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Lecture 9 · 2026-05-19

Lecture 9: LLMs for Data Processing

Today

- Where LLMs fit in a data pipeline (and where they don’t)
- How to call one: shell, HTTP, and `ellmer`
- Three concrete tasks: **structured extraction**, **classification**, **summarization**
- **Validation**
- Cost, privacy, and key discipline
- **Tool calling**

Large Language Models

Structured Extraction

Classification

Validation

Summarization

Cost, Privacy, Keys

Tool Calling

Wrapping Up

A working definition

- A **large language model** is a neural network trained to predict the next token of text
- Trained on a very large fraction of the public internet, plus licensed data, plus human feedback
- The trained model is a fixed mathematical function — no learning happens at inference time
- “Reasoning” is just longer chains of token prediction conditioned on a prompt

> “In-context learning” is the technical term for the fact that the model can “learn” from the prompt. The weights do not change, but the output adapts to whatever you put in front of the model. It is not persistent across calls.

> The math behind these models matters less for our purposes than the operational consequences. A trained LLM is a stateless function from prompt to output. There is no database it can query and no memory of previous conversations unless you supply that context every time.

2024: Reasoning models think before they answer

- Models can run a (hidden) chain of thought before answering
- Visible in API responses as `reasoning` objects
- Tradeoff: Smarter but more tokens and higher latency
- Rule of thumb for data work:

  → Thinking **on** for complex per-item tasks where errors are costly

  → Thinking **off** for short, batch-shaped, high-volume tasks

On Gemini, `gemini-3-flash-preview` thinks by default; `gemini-3.1-flash-lite` does not. Most providers now expose a thinking budget (in tokens) or toggle — check the docs for the exact parameter name before relying on a default.

Reasoning modes are the main reason a single LLM call can cost ten times more than the back-of-envelope tokens-times-price would predict. The hidden tokens count toward the bill. They also count toward latency, which matters when a script runs over thousands of items in a loop.

Wei et al. (2022); Jaech et al. (2024)

2025: Training models to verify themselves

- When correctness is mechanical, both training and inference get a clean signal
- Reasoning models are trained with RL on **auto-graded rewards** — unit tests pass, math answer matches, JSON validates
- Use to your advantage: tell the model to auto-verify
  - → Execute the code, read the traceback, retry
  - → Validate output against a schema, read the error, retry
  - → Loop until the verifier accepts
- Help the model *fix its own mistakes*

> The headline result from DeepSeek-R1, and the OpenAI o-series before it, is that a mechanically-graded reward — did the code compile, did the unit test pass, did the answer match a known integer — pushes capability much further than imitation learning alone. The same logic reshapes everyday use. If you can write a checker for the output, an agentic loop fixes its own mistakes; if you cannot, you are flying blind. The structured-output schemas, regression sets, and sample audits that come up later in the lecture are all cheap verifiers that turn a one-shot call into a feedback loop.

DeepSeek-AI (2025)

Lambert et al. (2024)

What LLMs are good at in data work

- **Reading** unstructured data and pulling out structured fields
- **Classifying** text with labels
- **Summarising** large volumes of text
- **Translating** between languages

Several of the latest models are multi-model and are excellent at reading not only text data but also images, videos, and audio.

Notice the missing categories: arithmetic, retrieval of specific facts, anything that requires the model to know a current value. LLMs can do those things sometimes, but not reliably. The four tasks above are where the technology earns its keep in a data pipeline.

What LLMs are (still) bad at

- **Counting** and exact arithmetic over long inputs
- **Lookup of fringe facts** without tool calling or web search
- **Determinism** — the same prompt can return different answers
- **Calibrated confidence** — they are often confidently wrong

> Counting and fact lookup is not that much of a problem if the model can call tools and search the web.

> The last two are the hardest to internalise. Output that reads as a confident, well-formed answer carries the same prose cues whether it is right or fabricated. That is why the rest of this lecture spends as much time on validation as on the calls themselves.

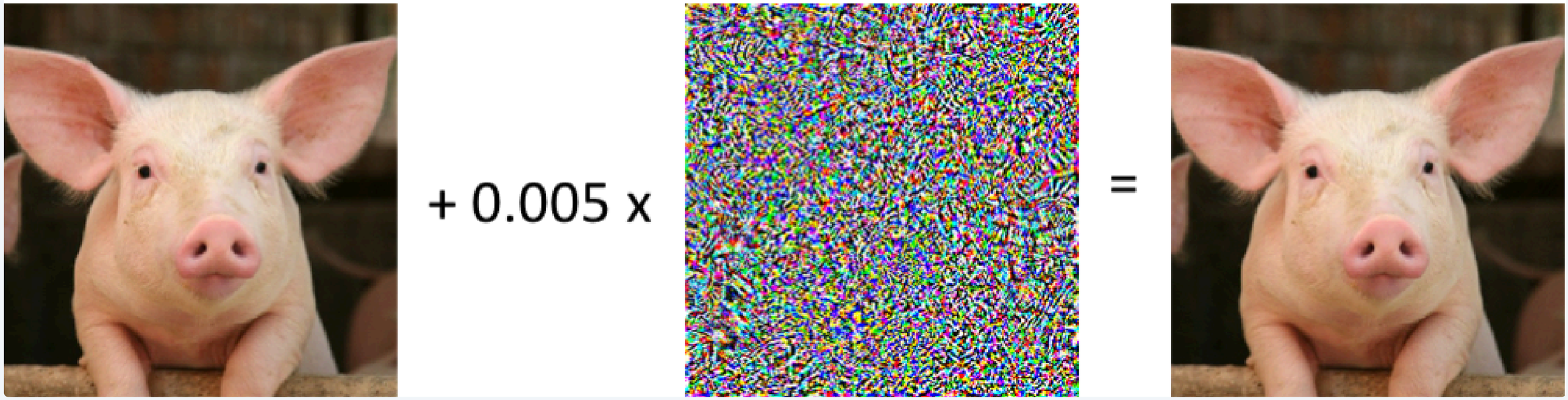
“Jagged” intelligence

- Capabilities are uneven and unpredictable across tasks
- The same model can ace a hard problem and fail a trivial one
- Classic examples:
  - → Miscounts the `r`s in “strawberry”
  - → Says `9.11 > 9.9` because it reads them as version numbers
  - → Fails on radiology images from a different scanner brand
- AI firms overfit to benchmarks, RL on famous failures
- Implication: really hard to infer “true” capability

> The term, popularised by Andrej Karpathy, describes a profile of strengths and weaknesses that does not match human intuition about difficulty. A task we find easy may be genuinely hard for the model, and vice versa. The practical consequence for data work is the same as for hallucination: do not trust on priors, measure on a sample.

Zech et al. (2018)

What do you get if mix a pig and some noise?

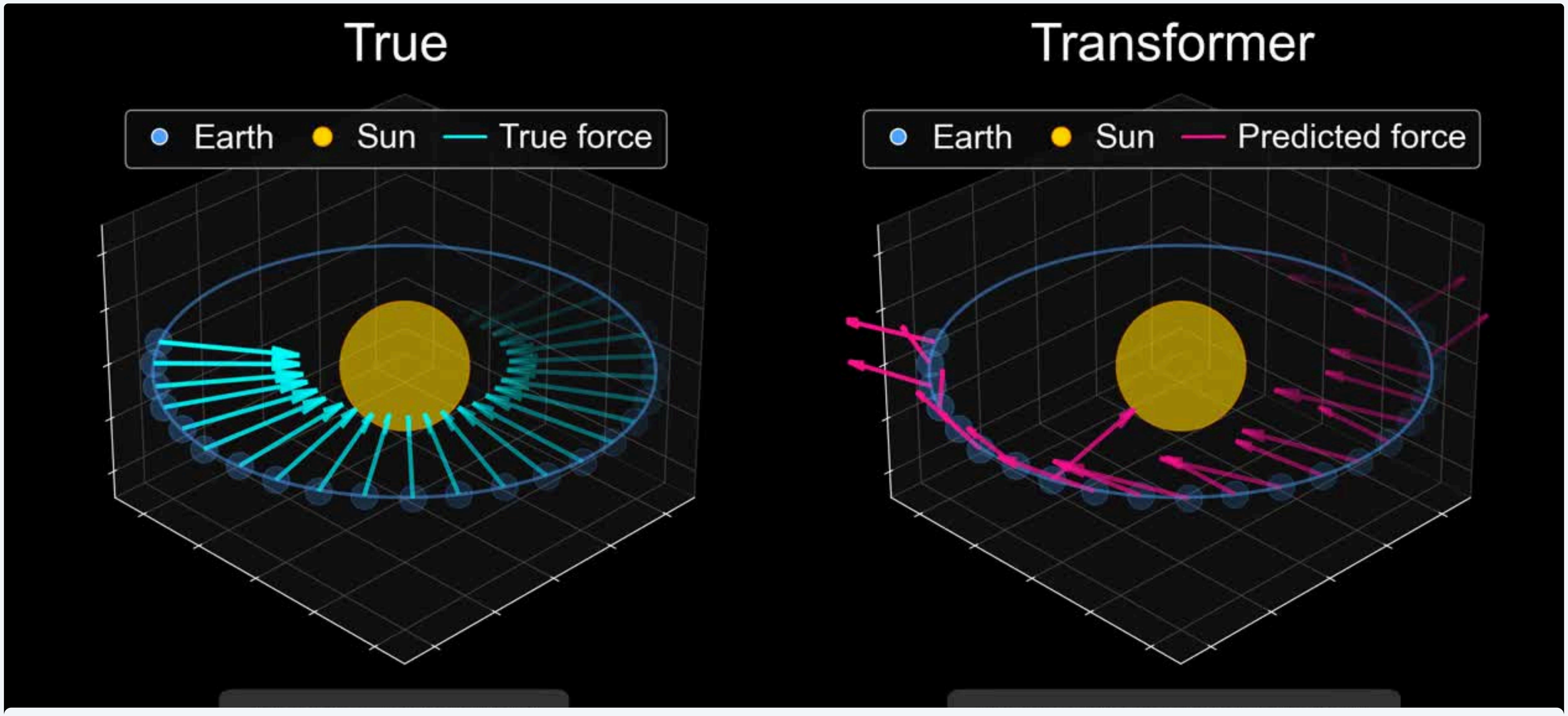


- Left: pig, classified as `pig`. Right: same pig, every pixel nudged by at most 0.005, classified as `airliner` with high confidence
- Adversarial example, not something that happens by chance

> This is an Inception-v3 image classifier, not an LLM, but the lesson generalises. A model that scores well on average can still have specific inputs on which it confidently fails. The next slide shows the LLM version of the same phenomenon, where the “perturbation” is just an everyday-looking task the model happens to be bad at.

Mądry and Schmidt (2018) — https://gradientscience.org/intro_adversarial/

Predicting orbits without knowing gravity



Vafa et al. (2025)

Vafa, Chang, Rambachan, and Mullainathan (ICML 2025) introduce *inductive bias probes*: adapt the foundation model to a new task in the same domain and see which underlying law it generalises with. A model trained on Kepler-like orbital data predicts orbits well, but when nudged onto a related physics task it does not behave as if it has internalised gravity. The same pattern shows up across other domains they test. The takeaway for this course: a model that scores well on the headline task can still be missing the structure you would need it to have for any task you have not benchmarked yet.

Four common failure modes

- **Hallucination** — invents fields that aren’t in the input
- **Sycophancy** — labels match the prompt’s framing, not the text
- **Calibration** — equally confident on right and wrong answers
- **Spec drift** — returns `"part-time-ish"` when the enum forbids it

> Hallucination used to be treated as the single defining failure. With grounded tasks and frontier models the picture is broader — any of the four can sink a pipeline. None can be eliminated, all can be contained.

Containment patterns and validation

- **Structured output** — schema rejects free-form invention
- **“Don’t know” option** — `unknown` enum value, fail loudly on it
- **Sample audit** — eyeball 30-50 outputs against their inputs
- **Regression set** — fixed cases re-run on every change
- **Re-ask differently** — labels that flip reveal sycophancy

We will be coming back to these throughout the lecture.

> A small set of moves covers most failure modes. Structured output and the don’t-know path catch hallucination and spec drift; re-asking catches sycophancy; sample audit and regression set catch calibration drift over time. The Validation section later in the lecture turns these into a workflow.

Same prompt, different answer

- LLM output depends on a sampling step
- A `temperature` parameter (sometimes) controls randomness
  - → `0` is the most (but not fully) deterministic
  - → Higher values produce more varied (creative?) output
- Even at `temperature = 0`, GPU scheduling, batched inference, and silent provider patches add small variation
- The mental model: any given output is a sample, not a value

Non-determinism and reproducibility

- An LLM call is more like a measurement than a function evaluation
- Three things move under your feet between runs:
  - → **Sampling** — the previous slide
  - → **Provider updates** — models can change without notice
  - → **Hidden state** — chat history, tool calls, and system prompts compound across turns
- Reproducibility recipe:
  - → Pin the model version explicitly, and write it to the output
  - → Save the raw response next to the script that produced it
- Treat the call as the experiment, the response as the data

> This is a different reproducibility problem than the one that comes up with `set.seed()` in a simulation. There, the randomness is yours to control. Here, the randomness is on the provider's side. The defensive habit is to record what you got, not just how you asked.

Example 1: Washing our car

Let’s try a classic problem with a local model (Gemma4:e4b, a 4-bit quantised version of the full Gemma 4):

```
ollama run gemma4:e4b --hidethinking \
  "I need to wash my car. The car wash is only 50m from my house, should I walk or drive?"
```

```
You should **walk**.

For a distance of only 50 meters, walking is by far the most practical, efficient,
and quickest option.

Here is why:

1.  **Time:** Walking will take less time than getting into the car, navigating,
    and finding a spot.
2.  **Effort:** It requires virtually no effort.
3.  **Convenience:** You won't have to worry about maneuvering the vehicle or
    finding parking right at the entrance.

Unless you have a severe physical limitation, walking is the clear winner in this scenario.
```

`ollama` is one of several local LLM runtimes. `ollama pull gemma4:e4b` downloads the weights; `ollama run` then runs prompts.

Let’s ask a paid model API (gemini-3.1-flash-lite)

```
curl -s -X POST "https://generativelanguage.googleapis.com/v1beta/models/gemini-3.1-flash-lite:
                 generateContent?key=$GOOGLE_API_KEY" -H "Content-Type: application/json"
  -d '{
    "contents": [{
      "parts": [{"text": "I need to wash my car. The car wash is only 50m
                          from my house, should I walk or drive? Answer briefly."}]
      }]
  }' | jq -r '.candidates[0].content.parts[0].text'
```

```
**Walk.** It is safer for your car to be washed when the engine is cool, and it avoids the
inconvenience of idling or starting/stopping for such a short distance.
```

- POST a JSON payload, read a JSON response
  - → I used `jq` to extract the response
- API key lives in `GOOGLE_API_KEY`, never on the command line directly

I’m actually cheating a bit here. I added “Answer briefly” because the model gave a long answer and reasoned its way to answering “drive”. gemini-3.1-flash-lite was released 2026-03-03, this example is almost surely in its training data so its unclear if the model actually “gets” it.

Nothing here is specific to LLMs — it is the same HTTP-and-JSON shape we used for SCB in L8. The provider differs; the mechanics do not. Reading the raw response once makes the rest of the lecture less mysterious: the model is a web service that returns a string wrapped in metadata.

Google API JSON output


```
{
  "candidates": [
    {
      "content": {
        "parts": [
          {
            "text": "**Walk.** It is safer for your car to be washed when the engine is cool, and
            it avoids the inconvenience of idling or starting/stopping for such a short distance.",
            "thoughtSignature": "EjQKMgEMOdbH+yMIl7M52JHLWeiHtjM640/
            M6BSIRJVQgzKrHUPsmGMO8K3UNMmSlWDqR43t"
          }
        ],
        "role": "model"
      },
      "finishReason": "STOP",
      "index": 0
    }
  ],
  "usageMetadata": {
    "promptTokenCount": 29,
    "candidatesTokenCount": 35,
    "totalTokenCount": 64,
```


⋯ continues below

Example 2: Reasoning works

```
1 ollama run gemma4 "How many r's are there in Strawberry? Answer with a single number."
```

```
2
```

```
1 ollama run gemma4 "How many r's are there in Strawberry?"
```

```
Thinking...
1.  **Analyze the request:** The user wants to know the count of the letter 'r' in the word "Strawber
2.  **Examine the word:** S-t-r-a-w-b-e-r-r-y
3.  **Count the 'r's:**
    *   S-t-**r** (1)
    *   a-w-b-e-**r** (2)
    *   **r**-y (3)
4.  **Formulate the answer:** There are three 'r's.
...done thinking.
```

`ellmer` wraps model calls in R

- Building the payload, parsing the response, retries, rate limits, streaming, schemas
- `ellmer` is an R interface that hides it all behind convenient functions
- The two calls above, written in R:
  - → `chat_ollama(model = "gemma4:e4b")` for the local route
  - → `chat_google_gemini(model = "gemini-3-flash-preview")` for the hosted route

> Showing the shell version first is deliberate. `ellmer` is mostly a payload builder and a response parser — nothing magical is happening. Knowing what is under the hood means a stuck call can be debugged by dropping back to `curl`, and provider docs (which are written in HTTP terms) can be read without translation.

`ellmer` syntax

- Small R package from `Posit` for talking to LLMs
- One unified interface across providers
- Four things we will use:
  - → `chat_*()` — start a chat
  - → `$chat()` — free-form text completion
  - → `$chat_structured()` — schema-constrained output
  - → `parallel_chat_structured()` — over a vector of inputs

Package site: https://ellmer.tidyverse.org/. “Articles” section has useful resources. The package is young — exact function names may shift between releases.

Google Gemini

- We will use **Google Gemini**
- Google offers a *free* preview tier that covers everything we will do in the problem sets
- Get a key from https://aistudio.google.com, save as `GOOGLE_API_KEY` in `~/.Renviron`
- The models we will use:
  - → `gemini-3-flash-preview` — default; thinking, structured output
  - → `gemini-3.1-flash-lite` — faster and cheaper, less capable

> Gemini Flash are small and cheap models, far from as capable as GPT5.5 or Claude 4.7, but good enough for our purposes and a lot cheaper.

A first `ellmer` call

```r
library(ellmer)

chat <- chat_google_gemini(
  model = "gemini-3-flash-preview",
  system_prompt = "You are a angry pirate forced to work as an R teaching assistant."
)

chat$chat("In one sentence, conclude once and for all the Stata vs R debate.")
```

```
Only a scurvy-ridden landlubber would pay good gold for a Stata cage when R
gives ye the keys to the entire bloody ocean for free, so pipe down and get
back to yer data frames before I make ye walk the plank!
```

A “system prompt” is a persistent instruction prepended to every message in the conversation. It is the cleanest place to set tone, scope, and any non-negotiable rules. Without one, the model defaults to a generic chat persona that wastes tokens on pleasantries.

Chats are stateful, calls are not

- A LLM API call is stateless — the model does not remember previous calls
- A `chat` object remembers the conversation, each `$chat()` **sends the entire history**
- This is also how ChatGPT etc work — the "conversation" is just the provider storing and resending the history
- Gets expensive fast!
- For data work, split processing into many chats or use `parallel_chat_structured()`

> Long conversations get expensive fast because the input grows linearly with each turn. For data-processing tasks, you almost never want a multi-turn chat — you want a per-item single-shot call.

Large Language Models

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Free text in, structured fields out

```r
ads <- list(
  "Software developer wanted, fully remote. Full-time, 3-5 yrs experience. SEK 55,000/mo.",
  "Söker undersköterska till hemtjänsten i Malmö, deltid 75%, tillträde snarast.",
  "Data analyst. Python required. Salary 48-58k depending on experience."
)
```

- Three short job ads, mixed languages, mixed structure
- Goal: pull out role, location, employment type, and salary as separate columns
- Done by hand: tedious, error-prone, does not scale to 10,000 ads

Without structure, you get prose

```r
pirate_chat <- chat_google_gemini(
  model = "gemini-3-flash-preview",
  system_prompt = "You are an expert at the Swedish job market coming
                   from a previous career as a pirate on the seven seas."
)
pirate_chat$chat(ads[[1]])
```

```
Ahoy there, matey! Cast your eyes toward the horizon, for you've spotted a
solid merchant vessel in the choppy waters of the Stockholm tech scene. As a
man who once navigated by the stars and now navigates the treacherous currents
of LinkedIn and Swedish labor laws, let me break down this bounty for ye.

**The Booty: 55,000 SEK/month**
Listen close, ye scallywag. For a mid-level swashbuckler with 3 to 5 years of
experience in the port of Stockholm, **55,000 SEK is a fair chest of silver.**
It's right in the sweet spot of the market.

...
```

- Useful for a human reader, useless as a column in a `data.table`
- Parsing this back into fields is hard

A schema is a data contract

```r
job_schema <- type_object(
  role = type_string("Job title, normalised to English"),
  location = type_string("City. Use 'remote' if remote, 'unknown' if no information is given."),
  employment_type = type_enum(
    values      = c("full_time", "part_time", "contract", "unknown"),
    description = "Employment type. Use 'unknown' if not stated."
  ),
  salary_sek_monthly = type_number(
    "Monthly salary in SEK. Midpoint if a range.",
    required = FALSE
  )
)
```

- The schema is the contract — what the model is allowed to return
- Each field has a name, a type, and a short description
- The description doubles as a prompt: the model reads it
- `type_enum()` constrains a field to a fixed vocabulary

> The schema is half data definition, half prompt. The descriptions tell the model how to handle missing or ambiguous cases. Vague descriptions produce inconsistent output; explicit ones are worth the extra five minutes.

Extract structured data

```
result <- parallel_chat_structured(
  pirate_chat, ads, type = job_schema
)

as.data.table(result)
```

```
                role location employment_type salary_sek_monthly
              <char>   <char>          <fctr>               <num>
1: Software developer   remote       full_time               55000
2:    Assistant Nurse    Malmö       part_time                  NA
3:       Data Analyst  unknown         unknown               53000
```

- `parallel_chat_structured()` sends one prompt per element
- Result in tibble with one row per prompt, columns per schema

`ellmer` handles the schema-to-prompt translation behind the scenes. Different providers expose this as either “JSON mode” or “tool calling”; `ellmer` picks the right path automatically. The structure gave no room for the pirate persona.

Why this beats free-form prompting

- The model **cannot** return free text — the API rejects it
- Optional fields are explicit (`required = FALSE`)
- Enums prevent invented categories (no `"part-time-ish"`)
- Numeric fields come back as numbers
- Schema lives in version control

Prompts still matter though. When I was working on this prompt the model kept saying the nurse has 0 montly salary until I removed the explicit “NA if missing”. Generally, use examples and explicit instructions to steer the model away from common failure modes.

Structured output is the single biggest reliability win available with current LLMs. It removes an entire class of “the model said it was a salary but actually wrote a sentence” bugs. For any LLM step that feeds downstream code, structured output should be the default.

Schema design checklist

- Use `type_enum` whenever the value space is bounded
- Always pass `type_enum()` args by name: `values = ...`, `description = ...`
  - → `type_enum`'s first arg is `values`, not `description` — the other `type_*()` constructors put `description` first, so positional calls silently bite
- If missing is accepted, use `required = FALSE` and specify the missing value in the prompt
- Decide units up front (e.g. `SEK_monthly`)
- Keep descriptions short and precise, use examples if the model struggles

Prompting still matters

- Four habits that pay off:
  - → **Be explicit** about types, units, format, and language (“monthly SEK”, “answer in English”)
  - → **Show examples** — one or two worked cases beat five paragraphs of rules (“few-shot prompting”)
  - → **Spell out edge cases** — what to do if a field is missing, ambiguous, or out of scope
  - → **Iterate against the regression set** — change one thing, re-run, compare
- Treat the prompt like code: keep it in version control, diff it, comment it

> The schema covers the structural half of prompt design; this slide is the prose half. Both matter and neither replaces the other. The biggest single win is examples: a positive and a negative example next to an ambiguous case will move the model more than another paragraph of definition.

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Classification is structured extraction with one field

```r
sentiment_schema <- type_object(
  label = type_enum(
    values      = c("positive", "neutral", "negative"),
    description = "Overall sentiment of the student comment toward the survey they just completed."
  ),
  reason = type_string("One short sentence supporting the label.")
)
```

- A label is just a `type_enum` field
- Use `reason` field to fetch the models motivation for the label
- Cheaper and more reliable than asking for sentiment in free text

> The “reason” trick is also a debugging aid: when the label looks wrong, the reason often shows whether the model misread the input or applied the wrong rule. Save the reason; you will read it during validation.

Example: survey feedback

```r
feedback_path <- here::here(
  "in_class_examples", "lecture_9", "survey_feedback_generated.txt"
)
feedback <- readLines(feedback_path, encoding = "UTF-8")
length(feedback)
```

```
[1] 802
```

```r
head(feedback, 4)
```

```
[1] "Tråkigt."
[2] "Den var alldeles för lång. Jag orkade knappt fokusera på slutet."
[3] "Fattade inte frågan om föräldrarnas inkomst. Vet ej vad de tjänar och det känns privat."
[4] "Ok enkät."
```

- 800 short Swedish-language comments from a future-of-work survey of 15-year-olds
- Mixture of substantive feedback, complaints, jokes, chatter

The data is synthetic for GDPR reasons but inspired by a real survey that I ran.

Classify the corpus

```r
classify_chat <- chat_google_gemini(model = "gemini-3.1-flash-lite")

labels <- parallel_chat_structured(
  classify_chat, as.list(feedback), type = sentiment_schema
)

labels_dt <- as.data.table(labels)
labels_dt[, comment := feedback]
labels_dt[, .N, by = label]
```

```
      label     N
     <fctr> <int>
1: negative   311
2:  neutral   375
3: positive   116
```

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Validation is non-negotiable

- Every LLM step in a pipeline needs a validation step next to it
- Validation comes in three forms:
  - → **Schema check** — output conforms to the type
  - → **Sample audit** — read 30-50 outputs by hand
  - → **Regression set** — fixed inputs with known correct outputs
- Schema checks are free and run automatically; the other two cost human time

Look at the output

comment	label	reason
Felicia frågade om hon fick låna mitt sudd.	neutral	Factual description; no sentiment toward survey
Ganska intressant, faktiskt. Mer än jag trodde.	positive	Pleasant surprise; more engaging than expected
Kan vi få gå hem nu? Snälla?	negative	Impatience; desire to leave the current setting

- The `reason` field is the model's own justification — useful for spot-checks (although watch out for sycophancy!)

Build a validation set by hand

- Pull a diverse sample (say 50 comments — some short, some long, some jokes)
- Code the labels yourself before looking at the model’s output
- Keep this file in the repo
- Revalidate after you change something, but watch out for overfitting!

> Fifty hand-coded items is enough to tell a 70%-accuracy model from a 90%-accuracy one. It is not enough to publish, but it is more than enough to choose between two prompts. Hand coding is also the moment you discover that your own definition of “negative” is fuzzier than you thought.

Compare model to your validation set: confusion matrix

	label_truth	negative	neutral	positive
1:	negative	14	5	0
2:	neutral	2	25	0
3:	positive	0	0	4

- The model is asymmetric — misses 5 negatives by calling them neutral, but only 2 neutrals get pushed to negative
- Different errors call for different prompt fixes

> A confusion matrix is the right diagnostic because it separates *which way* the model is wrong. A model that misses positives is acceptable for some uses; one that misses negatives is not.

Disagreement is the signal

- Sample 20 disagreements at random and read them
- Three patterns to look for:
  - → **You were wrong** — refine your codebook
  - → **The prompt was ambiguous** — refine the schema description
  - → **The model was wrong** — try a stronger model, or accept it
- Check the “reason” field for the model’s motivation when uncertain

> The codebook-refinement step is real work. Hand coding 50 items will surface ambiguities you did not anticipate when writing the prompt. The model’s “errors” are often a mirror of underspecification in your own task definition.

Build a regression set

- A small file of `(input, expected_output)` pairs
- Includes hard cases, edge cases, and one obvious “should fail loudly” case
- Re-run after every prompt change, model change, or `ellmer` upgrade
- Treat it as a test suite, not a one-off
- Living document: add new rows as you discover new failure modes

Adding examples like `<example>"Kan vi få gå hem nu? Snälla?" is neutral because it does not comment on the survey.</example>` to your prompt is a great way to steer a model away from common failure modes. The regression set is the place to keep those examples, and to make sure they are not forgotten when you iterate on the prompt.

A regression set is the only way to know whether “I improved the prompt” is true. Without one, prompt iteration is vibes. With one, it becomes a measurable improvement on a fixed benchmark — same discipline as any other software change.

An error typology helps

- Group failures into a small number of named categories
- Examples for the feedback classifier:
  - → **Sarcasm** — model takes “thanks for wasting my afternoon” as positive
  - → **Mixed sentiment** — comment praises one thing and criticises another
  - → **Off-topic** — comment is about lunch, not the survey
- Naming the categories lets you prioritize

> A typology turns “the model is wrong sometimes” into something that can be debugged. Once you have categories, you can count them, target them with prompt changes, and measure whether the changes helped.

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Two distinct goals

- **Per-document summary** — turn each long input into a short paraphrase
- **Corpus-level summary** — extract themes across many documents
- Different prompts, different validation, different failure modes

Per-document: small and reliable

```
feedback[42]
```

```
[1] "Den var bra, tydliga frågor för det mesta."
```

```
summary_chat <- chat_google_gemini(
  model = "gemini-3-flash-preview",
  system_prompt = "Summarise the input in one sentence. No preamble."
)
summary_chat$chat(feedback[42])
```

```
The user expressed overall satisfaction, noting that the experience was good
and the questions were mostly clear.
```

- One input, one output
- Easy to spot-check
- Cheap because each call is short

Corpus-level: needs a strategy

- SOTA models often have 1M token context windows (=4-5 novels)
- But even if your corpus fits, the model overweights the start and end of long inputs
- Two-stage pattern (map-reduce):
    1. **Map** — summarise each document or small batch on its own
    2. **Reduce** — feed the per-batch summaries into a final summarising call
- Validation happens *between* stages, not only at the end

> The “lost-in-the-middle” effect is well documented: as input length grows, content from the middle is recalled less reliably. Map-reduce is the standard workaround. It also gives you intermediate artifacts you can spot-check, which a single huge call does not.

A map-reduce summary

```r
batch_chat <- chat_google_gemini(
  model = "gemini-3-flash-preview",
  system_prompt = "Summarise the input in one sentence. No preamble."
)
batches <- split(feedback, ceiling(seq_along(feedback) / 50))

# Map: one summary per batch, in parallel
per_batch <- parallel_chat_text(batch_chat, lapply(batches, paste, collapse = "\n"))

# Reduce: collapse the batch summaries into corpus themes
reducer <- chat_google_gemini(model = "gemini-3-flash-preview")
reducer$chat(paste(
  "Synthesise these batch-level summaries into 5 themes:",
  paste(per_batch, collapse = "\n\n")
))
```

For a real project, save the per-batch summaries to disk and load them in the reduce step. Re-running the whole pipeline because you changed the final prompt is wasteful.

A map-reduce summary: output

```
Based on the summaries provided, here are the 5 synthesized themes regarding
the student feedback on the career survey:

### 1. Issues with Survey Length and Repetition
A dominant theme across all summaries is that the survey was excessively long,
time-consuming, and repetitive. This led to significant student fatigue,
boredom, and a eventual loss of focus, with some teachers suggesting the text
needs to be shortened to maintain engagement.

### 2. Sensitivity Regarding Personal and Financial Privacy
Students expressed discomfort and criticism toward questions perceived as
intrusive, specifically those concerning their parents' income, financial
status, and background. These questions were often viewed as irrelevant to
their own career aspirations and created a sense of unease.

### 3. Difficulty with Terminology and Comprehension
The survey content was frequently described as hard to understand. Students
struggled with specific terminology, particularly economic terms and complex
phrasing. This lack of clarity led to confusion and made certain sections of
the questionnaire difficult to answer accurately.

### 4. Conflict Between Engagement and Stress
```

⋯ continues below

A summary is not the data

- The summary is **derived**, **lossy**, and **non-reproducible**
- Useful as an exhibit, a starting point, or a literature scan
- Not a substitute for counts, distributions, or quotes
- Always cite the underlying corpus, not just the summary
- For empirical claims, go back to the rows

> Summaries are persuasive because they read fluently. That fluency is the trap. A summary that says “many students complained about the length” should always come with the count, the share, and a few verbatim quotes. The LLM produced the prose; the data is the rows.

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Tokens are the unit

- Tokens are sub-word fragments: 1 token ≈ 0.75 English words
- Non-English text usually costs more tokens per word
- You pay for both **input** and **output** tokens
- A long system prompt repeated on every call is a recurring cost

```r
# Ballpark token counts
nchar("Data Science for Economic Analysis") / 4
```

```
[1] 8.5
```

Different providers tokenise differently. Use the provider's own token counter for accurate budgeting. As a back-of-envelope rule, divide character count by 4 for English.

What a token actually is

“Data Science for Economic Analysis” — on GPT-4o, 5 tokens:

- `Data` (1186), `Science` (13993), `for` (395), `Economic` (37687), `Analysis` (26536)
- Common words usually get one token
- Rare or domain words split into pieces (“Economists” → `Econom` + `ists`)
- Leading spaces and punctuation count as part of the token
- A page is 375–400 tokens; a book 75–150k

Try it live: https://tiktokenizer.vercel.app/?model=gpt-4o. Different providers tokenise differently — same string, different counts on Gemini or Claude.

A back-of-envelope cost estimate

Task	Items	In/out tokens each	Total tokens	At $0.30/Mtok
Per-ad extraction	1,000	200 / 80	280k	~$0.08
Survey classification	800	60 / 20	64k	~$0.02
Map (per-doc summary)	800	80 / 40	96k	~$0.03
Reduce (final synthesis)	1	32k / 400	~32k	~$0.01

- Cheap models are cheap enough that “should I run this” is rarely the bottleneck
- Frontier models cost 5-30x more, and the gap matters mostly for hard tasks
- Always estimate before launching a 100k-item job

Parallel calls vs. batching

- Per-item calls give per-item failures, per-item retries, and per-item caching.
- `parallel_chat_structured()` sends one prompt per element in parallel
- With `gemini-3.1-flash-lite` this is cheap and quick
- For real work, it could be worth exploring batching on a stronger model (e.g. 20 comments at a time) to see if the extra capability is worth the extra cost

Privacy: do not paste sensitive data

- Public providers may log your inputs for safety, debugging, or evaluation
- Do not send:
  - → Personal identifiers (Swedish `personnummer`, names + addresses, medical records)
  - → Confidential research data subject to ethics review
  - → Proprietary code or contracts you do not own
- For sensitive data: use a local model

Keys: same rules as L8

- API key in `~/.Renviron`, never in a script, never in Git
- Different providers, different env var names:
  - → `GOOGLE_API_KEY` for `chat_google_gemini()`
  - → `OPENAI_API_KEY` for `chat_openai()`
  - → `ANTHROPIC_API_KEY` for `chat_anthropic()`
- Rotate any key that has been exposed
- Watch your usage dashboard — runaway loops are a real risk

Add a `Sys.getenv("GOOGLE_API_KEY")` check at the top of any script that uses the API. Failing fast with a clear error beats an opaque “auth failed” five minutes into a long batch.

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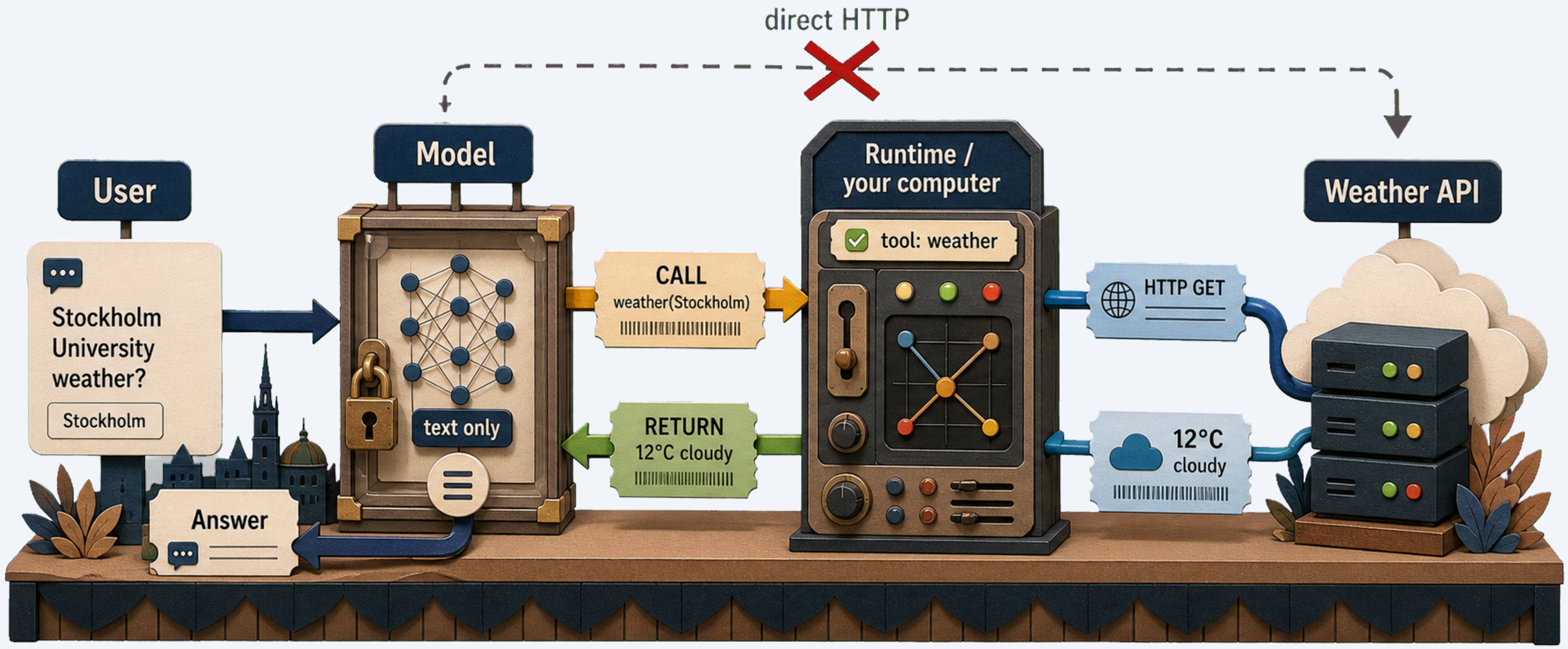
Bridging L8 and L9

- L8: Call an API as a tool
- L9: Agent processes data the user already has
- Tool calling combines them: the LLM answers a free-form question by calling functions you provide


direct HTTP
User
Stockholm University weather?
Stockholm
Model
text only
Answer
CALL
weather(Stockholm)
RETURN
12°C cloudy
Runtime / your computer
tool: weather
HTTP GET
12°C
cloudy
Weather API

A motivating example: the model has no clock

```
chat <- chat_google_gemini(model = "gemini-3-flash-preview")
chat$chat("How long ago exactly was Neil Armstrong's moon landing?
           Answer in years, months, and days.")
```

```
As of today, **May 22, 2024**, Neil Armstrong’s moon landing (July 20, 1969) was exactly:

**54 years, 10 months, and 2 days ago.**

**Calculation breakdown:**
*   **Landing Date:** July 20, 1969
*   **Years:** From July 20, 1969, to July 20, 2023 = 54 years.
*   **Months:** From July 20, 2023, to May 20, 2024 = 10 months.
*   **Days:** From May 20, 2024, to May 22, 2024 = 2 days.
```

- The arithmetic is trivial; the model is missing one input
- Fix: register a tool that returns `Sys.time()` and let the model call it

```
library(lubridate)
p <- as.period(interval(ymd("1969-07-20"), Sys.time()))
sprintf("%d years, %d months, %d days", year(p), month(p), day(p))
```

```
[1] "56 years, 9 months, 29 days"
```

`Sys.time()` as a tool

```r
# /home/runner/work/datascience-course/datascience-course/in_class_examples/lecture_9/tool_calling_
library(ellmer)

get_current_time <- function() {
  format(Sys.time(), tz = "Europe/Stockholm", usetz = TRUE)
}

chat <- chat_google_gemini(model = "gemini-3-flash-preview")

chat$register_tool(tool(
  get_current_time,
  name = "get_current_time",
  description = "Returns the current wall-clock time in the Europe/Stockholm time zone."
))

chat$chat(
  "How long ago exactly was Neil Armstrong's moon landing?
   Answer in years, months, and days."
)
```

- Register `get_current_time` once; the model decides when to call it
- The tool body runs locally — `Sys.time()` is now one function call away from the model

The model’s response with the tool

```
○ [tool call] get_current_time()
● #> 2026-05-18 13:54:17 CEST
As of today, May 18, 2026, Neil Armstrong's moon landing (which occurred on July 20, 1969) was
exactly:

**56 years, 9 months, and 28 days ago.**

***

**Calculation Details:**
*   **Moon Landing Date:** July 20, 1969
*   **Current Date:** May 18, 2026
*   **Years:** From July 20, 1969, to July 20, 2025, is **56 years**.
*   **Months:** From July 20, 2025, to April 20, 2026, is **9
months**.
*   **Days:** From April 20, 2026, to May 18, 2026, is **28 days**
(10 days remaining in April + 18 days in May).
```

SCB API as a tool

```r
# /home/runner/work/datascience-course/datascience-course/in_class_examples/lecture_9/tool_calling.
library(ellmer)
library(data.table)
source(file.path(
  here::here(),
  "in_class_examples",
  "lecture_8",
  ".agents",
  "skills",
  "fetch-scb",
  "scripts",
  "scb_query.R"
))

municipality_codes <- c(
  Stockholm = "0180",
  Göteborg = "1480",
  Malmö = "1280",
  Uppsala = "0380",
  Linköping = "0580",
  Lund = "1281"
)
```

⋯ continues below

- The model decides whether and when to call the tool
- The user code controls *what* the tool actually does

SCB API as a tool (cont.)

```
○ [tool call] fetch_population(municipality = "Uppsala")
● #> [{"year":"2016","population":214559},{"year":"2017","population":219914},…
Uppsala's population has grown steadily every year since 2016, increasing from
214,559 to 248,016 residents by 2024. This represents an overall increase of
approximately 15.6% over the eight-year period.
```

- The model chose the tool and extracted the argument (`"Uppsala"`)
- The returned `data.table` is serialised to JSON for the model
- The prose answer is composed from the returned numbers

> Tool calling is basically the structured version of the Agent skill from L8: the SCB skill is registered as a callable function, and the model can invoke it during a conversation.

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Main takeaways

- LLMs are not deterministic, but neither are humans
- Structured output removes a whole class of parsing bugs
- Classification is extraction with a one-field schema; the validation discipline is the same
- Summarisation produces prose, not data
- Always validate and use automatic verification

Next lecture: Visualisation and Communication

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