# Span Queries: a Declarative Map/Reduce Approach to Scale-up and Scale-out Inferencing

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# What if we had a SQL for GenAI?

# SQL • SQL lets apps prepare the backend for future queries • SQL lets apps separate concerns of imperative app logic and declarative data logic • SQL lets app express bulk analytical queries

#### How can we apply this to GenAI?

- Map/Reduce
- Spans
- Dependent/independent sub-sequences

## A Span Query is an expression tree over g, x, +

g: generate

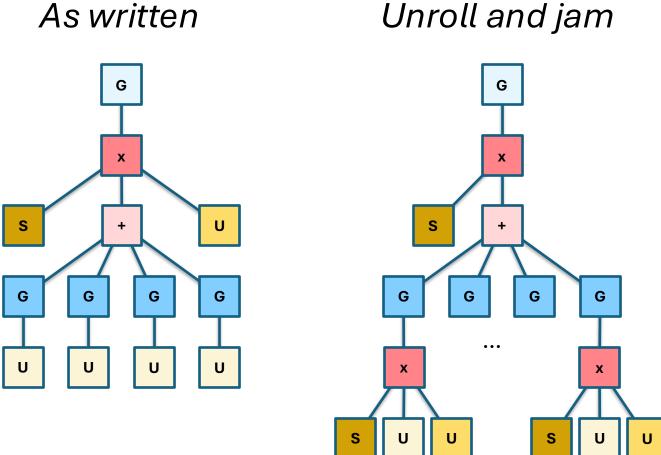
x: depends-on/attend-to

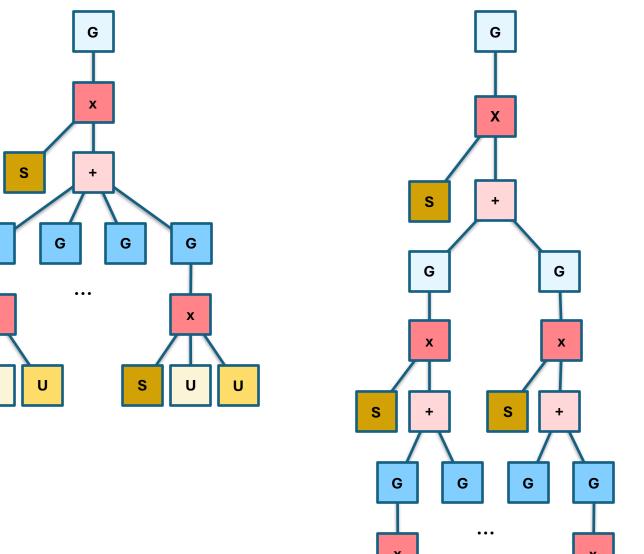
+: independent

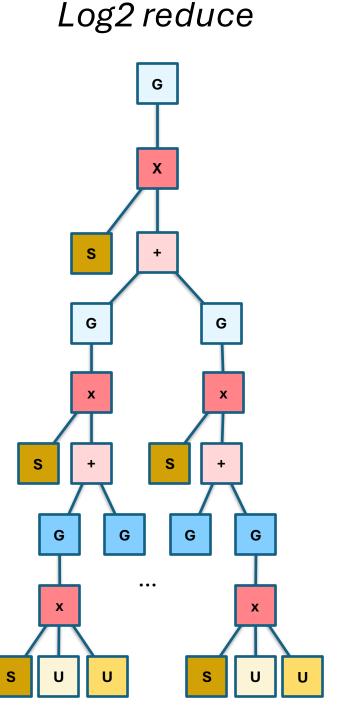
Textual Representation (note: not proposing as DSL)

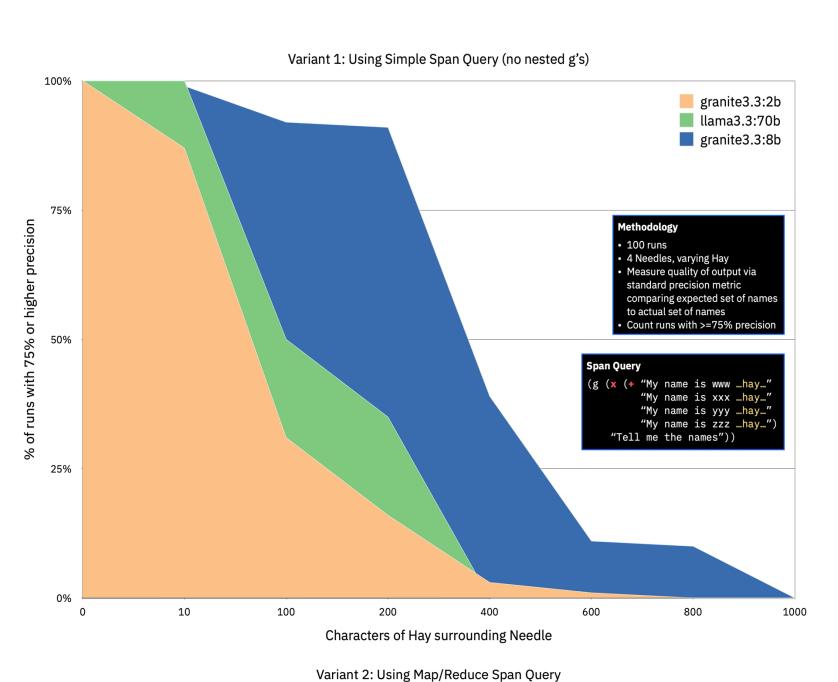
```
(g (x (system "A good email is...")
(+ (g (user "an introductory email"))
   (g (user "an introductory email"))
   (g (user "an introductory email"))
   (g (user "an introductory email"))
(user "I am applying to IBM")))
```

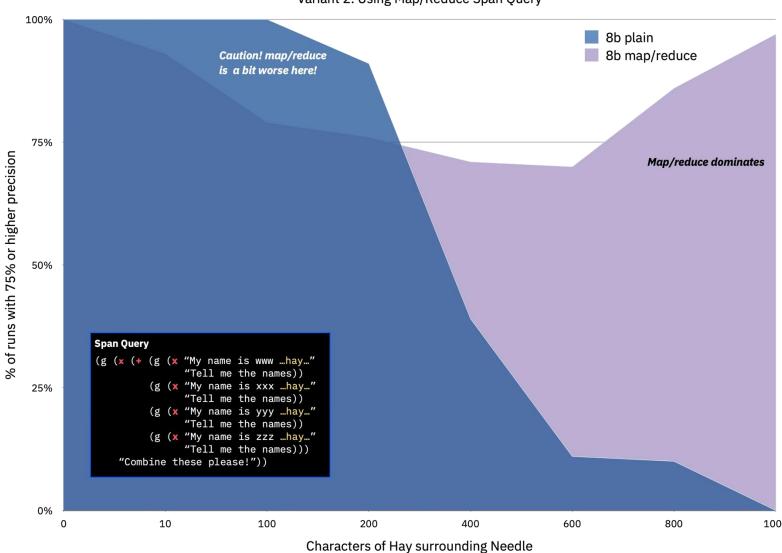
### Tree representation











## Strike Points Across the Stack

- How can **vLLM scale-up** better when given the dependence relations implicit in a span query?
- How can **llm-d scale-out** better in light of a map/reduce query structure?
- Does the backend benefit from "prepared statements I.e. being given, in advance, templated queries?
- Can we simplify client libraries by leveraging a SQLlike separation of concerns?
- Can we **consolidate inference scaling patterns** around queries? How many of them can be expressed as queries?

#### PDL\*, Ember, etc. **Kubernetes Span Query GET** /completions Select InferencePool **Wire Protocol** from model name **Span Query Body-based** (OAI spec) Routing **Planning Inference Gateway** (e.g. Envoy) Extensible library of Inference scrapers, scorers, Select optimal model Scheduler filterers for load-, KV-Route to replica based on state and P/D- aware routing selected pods Support span operations g, x, + Inference Pool Load, KV Variant A (e.g. Prefill) Variant B (e.g. Decode) Cache Report Shared Prefix Caching e.g. NIXL, DCN Translate capacity vLLM vLLM bounds, saturation Variant measurements, Autoscaler Update and traffic mix to Independent Prefix Caching replicas variant count e.g. LMCache, Dynamo KVBM, Host Memory Nodes Google intel. **OVIDIA.**

\*could be span query client syntax

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