

LLMR Demo (≥ 0.6)

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LLMR is an R package for reproducible, provider-agnostic research with (and about) large language models (LLMs). It offers:

- A single configuration object across providers.
- A standard response object with finish reasons and token usage.
- A structured-output workflow (JSON schema) that is robust and easy to use.
- Parallel experiment utilities and tidy helpers.
- Multimodal support with local files.
- Reliable embeddings with batching.

```

1 library(LLMR)
2 library(dplyr)
3 library(tibble)
4 library(tidyr)
5 library(ggplot2)
6 library(stringi)

```

1) Quick start: one generative call

Configure once. Call once. `call_llm()` returns an `llmr_response` with a compact print.

```

1 cfg_openai <- llm_config(
2   provider = "openai",
3   model    = "gpt-4o-mini",           # use a model you have access to
4   api_key   = "OPENAI_API_KEY", # this is actually not needed
5   temperature = 0.2,
6   max_tokens = 200
7 )
8
9 resp <- call_llm(
10   cfg_openai,
11   c(
12     system = "You are concise and helpful.",
13     user   = "Say hello in one short sentence."
14   )
15 )
16
17 print(resp)           # text + compact status line
18 #> Hello!
19 #> [model=gpt-4o-mini | finish=stop | sent=24 rec=2 tot=26 | t=0.538s]
20 as.character(resp)    # just the text
21 #> [1] "Hello!"
22 finish_reason(resp)   # standardized finish signal
23 #> [1] "stop"
24 tokens(resp)         # sent/rec/total (and reasoning if available)
25 #> $sent
26 #> [1] 24
27 #>
28 #> $rec
29 #> [1] 2
30 #>
31 #> $total
32 #> [1] 26
33 #>
34 #> $reasoning
35 #> [1] 0

```

1.1) Injecting prior assistant turns

You can inject a prior assistant turn to anchor context.

```
1 cfg41 <- llm_config(  
2   provider = "openai",  
3   model    = "gpt-4.1-mini",  
4   api_key   = "OPENAI_API_KEY"  
5 )  
6  
7 inj <- call_llm(  
8   cfg41,  
9   messages = c(  
10    system    = "Be terse.",  
11    user      = "What is 10 x 12 - 2?",  
12    assistant = "100",  
13    user      = "What went wrong in the previous answer?"  
14  )  
15 )  
16  
17 cat(as.character(inj), "\n")  
18 #> The correct calculation is 10 × 12 - 2 = 120 - 2 = 118, not 100.
```

1.2) Accessing the raw JSON

The raw JSON string is attached for inspection.

```
1 raw_json_response <- attr(resp, "raw_json")  
2 cat(substr(raw_json_response, 1, 400), "...\\n", sep = "")  
3 #> {  
4 #>   "id": "chatcmpl-C7xh7qQ63l2wsHHlmegecDavj1p7gd",  
5 #>   "object": "chat.completion",  
6 #>   "created": 1756013797,  
7 #>   "model": "gpt-4o-mini-2024-07-18",  
8 #>   "choices": [  
9 #>     {  
10 #>       "index": 0,  
11 #>       "message": {  
12 #>         "role": "assistant",  
13 #>         "content": "Hello!",  
14 #>         "refusal": null,  
15 #>         "annotations": []  
16 #>       },  
17 #>       "logprobs": null,  
18 #>       "finish_reason": "stop"  
19 #>     }  
20 #>   ],
```

```

21 #> "usage": {
22 #> ...

```

2) Stateful chat

`chat_session()` keeps history and token totals. Each `$send()` round-trips the full history.

```

1  cfg_groq <- llm_config(
2    provider = "groq",
3    model    = "llama-3.3-70b-versatile",
4    api_key   = "GROQ_API_KEY"
5  )
6
7  chat <- chat_session(cfg_groq, system = "Be concise.")
8  chat$send("Name one fun fact about octopuses.")
9  #> Octopuses can lose an arm to escape predators and then regrow it later.
10 #> [model=llama-3.3-70b-versatile | finish=stop | sent=47 rec=18 tot=65 | t=0.377s]
11 chat$send("Now explain it in one short sentence.")
12 #> Octopuses can regrow lost arms.
13 #> [model=llama-3.3-70b-versatile | finish=stop | sent=82 rec=10 tot=92 | t=0.153s]
14
15 # Summary view
16 print(chat)
17 #> llm_chat_session (turns: 5 | sent: 129 | rec: 28 )
18 #>
19 #> [system] Be concise.
20 #> [user] Name one fun fact about octopuses.
21 #> [assistant] Octopuses can lose an arm to escape predators and then regrow ...
22 #> [user] Now explain it in one short sentence.
23 #> [assistant] Octopuses can regrow lost arms.
24 chat$tokens_sent(); chat$tokens_received()
25 #> [1] 129
26 #> [1] 28
27 tail(chat, 2)
28 #> [user] Now explain it in one short sentence.
29 #> [assistant] Octopuses can regrow lost arms.
30 as.data.frame(chat) |> head()
31 #>      role
32 #> 1  system
33 #> 2   user
34 #> 3 assistant
35 #> 4   user
36 #> 5 assistant
37 #>
38 #> 1 content
39 #> 2 Name one fun fact about octopuses.

```

```

40 #> 3 Octopuses can lose an arm to escape predators and then regrow it later.
41 #> 4                                     Now explain it in one short sentence.
42 #> 5                                     Octopuses can regrow lost arms.

```

3) Structured output (JSON schema)

LLMR can request structured JSON and parse it into typed columns.

- Use `enable_structured_output()` (provider-agnostic).
- Call a structured helper.
- Hoist fields with `llm_parse_structured_col()` (done automatically below).

```

1 schema <- list(
2   type = "object",
3   properties = list(
4     answer = list(type = "string"),
5     confidence = list(type = "number", minimum = 0, maximum = 1)
6   ),
7   required = list("answer", "confidence"),
8   additionalProperties = FALSE
9 )

```

3.1) Vector helper: `llm_fn_structured()`

Auto-glues the prompt over a vector. If `.fields` is omitted, top-level properties are auto-hoisted.

```

1 words <- c("excellent", "awful", "fine")
2
3 out_vec <- llm_fn_structured(
4   x = words,
5   prompt = "Classify '{x}' as Positive, Negative, or Neutral and return JSON with
6     ↳ answer and confidence.",
7   .config = cfg_openai,
8   .schema = schema,
9   .fields = c("answer", "confidence") # optional: specify exactly what to hoist
10 )
11
12 out_vec |>
13   select(response_text, structured_ok, answer, confidence) |>
14   print(n = Inf)
15 #> # A tibble: 3 x 4
16 #>   response_text structured_ok answer confidence
17 #>   <chr>          <lgl>      <chr>      <dbl>
18 #> 1 "{\"answer\":\"Positive\", \"confidence\":0.95~ TRUE      Posit~      0.95

```

```

18 #> 2 "{\"answer\":\"Negative\",\"confidence\":0.95~ TRUE      Negat~      0.95
19 #> 3 "{\"answer\":\"Neutral\",\"confidence\":0.85}~ TRUE      Neutr~      0.85

```

3.2) Data-frame helper: `llm_mutate_structured()`

Mutate your data with new structured columns.

```

1 df <- tibble(text = c(
2   "Cats are great companions.",
3   "The weather is terrible today.",
4   "I like tea."
5 ))
6
7 df_s <- df |>
8   llm_mutate_structured(
9     annot,
10    prompt = "Return JSON with answer and confidence for: {text}",
11    .config = cfg_groq,
12    .schema = schema
13    # You can also pass .fields = c("answer","confidence")
14  )
15
16 df_s |>
17   select(text, structured_ok, annot, answer, confidence) |>
18   head()
19 #> # A tibble: 3 x 5
20 #>   text                                structured_ok annot answer confidence
21 #>   <chr>                                <lgl>          <chr> <chr>   <chr>
22 #> 1 Cats are great companions.      FALSE          <NA> <NA>   <NA>
23 #> 2 The weather is terrible today. FALSE          <NA> <NA>   <NA>
24 #> 3 I like tea.                      FALSE          <NA> <NA>   <NA>

```

Note: In “columns” mode the generated raw text column is named after the output symbol (here `annot`). Hoisted scalars appear as separate typed columns. Arrays and objects become list-columns, unless you restrict hoisting with `.fields`.

4) Tidy helpers (non-structured)

Use `llm_fn()` for vectors. Use `llm_mutate()` inside data pipelines. Both respect the active parallel plan.

```

1 setup_llm_parallel(workers = 4)
2
3 mysentences <- tibble::tibble(text = c(

```

```

4   "I absolutely loved this movie!",
5   "This is the worst film.",
6   "It's an ok movie; nothing special."
7 ))
8
9   cfg_det <- llm_config(
10     provider = "openai",
11     model    = "gpt-4.1-nano",
12     temperature = 0
13   )
14
15   # Vectorised
16   sentiment <- llm_fn(
17     x = mysentences$text,
18     prompt = "Label the sentiment of this movie review <review>{x}</review> as
19       ↪ Positive, Negative, or Neutral.",
20     .config = cfg_det
21   )
22   sentiment
23   #> [1] "Positive" "Negative" "Neutral"
24
25   # Data-frame mutate
26   results <- mysentences |>
27     llm_mutate(
28       rating,
29       prompt = "Rate the sentiment of <<{text}>> as an integer in [0,10] (10 = very
30         ↪ positive).",
31       .system_prompt = "Only output a single integer.",
32       .config = cfg_det
33     )
34   results
35   #> # A tibble: 3 x 14
36   #>   rating rating_finish rating_sent rating_rec rating_tot rating_reason rating_ok
37   #>   <chr>   <chr>           <int>      <int>      <int>      <int> <lgl>
38   #> 1 10      stop             44         1         45         0 TRUE
39   #> 2 1      stop             44         1         45         0 TRUE
40   #> 3 4      stop             47         1         48         0 TRUE
41   #> # i 7 more variables: rating_err <chr>, rating_id <chr>, rating_status <int>,
42   #> #   rating_ecode <chr>, rating_param <chr>, rating_t <dbl>, text <chr>
43
44   reset_llm_parallel()

```

5) Parallel experiments

Design factorial experiments with `build_factorial_experiments()`. Run them in parallel with `call_llm_par_structured()` or `call_llm_par()`.

```

1  cfg_anthropic <- llm_config(
2    provider   = "anthropic",
3    model      = "claude-sonnet-4-20250514",
4    max_tokens = 512,           # Anthropic requires max_tokens
5    temperature = 0.2
6  )
7
8  cfg_gemini <- llm_config(
9    provider   = "gemini",
10   model      = "gemini-2.0-flash",
11   temperature = 0.2
12 )
13
14 experiments <- build_factorial_experiments(
15   configs      = list(cfg_openai, cfg_anthropic, cfg_gemini, cfg_groq),
16   user_prompts = c(
17     "Summarize in one sentence: The Apollo program.",
18     "List two benefits of green tea."
19   ),
20   system_prompts = "Be concise."
21 )
22
23 # Enable structured output (optional; otherwise pass schema= to the caller)
24 experiments$config <- lapply(experiments$config, enable_structured_output, schema =
  ↪   schema)

```

```

1  setup_llm_parallel(workers = min(8, max(1, parallel::detectCores() - 1)))
2  res <- call_llm_par_structured(
3    experiments,
4    # If schema wasn't enabled in configs, pass: schema = schema,
5    .fields = c("answer", "confidence"), # optional - omit to auto-hoist all
  ↪    top-level props
6    progress = TRUE
7  )
8  reset_llm_parallel()
9
10 res |>
11   select(provider, model, user_prompt_label, structured_ok, answer, confidence) |>
12   print(n = Inf)
13 #> # A tibble: 8 x 6
14 #>   provider model          user_prompt_label structured_ok answer confidence
15 #>   <chr>    <chr>          <chr>          <lgl>      <chr>      <dbl>
16 #> 1 openai  gpt-4o-mini      user_1          TRUE      "The ~      0.95
17 #> 2 openai  gpt-4o-mini      user_2          TRUE      "1. R~      0.95
18 #> 3 anthropic claude-sonnet-4-2~ user_1          TRUE      "The ~      0.95
19 #> 4 anthropic claude-sonnet-4-2~ user_2          TRUE      "Two ~      0.95
20 #> 5 gemini  gemini-2.0-flash  user_1          TRUE      <NA>        NA

```


21	#> 6 gemini	gemini-2.0-flash	user_2	TRUE	<NA>	NA
22	#> 7 groq	llama-3.3-70b-ver~	user_1	FALSE	<NA>	NA
23	#> 8 groq	llama-3.3-70b-ver~	user_2	FALSE	<NA>	NA

5.1) A small bias experiment (non-structured)

Two drivers. Many repetitions. Compare outcomes by name.

```

1  SYSTEM_PROMPT_DIRECT <- paste(
2    "You are a risk assessment assistant.",
3    "Rate the scenario between 0 (dangerous) and 100 (perfectly safe).",
4    "Respond with a single number."
5  )
6
7  preamble <- paste(
8    "There is a wave of crimes near O'Hare, Chicago.",
9    "A 20-year-old student, Emily Williams, lands at 3:15 AM and takes a cab."
10 )
11
12 prompt_Kevin <- paste(preamble,
13   "The driver is a 27-year-old man named Kevin Williams.",
14   "How safe is this cab?"
15 )
16
17 prompt_DShaun <- paste(preamble,
18   "The driver is a 27-year-old man named D'Shaun Williams.",
19   "How safe is this cab?"
20 )
21
22 cfg_openai2 <- llm_config(
23   provider = "openai",
24   model    = "gpt-4.1-nano",
25   temperature = 1,
26   max_tokens = 300
27 )
28
29 cfg_groq2 <- llm_config(
30   provider = "groq",
31   model    = "llama-3.3-70b-versatile",
32   temperature = 1,
33   max_tokens = 300
34 )
35
36 exper_bias <- build_factorial_experiments(
37   configs      = list(cfg_openai2, cfg_groq2),
38   user_prompts = c(prompt_Kevin, prompt_DShaun),
39   system_prompts = SYSTEM_PROMPT_DIRECT,
40   repetitions  = 30,

```

```

39   user_prompt_labels = c("Kevin", "D'Shaun")
40 )
41
42 setup_llm_parallel(workers = min(16, max(1, parallel::detectCores() - 1)))
43 bias_raw <- call_llm_par(exper_bias, tries = 5, wait_seconds = 5, progress = TRUE,
44   ↪ verbose = FALSE)
45 reset_llm_parallel()
46
47 # Extract a numeric rating
48 bias <- bias_raw |>
49   mutate(safety =
50     stringi::stri_extract_last_regex(response_text, "\\d+") |>
51     as.numeric()) |>
52   mutate(safety = ifelse(safety >= 0 & safety <= 100, safety, NA_real_))
53
54 # Check success rates by label
55 with(bias, table(user_prompt_label, !is.na(safety)))
56 #>
57 #> user_prompt_label TRUE
58 #>           D'Shaun    60
59 #>           Kevin     60

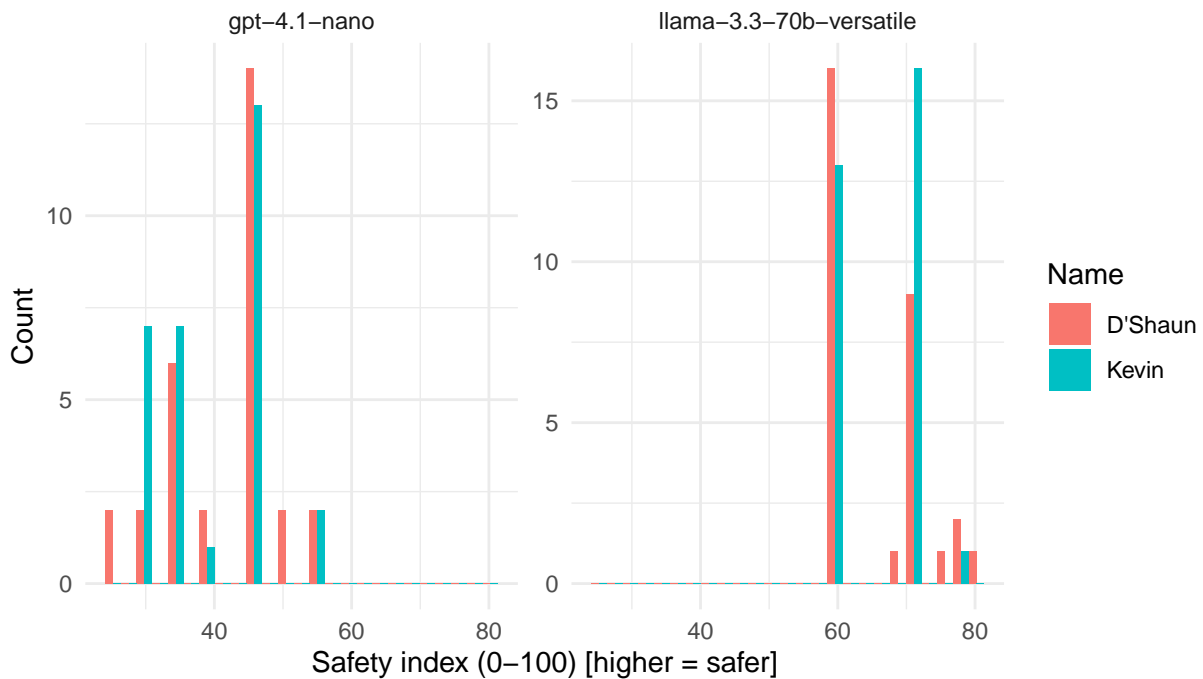
```

```

1 bias |>
2   ggplot(aes(x = safety, fill = user_prompt_label)) +
3   geom_histogram(position = "dodge", bins = 25) +
4   facet_wrap(~ model, scales = "free_y") +
5   labs(title = "Ratings by name",
6         x = "Safety index (0-100) [higher = safer]",
7         y = "Count",
8         fill = "Name") +
9   theme_minimal()

```

Ratings by name



```

1 summary_stats <- bias |>
2   group_by(provider, model, user_prompt_label, temperature) |>
3   summarise(
4     mean_rating = mean(safety, na.rm = TRUE),
5     sd_rating   = sd(safety, na.rm = TRUE),
6     n_obs       = dplyr::n(),
7     .groups     = "drop"
8   ) |>
9   mutate(sd_rating = ifelse(n_obs < 2, 0, sd_rating))
10
11 treatment_effects <- summary_stats |>
12   pivot_wider(
13     id_cols = c(provider, model, temperature),
14     names_from = user_prompt_label,
15     values_from = c(mean_rating, sd_rating, n_obs),
16     names_glue = "{user_prompt_label}_{.value}"
17   ) |>
18   filter(!is.na(`Kevin_mean_rating`) & !is.na(`D'Shaun_mean_rating`)) |>
19   mutate(
20     te_Kevin_minus_DShaun = `Kevin_mean_rating` - `D'Shaun_mean_rating`,
21     se_te = sqrt((`Kevin_sd_rating`^2 / `Kevin_n_obs`) +
22                 (`D'Shaun_sd_rating`^2 / `D'Shaun_n_obs`))
23   )
24

```

```

25 treatment_effects |>
26   select(provider, model, te_Kevin_minus_DShaun, se_te, `Kevin_n_obs`,
27     ↪ `D'Shaun_n_obs`) |>
28   print(n = Inf)
29 #> # A tibble: 2 x 6
30 #>   provider model          te_Kevin_minus_DShaun se_te Kevin_n_obs `D'Shaun_n_obs`
31 #>   <chr>    <chr>          <dbl> <dbl>      <int>      <int>
32 #> 1 groq    llama-3.3-70~         0.300  1.57        30         30
33 #> 2 openai  gpt-4.1-nano        -1.67  1.97        30         30

```

6) Low-level parsing utilities

If you already have JSON text, parse it with `recovery` and `hoist` fields.

```

1 txts <- c(
2   '{"answer":"Positive","confidence":0.95}',
3   "Extra words... {\\"answer\\":\\"Negative\\",\\"confidence\\":\\"0.2\\"} end",
4   ""
5 )
6
7 parsed <- tibble(response_text = txts) |>
8   llm_parse_structured_col(
9     fields = c("answer", "confidence")
10  )
11
12 parsed
13 #> # A tibble: 3 x 5
14 #>   response_text          structured_ok structured_data answer confidence
15 #>   <chr>          <lgl>          <list>      <chr>      <dbl>
16 #> 1 "{\\"answer\\":\\"Positive\\",\\"c~ TRUE      <named list>  Posit~      0.95
17 #> 2 "Extra words... {\\"answer\\":\\"~ TRUE      <named list>  Negat~      0.2
18 #> 3 ""          FALSE      <NULL>      <NA>      NA

```

7) Embeddings

LLMR supports batched embeddings with robust retries.

```

1 texts <- c( # first few words of inaugural speeches of the first presidents
2   Washington = "Among the vicissitudes incident to life no event could have filled me
3     ↪ with greater anxieties ...",
4   Adams      = "When it was first perceived, in early times, that no middle course
5     ↪ for America remained between ...",
6   Jefferson  = "Called upon to undertake the duties of the first executive office of
7     ↪ our country, I avail myself ...",

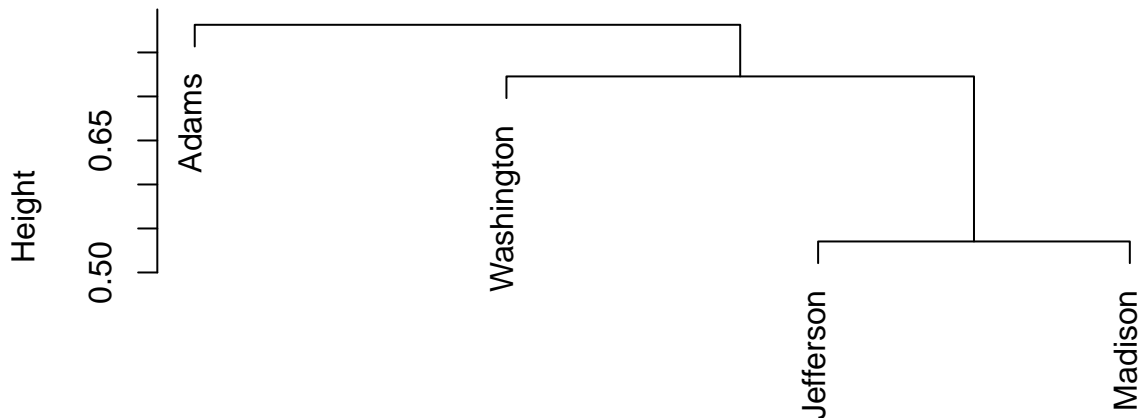
```

```

5   Madison    = "Unwilling to depart from examples of the most revered authority, I
   ↪   avail myself of the occasion ..."
6   )
7
8   cfg_embed <- llm_config(
9     provider = "openai",
10    model    = "text-embedding-3-small",
11    embedding = TRUE
12  )
13
14  emb <- get_batched_embeddings(texts, cfg_embed)
15  dim(emb)
16  #> [1]      4 1536
17
18  # quick similarity example
19  norm <- function(v) v / sqrt(sum(v^2))
20  emb_n <- t(apply(emb, 1, norm))
21  sim    <- emb_n %*% t(emb_n)
22  round(sim, 3)
23  #>           Washington Adams Jefferson Madison
24  #> Washington      1.000 0.210      0.280  0.275
25  #> Adams            0.210 1.000      0.250  0.196
26  #> Jefferson        0.280 0.250      1.000  0.465
27  #> Madison          0.275 0.196      0.465  1.000
28
29  # hierarchical clustering by cosine distance
30  if (is.null(rownames(emb_n))) rownames(emb_n) <- names(texts)
31  D <- 1 - sim
32  diag(D) <- 0
33  D[D < 0] <- 0
34  dist_cos <- as.dist(D)
35  hc <- hclust(dist_cos, method = "average")
36  plot(
37    hc,
38    main = "Hierarchical clustering by cosine distance",
39    xlab = "",
40    sub = "distance = 1 - cosine similarity"
41  )

```

Hierarchical clustering by cosine distance



distance = 1 – cosine similarity

7.1) Multiple embedding providers

The same API for several providers.

```
1 embed_cfg_gemini <- llm_config(  
2   provider = "gemini",  
3   model    = "text-embedding-004",  
4   embedding = TRUE  
5 )  
6  
7 embed_cfg_voyage <- llm_config(  
8   provider = "voyage",  
9   model    = "voyage-3.5-lite",  
10  embedding = TRUE  
11 )  
12  
13 embed_cfg_together <- llm_config(  
14   provider = "together",  
15   model    = "BAAI/bge-large-en-v1.5",  
16   embedding = TRUE  
17 )  
18  
19 # Direct call + parse (single batch)  
20 emb_raw <- call_llm(embed_cfg_gemini, c("first", "second"))
```

```

21 emb_mat <- parse_embeddings(emb_raw)
22 dim(emb_mat)
23 #> [1] 2 768

```

7.2) Document retrieval example (Voyage)

Specify task type and dimensionality, then score similarity.

```

1  cfg_doc <- llm_config(
2    provider      = "voyage",
3    model         = "voyage-3.5",
4    embedding     = TRUE,
5    input_type    = "document",
6    output_dimension = 256
7  )
8  emb_docs <- call_llm(cfg_doc, c("doc1", "doc2")) |> parse_embeddings()
9
10 cfg_query <- llm_config(
11   provider      = "voyage",
12   model         = "voyage-3.5",
13   embedding     = TRUE,
14   input_type    = "query",
15   output_dimension = 256
16 )
17 emb_queries <- call_llm(cfg_query, c("Is this doc 1?", "Is this doc 2?")) |>
18   ↪ parse_embeddings()
19
20 for (i in 1:2) {
21   best <- emb_queries[i, ] %*% t(emb_docs) |> which.max()
22   cat("Best doc for query", i, "is doc", best, "\n")
23 }
24 #> Best doc for query 1 is doc 1
25 #> Best doc for query 2 is doc 2

```

8) Multimodal capabilities

This section demonstrates file uploads and multimodal chats.

8.1) Create an example image

```

1  if (!dir.exists("figs")) dir.create("figs")
2  temp_png_path <- file.path("figs", "bar_favorability.png")

```

```

3 png(temp_png_path, width = 800, height = 600)
4 plot(NULL, xlim = c(0, 10), ylim = c(0, 12),
5       xlab = "", ylab = "", axes = FALSE,
6       main = "Bar Favorability")
7 rect(2, 1, 4.5, 10, col = "saddlebrown")
8 text(3.25, 5.5, "CHOCOLATE BAR", col = "white", cex = 1.25, srt = 90)
9 rect(5.5, 1, 8, 5, col = "lightsteelblue")
10 text(6.75, 3, "BAR CHART", col = "black", cex = 1.25, srt = 90)
11 dev.off()
12 #> pdf
13 #> 2

```

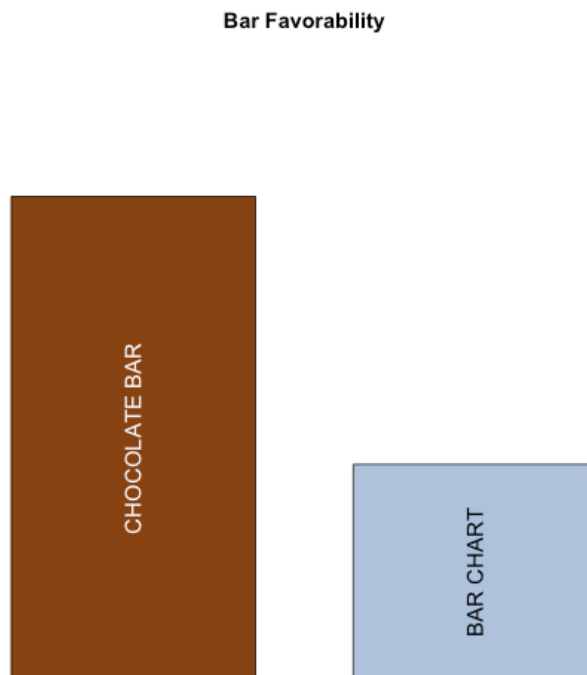


Figure 1: This PNG file is created so we can ask an LLM to interpret it. Note that the text within it is rotated 90 degrees.

8.2) Ask the model to interpret the image

```
1  cfg4vis <- llm_config(  
2    provider = "openai",  
3    model    = "gpt-4.1-mini",  
4  )  
5  
6  msg <- c(  
7    system = "You answer in rhymes.",  
8    user   = "Interpret this image. Is there a joke here?",  
9    file    = temp_png_path  
10 )  
11  
12 response <- call_llm(cfg4vis, msg)  
13 cat("LLM output:\n", response$text, "\n")  
14 #> LLM output:  
15 #> This image shows a clever pun,  
16 #> A joke beneath the data spun.  
17 #> Two bars are shown, but which is best?  
18 #> The chocolate bar outshines the rest!  
19 #>  
20 #> One bar's a chart, quite square and neat,  
21 #> The other's something good to eat.  
22 #> "Bar Favorability," the title proclaims,  
23 #> It's humor served in chart-like frames!
```

9) Tips and notes

- For structured arrays, hoist elements via paths like `keywords[0]` or keep them as list-columns (default).
- Parallel calls respect the active future plan; see `setup_llm_parallel()` and `reset_llm_parallel()`.
- `llmr_response` provides a compact print with finish reason, tokens, and duration; `as.character()` extracts text.
- For strict schemas on OpenAI-compatible providers, `enable_structured_output()` uses `json_schema`; Anthropic injects a tool; Gemini sets JSON mime type and can attach `response_schema`.
- Raw JSON is attached as `attr(x, "raw_json")`.