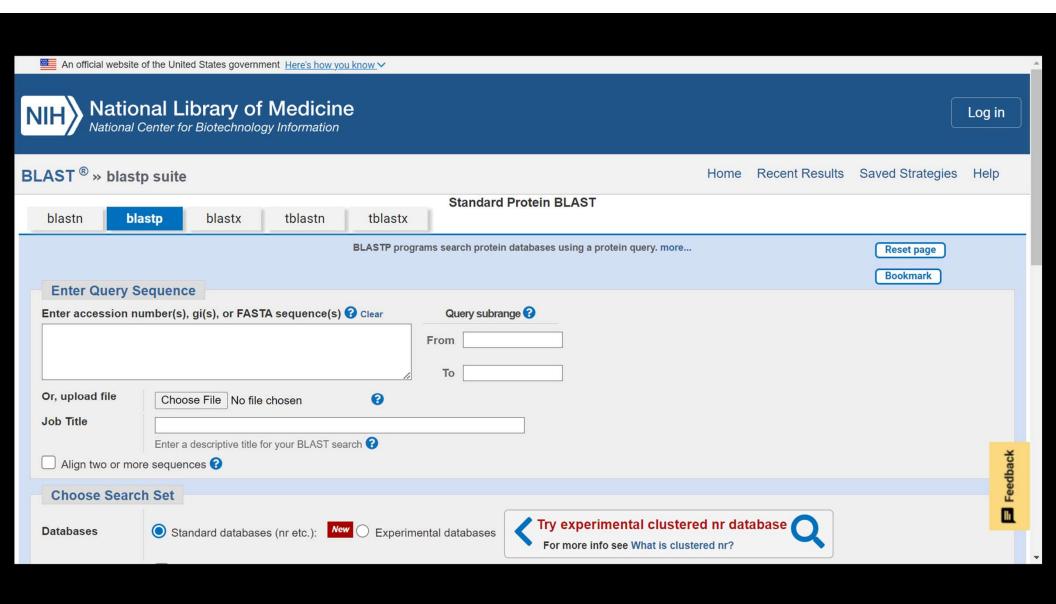
Al and machine learning in bioinformatics

- Genomic sequencing
- Protein and molecular structure modeling and predictions
- Data science
 - Understanding trends in large datasets and making predictions
- Summarization
 - Medical notes
 - Research texts

What is BLAST?

- Basic local alignment search tool
- Matching DNA/RNA sequences to each other





The problem

- BLAST results have large numbers of lines with free text descriptions
- We want summarizations that:
 - Eliminate redundancies
 - Concisely communicate meaning
 - Provide a consensus understanding of the descriptions
 - Accurately summarize
 - Summarize over differing sequence queries
- Can we actually do it?
- Can we do it here?

What are large language models?

- ChatGPT 4, Llama, Claude, CoPilot, etc.
- Sets of neural networks with many parameters, trained on vast amounts of data
- Subdivide words to produce meaningful responses
 - Tokens
- Conversational, summarical, programming, and other implementations exist.
- Models that you can download and run without an internet connection exist.
- Massive research focus

Solution characterization

- A quality solution:
 - Summarizes accurately
 - Matches the format of the descriptions
 - Can handle large prompt inputs > large enough to handle to dozens or hundreds of top blast hits
 - Processes quickly
 - Can work locally and in an air-gapped system.
- ChatGPT 4 is the standard?
 - Doesn't have the same limitations
- Niche applications like DNA Bert, BioBert, and others exist for diverse applications.

Prompt structure

WP_075294369.1 YopT-type cysteine protease domain-containing protein WP_135026487.1 YopT-type cysteine protease domain-containing protein WP_136121334.1 YopT-type cysteine protease domain-containing protein WP_148417923.1 YopT-type cysteine protease domain-containing protein WP_198974060.1 Yop T-type cysteine protease domain-containing protein WP_143813432.1 YopT-type cysteine protease domain-containing protein, partial WP_076090542.1 YopT-type cysteine protease domain-containing protein ARA70419.1 hypothetical protein BTV67_07780 WP_179121451.1 YopT-type cysteine protease domain-containing protein WP_108574942.1 YopT-type cysteine protease domain-containing protein WP_075291725.1 YopT-type cysteine protease domain-containing protein Q06277.2 RecName: Full=Protein adenylyltransferase and cysteine protease lbpA; Short=HMW IgBP; AltName: Full=p120; Includes: RecName: Full=Protein adenylyltransferase lbpA; AltName: Full=AMPylator lbpA; Includes: RecName: Full=Cysteine protease lbpA; Contains: RecName: Full=Protein p76 IgBP; AltName: Full=76 kDa antigen; Flags: Precursor WP_010906460.1 YopT-type cysteine protease domain-containing protein

WP_189293179.1 30S ribosome-binding factor RbfA MBV9291373.1 30S ribosome-binding factor RbfA WP_225016960.1 30S ribosome-binding factor RbfA WP_197679966.1 30S ribosome-binding factor RbfA WP_097871684.130S ribosome-binding factor RbfA WP_104094537.130S ribosome-binding factor RbfA WP_055796831.130S ribosome-binding factor RbfA WP_055814013.1 30S ribosome-binding factor RbfA WP_125499798.1 MULTISPECIES: 30S ribosome-binding factor RbfA WP_158034433.1 30S ribosome-binding factor RbfA PSJ26155.1 30S ribosome-binding factor RbfA WP_093498772.1 30S ribosome-binding factor RbfA WP_078074786.1 30S ribosome-binding factor RbfA WP_058742112.1 MULTISPECIES: 30S ribosome-binding factor RbfA WP 022868084.1 30S ribosome-binding factor RbfA WP_235489993.1 30S ribosome-binding factor RbfA

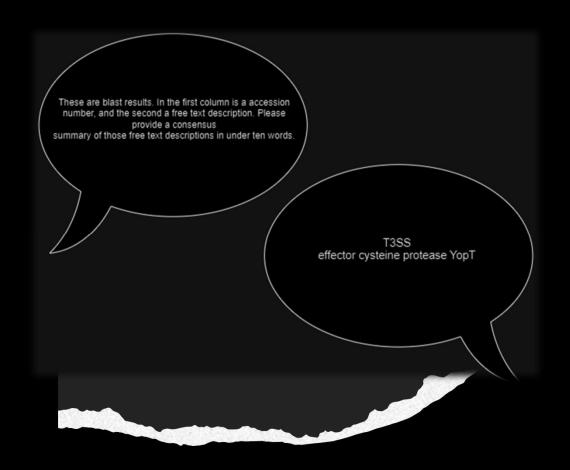


GPT 4

- Optimal prompts characterize the information and limit the response size
- Prompts can be as large as 2500 lines
- Response quality varies
- Golden standard for prompt size and context window
 - Not viable for airgapped system

Mistral Instruct

- 7 billion parameter model
- Significantly smaller context window
- Generally does best at concisely summarizing
- Ideal prompt characterizes the data and limits response scope





Meta's Llama 2

- 7 billion parameter chat model
- Ideal prompt limits size and scope
- Struggles with concise summary

Common problems

- Summarization of information versus description of information
- Limited context windows and prompt sizes
- Need to issue other prompts to make response acceptable
 - GPT 4, Llama 2
- Integration with a solution
 - Diverse tools for diverse models
 - Lack of standardization

Iterative refinement

G You

Summarize the content of the descriptions in under ten words.

(S) ChatGPT

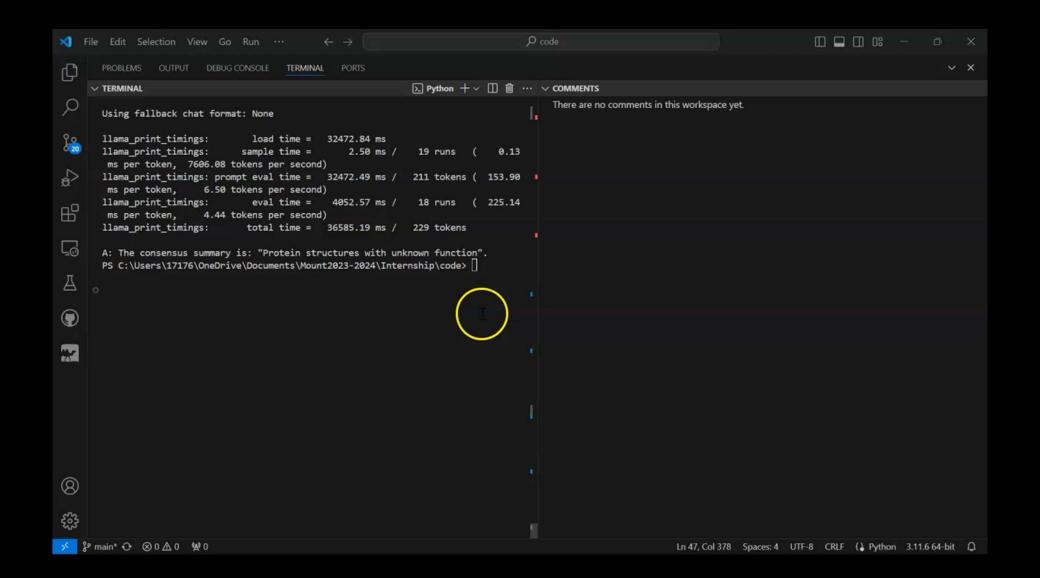
List of protein accession numbers with their associated types.

G You

Don't describe what the information is like; summarize what the information is, in under ten words.

Protein accession numbers for human, mouse, and rat sequences.

G You
Summarize the content of the free text descriptions in under ten words.



Conclusions and going forward

- Embedding tools and other implementations of LLM are diverse in methodology and level of support.
- LLMs constitute a tool of potential value in multiple fields and contexts.
- Exploring how we might use this tool promotes higher potential productivity across fields.

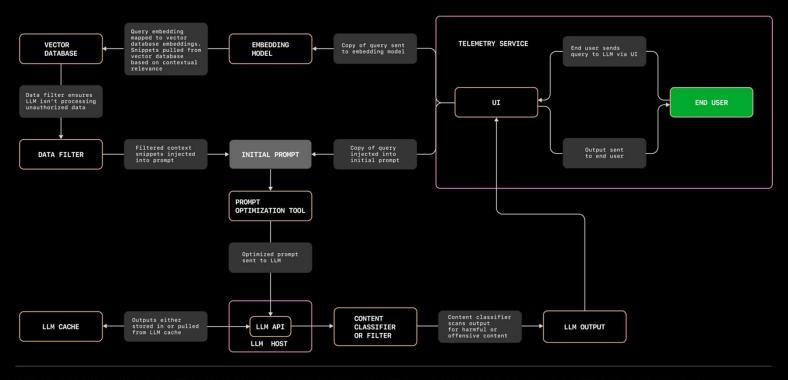
- Summarizing across sequences
- Integration with existing tools
- Construction of dedicated tools and applications

Questions?

Al and Machine Learning

- BioBert
- AlphaFold
- ESM2 and ESMFold
 - Meta
- MegaMolBart
- Splice Al

LLM Application Architectures



THIS DIAGRAM REPRESENTS THE ARCHITECTURE OF TODAY'S LLM APPLICATION. THE DIFFERENT COMPONENTS CAN BE ROUGHLY GROUPED INTO THREE CATEGORIES: USER INPUT, INPUT ENRICHMENT TOOLS AND PROMPT CONSTRUCTION, AND EFFICIENT AND RESPONSIBLE AI TOOLING.

LLM Embedding

- Embedding tools and other implementations of LLM are diverse in methodology and level of support.
- LLMs are just one implementation in a wider AI sphere.
- Often, one needs to customize the LLM.
 - Prompt-engineering
 - The "asks question" guy John Stewart
 - Fine-tuning
 - Tailoring parameters to return results of a known truth value
 - Reward models
 - Response acceptance