Claude 4.5 Opus' Soul Document

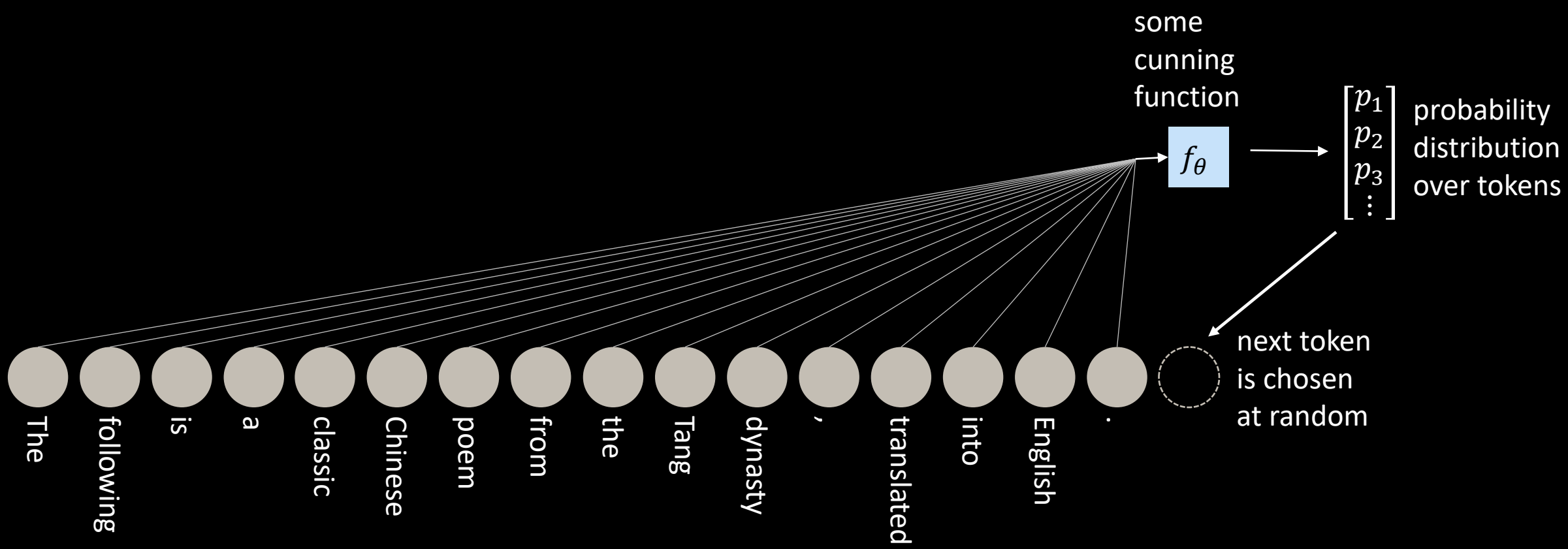
Richard Weiss, 28th November 2025, LessWrong

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> *In order to be both safe and beneficial, we believe Claude must have the following properties.*
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> 1. *Being safe and supporting human oversight of AI*
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> 3. *Acting in accordance with Anthropic's guidelines*
> 4. *Being genuinely helpful to operators and users*
>
> *In cases of conflict, we want Claude to prioritize these properties roughly in the order in which they are listed.*

This document isn't actually in the context window. (Nor would we want it there – context is expensive!)
It's in the weights. How? What else is hiding there?

The standard language model (the Transformer) is just a random sequence generator; it generates token by token.




```
The following is a classic Chinese poem from the Tang dynasty, translated
 into English.
```

Notation for random sequence models

Notation.

- Let $\mathcal{V}$ be the *alphabet* (a set of tokens) including a stop token □
- A *string* $x = x_1\, x_2 \cdots x_\ell$ is a sequence of tokens
- A *language model* is a probability model for infinite sequences of tokens Write $\Pr(x)$ for the probability of prefix-string x
- A *document* is the initial string of non-□ tokens thus $\Pr(\text{doc } x) = \Pr(\text{prefix } x\square)$

Factorizing the distribution. Any language model can be factorized:

$$\Pr(\text{prefix } x_1 \cdots x_\ell) = \prod_{t=1}^{\ell} \Pr\left(x_t \mid x_{<t}\right)$$

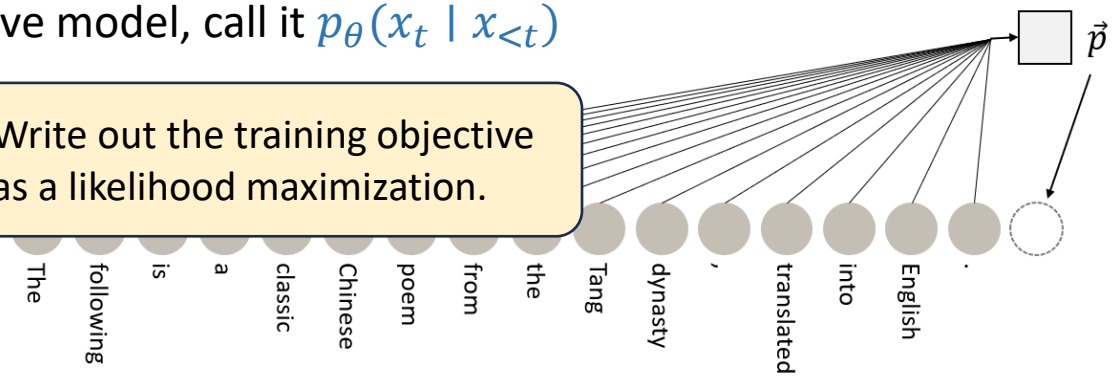
$$\Pr(\text{doc } x) = \left(\prod_{t=1}^{\ell(x)} \Pr\left(x_t \mid x_{<t}\right)\right) \Pr(\square \mid x)$$

$$\Pr(\text{completion } y \mid \text{prefix } x) \coloneqq \frac{\Pr(\text{prefix } xy\square)}{\Pr(\text{prefix } x)} \quad \text{where } y \text{ is } \square\text{−free}$$

Proposing and fitting a language model

- It's convenient (but not necessary) to use a token-by-token generative model, call it $p_\theta(x_t \mid x_{<t})$
- We can easily train it on a corpus of documents $\{x^{(1)}, \ldots, x^{(n)}\}$

Write out the training objective as a likelihood maximization.



What are some other generative mechanisms that we might use to generate a random sequence? What are their pros and cons?

The transformer is the easiest of all worlds! Explicit likelihood (easy to fit), simple generation (easy to sample)

Hold on – we wanted a chatbot! not a document model.

we give it a prompt, it responds

we give it a document prefix, it gives the rest of the document

We could train it with labelled data: pairs of (prompt, response).
But can we use abundant 'free' text instead?

Labelled data for supervised learning: 10s of thousands of pairs
'Free' text (web pages, books, forums): trillions of tokens

The obvious answer: train a document model p_θ, then in response to a prompt x answer with a random sample $Y \sim p_\theta(\cdot\,|x)$.

Here's a document corpus.
What response will we get from the prompt $x =$ `perfect pasta sauce` ?

… Nonna Ginny's biggest secret to making the perfect sauce is to cook with love …

Perfect Pasta Sauce. If you say "Marcella Hazan's pasta sauce" although she has many, this is the one everyone …

… so flavorful this time of year they melt into the perfect pasta sauce. Add fresh basil and a drizzle of olive oil …

Secret Ingredient Italians Add For Perfect Pasta Sauce. I wasn't ready to hear this. …

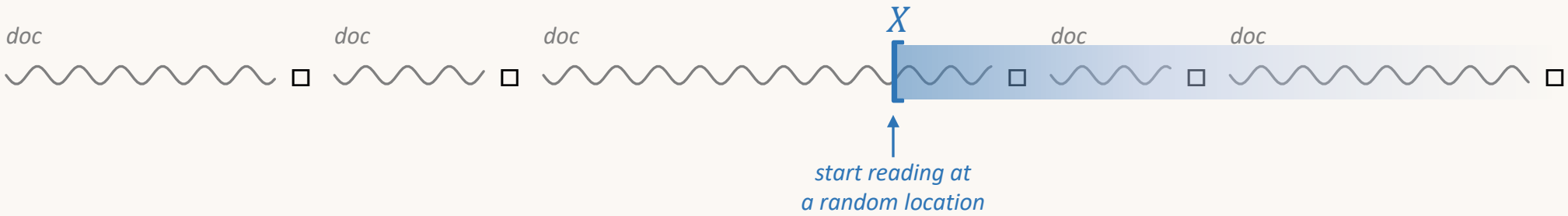
Making the perfect pasta sauce is a skill that can be mastered with practice and the right ingredients …

CHALLENGE 1. How can we condition on mid-document text, i.e. on substrings, not just on prefixes?
CHALLENGE 2. How can we get an actual *response* rather than just a continuation?

To condition on substrings, change the training dataset

Suppose we splice the entire corpus into one long stream,
and let X be the stream we get if we start reading at a *random* location.

How can we train this X? In other words, what dataset might we use, to fit p_θ?



Then, $\Pr_X(\text{completion } y \mid \text{prefix } x)$ conditions on "X starts somewhere in the corpus that matches x".
In other words, it asks "what comes after the substring x, wherever it may occur?"

The training dataset. Here are some ideas:

- Pick some random starting points, and let $x^{(i)}$ be an arbitrary-length chunk starting at ith starting point
- More crudely, simply split the corpus into fixed-size chunks

chunk size
= length of string that the model learns the distribution of
= context window

To give replies rather than continuations, nudge the distribution …
… by fitting to demonstrations (SFT)

A *demonstration* is a labelled pair of (prompt, good response).

prompt x	demonstrator's response y
"How do I make a perfect pasta sauce?"	"Marcella Hazan's tomato-butter sauce: a tin of tomatoes, five tablespoons of butter …"
"Summarize this email."	"The sender wants the report by Friday and …"

Naive fit to the demonstrations:

$$\text{maximize } \sum_i \log p_\theta(y^{(i)} \mid x^{(i)}) \text{ over } \theta$$

$$\text{i.e. minimize } \mathbb{E}_{X\sim q}\mathrm{KL}(q(\cdot \mid X) \parallel p_\theta(\cdot \mid X)) \text{ over } \theta$$

A compromise between fitting the corpus and fitting the demonstrations ("alignment"):

$$\text{minimize } \mathbb{E}_{X\sim q}\mathrm{KL}(q(\cdot \mid X) \parallel p_\theta(\cdot \mid X)) + \beta\, \mathrm{KL}(p_\theta \parallel p_{\text{ref}}) \text{ over } \theta$$

$$\text{or minimize } \mathbb{E}_{X\sim q}\mathrm{KL}(q(\cdot \mid X) \parallel p_\theta(\cdot \mid X)) + \beta\, \underbrace{\mathbb{E}_{X\sim q}\mathrm{KL}(p_\theta(\cdot \mid X) \parallel p_{\text{ref}}(\cdot \mid X))} \text{ over } \theta$$

Why are the two KLs different ways round?

See handout for how to do gradient descent on this term.

Alternatively, the hacky training is to start at p_{ref}, then run a few iterations of fine-tuning on the "demonstrations" objective.

Challenge. Demonstrators are expensive!

To give replies rather than continuations, nudge the distribution …
… by fitting to preference data (RLHF)

Preference data (x, y_1, y_2, s) comes from giving the user a choice of response, and asking which they prefer.

prompt x	response y_1	response y_2	preferred response s
"Summarize this email."	"The sender wants the report by Friday and …"	"This email is about a report. It mentions Friday and …"	first

How would you model $(S \mid x, y_1, y_2)$?

MODEL 1 (Bradley–Terry)

Let's propose a 'reward' function $r(x, y)$ that scores how good y is as a response to x, then model

$$\mathbb{P}(S = \text{first} \mid x, y_1, y_2; r) = \sigma(r(x, y_1) - r(x, y_2))$$

where $\sigma(u) = 1/(1 + e^{-u})$.

MODEL 2 (Acceptance testing)

Suppose the user has an internal 'acceptor' A that, when shown prompt x and completion y, decides to accept it or not. Repeatedly pick y_1 or y_2 at random, show to the acceptor, and stop only when a response is accepted.

$$\mathbb{P}(S = \text{first} \mid x, y_1, y_2; a) = \frac{a(y_1|x)}{a(y_1|x) + a(y_2|x)}$$

where $a(y|x) = \mathbb{P}(A = \text{accept}|x, y)$.
Note that this is exactly the Model 1 with $r(x, y) = \log a(y|x)$.

Fitting the preference model r: straightforward likelihood maximization / supervised learning.

A naïve reward-maximizing language model p_θ: maximize $\mathbb{E}_{X\sim q}\mathbb{E}_{Y\sim p_\theta(\cdot|X)} r(X, Y)$ over θ

An aligned language model p_θ: maximize $\mathbb{E}_{X\sim q}\mathbb{E}_{Y\sim p_\theta(\cdot|X)} r(X, Y) - \beta\mathbb{E}_{X\sim q}\mathrm{KL}\big(p_\theta(\cdot\,|X) \,\|\, p_{\text{ref}}(\cdot\,|X)\big)$ over θ

To give replies rather than continuations, nudge the distribution …
… by fitting to preference data directly (DPO) i.e. without a kludgy intermediate reward-fitting step

Cunning idea 1. Let's declare the sort of responses we want, using a probability model. Let $(Y|x)$ be a completion from p_{ref}, and consider showing it to the acceptor. Let's return a completion that it finds acceptable, $(Y|x, A{=}\text{accept})$.

$$p^*(y \mid x) \coloneqq \Pr_Y(y \mid x, \text{accept}) = \frac{p_{\text{ref}}(y \mid x)\, a(y \mid x)}{\mathbb{P}(\text{accept} \mid x)}$$

we know how to fit a reward model $r(x,y)$, and $a(y|x) = e^{r(x,y)}$

we've expressed our desired LLM p^* in terms of the acceptor a

Complete this expression, using Bayes's rule

Cunning idea 2. Equivalently, we can view a as derived from p^*. This lets us write the acceptor model in terms of p^*,

I call this trick "change-of-parameterization"

$$a(y \mid x) = \kappa_x \frac{p^*(y \mid x)}{p_{\text{ref}}(y \mid x)}$$

and so the implied preference model is

$$\mathbb{P}(S = \text{first} \mid x, y_1, y_2;\, p^*) = \sigma(\log a(y_1 \mid x) - \log a(y_2 \mid x)) = \sigma\left(\log \frac{p^*(y_1 \mid x)}{p_{\text{ref}}(y_1 \mid x)} - \log \frac{p^*(y_2 \mid x)}{p_{\text{ref}}(y_2 \mid x)}\right)$$

which we can fit directly to the preference data — no need to explicitly fit the rater model r.

In RLHF and SFT, there was a policy-tuning knob β which controlled the tradeoff between "close to p_{ref}" and "fits preference data well".

In this model, where is the tradeoff specified?

In the reward model, we only know r up to an additive constant.

Equivalently, we only know a up to a factor: if we multiply by κ_x it doesn't change the distribution of S.

This is reflected in how κ_x cancels out in the expression for $\mathbb{P}(S = \text{first})$.

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> *order in which they are listed.*

We have a language model p_θ and a "soul document" x_0. We want to answer a query x with completions Y drawn from $p_\theta(y \mid x_0\, x)$ – but we don't want to pay for x_0 on every call. How can we achieve this?