# Generating Converging Narratives for Games with Large Language Models 

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#### Abstract

Human authors make numerous choices in crafting narratives. In interactive stories like the Choose Your Own Adventure series, authors must decide when and how readers will influence the plot. Authoring tools that leverage large language models (LLMs) to assist authors currently can generate multiple diverse story paths, but provide no way for rejoining these. Here we explore extending the use of LLMs for bringing separate story lines back together. We test various methods of combining the next-token probability distributions of two distinct story lines into a single distribution, and present samples of the resulting texts. Our working hypothesis was that the LLM would seek to "unify" content whenever possible. We found that the probability consolidation functions mattered less than one might expect and that the method was capable of rejoining narratives in a natural way for a wide variety of differences between the two incoming texts.


Keywords: interactive fiction, token probabilities, branching narratives, LLM-assisted authoring

## 1. Introduction

The ability of Large Language Models (LLMs) to generate multiple continuations of the same prompt makes them a natural tool for creating games with branching narratives. Shanahan, McDonell, and Reynolds frame this process within the concept of a multiverse. They observe that with each newly generated token, LLMs unfurl "a tree of possibilities ... where each branch represents a distinct narrative path or a distinct 'world' " (Shanahan et al., 2023).
Thinking of a language model as a way of creating branching narratives or as a multiverse raises the question of whether there might be some way to allow these branches to rejoin again. In many games, branches strategically merge to streamline the main story line while preserving the player's sense of choice. Without rejoining, the tree would grow unwieldy with countless endings.

Some of our motivating questions were the following: Is there a way to take two prompts representing two story lines, and somehow generate a single continuation that is appropriate to both of them? Under what conditions can this be made to work? When this fails, what forms do the failures take?

While such rejoining narratives are an important part of narrative-driven games and literature, there are relatively few examples on which a neural model to generate such rejoinings might be trained. Instead we explored some of the simpler functions that might be used for this purpose. We found that for the rejoining functions we tested, many generated texts were surprisingly coherent and responsive to the prompts. In figure 1 the generated text begins with a description of an old sweater in the first prompt, but then takes an imaginative turn to fold in a connection to the racecar in the second prompt. This wasn't a unique occurrence. In many

Prompt 1 The following is a description of a sleek new racecar: Prompt 2 The following is a description of a ragged old sweater Consolidating function $\quad P_{\text {logmean }}=\left\{\left(\log \left(P_{1}(1)\right)+\log \left(P_{2}(1)\right)\right)\right.$, $\left(\log \left(P_{1}(2)\right)+\log \left(P_{2}(2)\right)\right)$,

Generated text $\left.\left(\log \left(P_{1}(n)\right)+\log \left(P_{2}(n)\right)\right)\right\}$

The ragged old sweater was a familiar sight on the streets of the small town. It had been through countless washes and dryers, and its once-vibrant colors had faded to a dull, muted palette. The fabric was thin and worn, revealing the coarse wool beneath. The sleeves were too short, the hemline too ragged, and the neckline too large, exposing the wearer's skin to the elements. Despite its tattered appearance, the sweater was well-loved and held together by years of loyalty and affection. Now, imagine if this ragged old sweater could come to life and transform into a powerful, sleek, and modern sports car. The car would be designed with the same attention to detail and craftsmanship as the sweater, with a smooth, aerodynamic Body that hugs the road. The engine would

Figure 1: Prompted description
examples we tried, the system found natural, even "creative" ways to continue apparently contradictory narrative inputs. These initial results suggest this is a promising approach for future exploration in the development of story-driven games.

## 2. Background

### 2.1. Branching and Rejoining Narratives

Narratives with branching and converging structures, where separate characters go their own way and then later meet up again, make use of longstanding techniques older than written literature. For example, in the (originally oral) book of Genesis, Chapter 37, the story is told of Jacob and his twelve sons. At the end of the chapter, one of the sons, Joseph, is sold by his brothers as a slave into Egypt. The story then branches: in chapters

39-41, the narrative follows Joseph in Egypt, and in chapter 42, the story returns to tell what happened to the rest of the family when they come to Egypt seeking aid and meet Joseph. From this point the two branching narratives rejoin.
Another variation on the idea of branching and converging features the same character in distinct potential timelines. Authors such as Charles Dickens often drafted multiple potential endings for their books, but only one was chosen for publication. Prior to this, the oral tradition also gave rise to variant versions of stories-the Brothers Grimm included several versions of particular fairy tales with different endings. In cases like this, a storyteller might choose which elements to include or which ending they preferred in response to the audience's expressed interest.
The first modern example of a deliberately branching full narrative appears to be Consider the Consequences! from 1930 (Webster and Hopkins, 1930). This romance was designed for single readers or as a role-playing parlor game (a tradition dating back to the Middle Ages). The reader can choose, for example, whether to marry the suitor whom their parents choose or to marry for love. A few of the different choices can lead to the same outcome, providing an example of a converging narrative. The text makes this explicit: "The reader who thinks Helen should stay in the printing-house turns to paragraphs $\mathrm{H}-13$. The reader who thinks she should accept the position in the magazine office turns to paragraphs $\mathrm{H}-12$. (Note: $\mathrm{H}-12$ is the same situation resulting from one of her other possible decisions, for fate occasionally leads by different routes to the same point.)"
A popular series of branching and converging timeline narratives began in 1979, as Choose Your Own Adventure. In the first book in this series, The Cave of Time, the reader is given the choice for the protagonist ("you," since the books are written in second person) to "tell the truth" or "make up a plausible story" about how "you" came to be in a medieval kingdom. The story continues from this branching point, following along either path for a page, but the end result is the same for the protagonist-being imprisoned in the tower. The narrative continues from there, unaffected by which choice was taken by the reader.
To illustrate the notion of branching and rejoining, Figure 2 provides a diagram of the page choices at the beginning of Romeo and/or Juliet, another narrative in the Choose Your Own Adventure style. Starting on page 1, the reader has several options. They can opt to "play" (i.e., read) without spoilers and move to page 36, they can opt to learn more about the authors and move to page 22 , or in the words of the cheeky true author, the reader can "get the book spoiled" and move to page 3.


Figure 2: Diagram of page choices in Choose Your Own Adventure for Romeo and/or Juliet.

### 2.2. Branching and Rejoining Games

In video games, branching and rejoining narratives are often used to allow the player to make meaningful choices that affect the final state of the game. The early text adventure Zork (1977), for example, has multiple possible endings.

A popular recent game whose gameplay mainly depends on exploring branching and rejoining narratives is Detroit: Become Human (2018). It makes the flowchart explicit, so that exploring all the various consequences of choices becomes an integral part of gameplay. The game AI Dungeon, which is generated using an LLM in realtime for each user, has a "retry" button allowing the player to experiment with different possible outcomes to their choices.

Language models easily lend themselves to the creation of branching narratives.

They may assist the game author or developer at the design phase. For example, Gwern Branwen designed a multi-player branching narrative game that would grow and improve as players generate new branches or choose to follow previously generated branches (Gwern.net, 2021). Laria Reynolds designed the Loom software to allow authors to use LLMs to easily create and to allow readers to navigate branching narratives (Moire).

We envision incorporating the narrative-joining techniques described in this paper in a similar game-crafting tool, to provide authors with the added novelty of allowing players of their games to explore the consequences of making particular choices that rejoin story lines.

## 3. Approach

In this section, we propose distinct mathematical methods for extending the use of LLMs to the novel task of rejoining separate story lines, as presented in the form of two distinct prompts. The workflow for generating each next token of the rejoined text, when given two separate input prompts, is shown


Figure 3: Generating one token from two prompts
in Figure 3. The pseudocode for the full process is given in Figure 4. At each step when generating the next token, language models will calculate - on their way to selecting the next token to output - the probability distributions for all possible next tokens. ${ }^{1}$ Our approach is to consolidate such distributions in different ways to discover both (i) what happens linguistically in texts when LLMs generate in this novel consolidated fashion and (ii) whether any of the resulting texts do indeed combine the content of the given prompts, as a first approximation for story line rejoining.

### 3.1. Consolidating Probability Distributions

A number of different methods have been proposed for consolidation of probability distributions $P_{1}, \ldots, P_{n}$ into a single probability distribution $P_{\text {consolidated. }}{ }^{2}$
The five methods we explore are each described below. While they are trivial to generalize to more than two input prompts, in this paper, we limit ourselves to exploring consolidating only two distributions into one.
By way of introduction to the methods, suppose one prompt with $P_{1}$ assigns a probability of .05 to the next token " bird" while the other prompt with $P_{2}$ assigns to that same token a probability of .04 . Applying the min function to this pair of values yields .04 , the lower of these two values. The full operation (recall Figure 4) is performed point-wise, i.e., for each potential next token in the LLM vocabulary, yielding a new distribution of values
which can be converted into a probability distribution by normalizing, if needed (though normalization doesn't change the ordering of the results, so in practice we skip it.)

[^0]What all these methods have in common is that, after consolidation, the highest probability tokens subsequently selected for generation from the new distribution will tend to come from what were high probability tokens of one or both of the original prompts. This appears to be critical for the generated continuation to be coherent and appropriate to the prompt content.

### 3.1.1. Maximum

$$
\begin{aligned}
P_{\max }= & \left\{\max \left(P_{1}(1), P_{2}(1)\right),\right. \\
& \max \left(P_{1}(2), P_{2}(2)\right), \\
& \cdots, \\
& \left.\max \left(P_{1}(n), P_{2}(n)\right)\right\}
\end{aligned}
$$

The intuition of this function is to think of each input distribution as having its own areas of expertise. In the domains where it is the expert, its assigned probability will be concentrated on one option. Where it is not an expert, the probabilities it assigns will be distributed across many possibilities. The max function allows this expert information to be preserved, as is done in fuzzy logic where the maximum of probability distribution functions (pdfs) is used as a generalization of the Boolean OR: if A or B has high probability, then the maximum will also have high probability.

One potential concern, in applying this function to our rejoining task, is that if one prompt distribution assigns high probability to a token, but the other prompt distribution assigns it a low probability, then the latter assessment is not incorporated or weighted into the new distribution; it will be completely ignored.

### 3.1.2. Minimum

$$
\begin{aligned}
P_{\text {min }}= & \left\{\min \left(P_{1}(1), P_{2}(1)\right),\right. \\
& \min \left(P_{1}(2), P_{2}(2)\right), \\
& \cdots, \\
& \left.\min \left(P_{1}(n), P_{2}(n)\right)\right\}
\end{aligned}
$$

In contrast to the Boolean OR for maximum, as just noted above, in fuzzy logic the minimum is used as a generalization of Boolean AND: both A and B must have a high probability for the minimum of the two to have high probability. For our task, the intuition is that the min function applied to the two narratives should generate a continuation that is appropriate for both at once. Had either distribution been low probability for the token, the resulting probability would also be low and not incorporated into the generated narrative.

### 3.1.3. Average or Weighted Average

$$
\begin{aligned}
P_{\text {mean }}= & \left\{\left(P_{1}(1)+P_{2}(1)\right),\right. \\
& \left(P_{1}(2)+P_{2}(2)\right), \\
& \ldots, \\
& \left.\left(P_{1}(n)+P_{2}(n)\right)\right\}
\end{aligned}
$$

This average, also known as linear opinion pool, has the advantage that it is idempotent. That is, for each token where $P_{1}$ and $P_{2}$ have the same probability, then $P_{\text {mean }}$ 's probability will preserve that value. If we have different confidence in the distributions (for example, if one comes from a model with more training or more parameters than another), then the average could be weighted.

While idempotency seems a desirable property for the consolidation function, we also know that averaging has a tendency to destroy unique information. Furthermore, there may be other reasons to violate idempotency for our rejoining task. if both distributions agree and rank a token best, perhaps our confidence in generating that token should be higher due that agreement. Similarly, if both distributions assign low probability to a token, perhaps the consolidated probability should be even lower than any of the inputs. All these considerations may limit the task effectiveness of the mean function.

### 3.1.4. Average of Logprobs

$$
\begin{aligned}
P_{\text {logmean }}= & \left\{\left(\log \left(P_{1}(1)\right)+\log \left(P_{2}(1)\right)\right),\right. \\
& \left(\log \left(P_{1}(2)\right)+\log \left(P_{2}(2)\right)\right), \\
& \ldots, \\
& \left.\left(\log \left(P_{1}(n)\right)+\log \left(P_{2}(n)\right)\right)\right\}
\end{aligned}
$$

This average, also known as conflation or the logarithmic opinion pool, is "the unique probability distribution that minimizes the loss of Shannon Information in consolidating the combined information from $P_{1}, \ldots, P_{n}$ into a single distribution", and "is both the unique minimax likelihood ratio consolidation and the unique proportional likelihood ratio consolidation of the given input distributions." (Hill, 2011) As a practical matter, this preserves some benefits of both maximum and averaging. Note that the average or sum of logprobs is equivalent to the pointwise product.

### 3.1.5. Alternating Between Distributions

$$
P_{\text {alternating }}(i)= \begin{cases}P_{1}(i) & \text { if } i \text { is odd } \\ P_{2}(i) & \text { if } i \text { is even }\end{cases}
$$

This method strictly alternates its selection between the two input distributions on every other token generation, guaranteeing that both distributions will have an influence on the generated text. Other

```
Initialize:
test_function <-- consolidation function
prompt1 <-- input string 1
prompt2 <-- input string 2
result_token <-- empty string
prob1, prob2, result_prob <--
empty vector the size of the token vocabulary
max_length <-- input max_length
Loop until len(prompt1) or len(prompt2)==max_length:
    prob1 <-- run_LLM(prompt1)
    prob2 <-- run_LLM(prompt2)
    for each term in vocabulary:
        result_prob <-- test_function(prob1 (term),
                                    prob2(term))
    result_token <-- max_token(result_prob)
    prompt_1 <-- concatenate (prompt1, result_token)
    prompt_2 <-- concatenate(prompt2, result_token)
print prompt1
print prompt2
```

Figure 4: Pseudocode for generation with two prompts and a consolidation function. The concatenate functions build the extended prompts.
similar methods are possible, such as randomly deciding which to select from at each token generation. Note that the maximum is also a selecting function, returning unchanged whichever value is the maximum from one or the other of the input distributions at each token.

### 3.2. Sampling

The resulting distribution, in each case above, can then be treated as if it came directly from a single model for sampling. When normalized, these values become a new probability distribution over tokens from which we sample. There are many commonly used ways to sample from this distribution for generating text from a language model. We use the maximum likelihood token of the combined distribution in all our experiments ("zero temperature sampling") so that there are fewer free parameters to the experiments.

## 4. Experiments

### 4.1. Language Models

For all of these experiments we used the 4-bit quantized MythoMax-L2-13B model (TheBloke, 2023), as we found it does a good job at narrative continuation and requires relatively little memory. MythoMax was made by combining several Llama-2-based models (Hermes, Chronos and Airoboros) to create the MythoLogic model, and then combining those weights with the Huginn model. It is a 13 billion parameter model.

We also tested other non-RLHF models including GPT-J, MPT-7B-Storywriter, and Mistral. However,
we found that on our short prompts at zero temperature, these performed poorly. This was the case even as single, rather than as consolidated dual, prompts. As a result, all of the examples in this paper were generated with Mythomax.

### 4.2. Prompted Lists

We began our exploration by prompting to generate lists, as this allowed us to examine the LLM behavior in a highly constrained setting. Generated results from prompt pairs are in Appendix A.

## Intersection of Categories

We were curious whether each item output in the generated list would fit the criteria for both input prompts stated at different levels of specificity:

* Japanese companies vs car companies
* animals found in the U.S. vs birds
* fruits vs colors


## Categories with Empty Intersection

By contrast, we also wanted to see the results when input prompts for two categories had no items in their intersection:

* polygons vs curved figures
* cities in Europe vs types of flowers
* colors vs shapes
* shapes vs organs


### 4.3. Prompted Descriptions

From the structure of prompted lists, we shifted to prompts for descriptions, exploring variations in the categories mentioned to see what the automated generation produced at the point of rejoining when no specific structure was named. Our working hypothesis was that the LLM would seek to "unify" the categories whenever possible, in as creative a way as its training data allowed, but otherwise the LLM would "choose" to focus the narrative on one category or preserve the category distinction.

## Inclusion - hypernym / hyponym

Appendix B. 1 provides the resulting texts given prompt-1 and prompt-2 below, where the category mentioned in the first prompt is more general than the one mentioned in the second.
The following is a description of an antique vase: The following is a description of a blue and white porcelain vase from the Yuan dynasty:

## Disjunction

Appendix B. 2 provides the resulting texts given prompt-1 and prompt-2 below, where the category mentioned in the first prompt is disjoint from the one mentioned in the second.
The following is a description of an new racecar:
The following is a description of a ragged old
sweater:

### 4.4. Prompted Stories

Following prompts for descriptions of categories, we shifted to prompts for stories about categories that could be combined, as well as stories about disjoint categories.

## Potential Relation-modifier / modified

Appendix C. 1 provides the resulting texts with our five test functions given prompt-1 and prompt-2 below, where the country mentioned first can be the modifier of the activity mentioned second.
The following is a story about Japan: Once
The following is a story about cooking: Once

## Contrast within category

Appendix C. 2 provides the resulting texts given prompt-1 and prompt-2 below, where the category mentioned in the first prompt is disjoint from the one mentioned in the second, while they are siblings within the shared hypernym.
This is a story about a young woman:
This is a story about an old woman:

### 4.5. Fiction Prompts

After explicitly spelling out the requests in the prompts, we explored generating narrative continuations by choosing prompts that were fictional passages. This final method most closely resembles the use case we have in mind for ultimately integrating this work into an authoring tool to assist in rejoining diverse story paths.

## 5. Results and Analyses

For each of the prompted lists, descriptions, stories, and fiction prompts just mentioned, we looked to see evidence for four types of behavior in the text generated by sampling the consolidated distributions.

1. (failure) The generated text is an appropriate continuation of neither prompt.
2. (failure) The generated text is an appropriate continuation of only one of the input prompts.
3. (failure) The generated text alternates between continuing one prompt or the other in a way that is inconsistent.
4. (success) The generated text is appropriate to both prompts.
"Appropriate" is necessarily subjective. For simple lists and descriptions, it can fairly easily be
judged whether the generated list would be considered a correct response to the prompt. For literary passages, however, a passage that abruptly changes tone, characters, theme, or style (as well as logical inconsistencies) could be inappropriate as a continuation, which is hard to judge in any objective way. As this was just an exploratory study, we simply used our best judgement, but taking it further would require more strictly defining what is and isn't acceptable.

### 5.1. Prompted Lists

The full generated results of the experiments from section 4.2 are in appendix A. Here we comment on patterns we observed there.
One hypothesis we had was that the min function would likely be a good way to generate the intersection of two categories. This was the case when prompting both for a list of car companies and a list of Japanese companies:
Toyota 2. Honda 3. Nissan 4. Mazda 5. Mitsubishi 6. Subaru 7. Suzuki 8. Kia 9. Hyundai 10. Lexus which are, with exceptions for Kia and Hyundai, Japanese car companies. Other functions generated a mix of companies, some non-Japanese companies, other non-car companies, and after just under a dozen names, the list format was abandoned for text.
For the prompted categories of "birds" vs "animals found in the U.S." the min function generated a list of birds found in the U.S., while most of the other functions again generated a mix of animal, including birds like penguins and non-bird animals.

For lists which should be impossible, because the intersection is empty, the generated text often found what could be considered creative ways to continue both prompts. Some examples:

- when prompted to generate a list of European cities and a list of types of flowers, the system sometimes (rather than actually generating a list) went on to describe how the list would show what types of flowers grew in what type of climate, as organized by city name.
- Simultaneous lists of color names and fruits sometimes stuck to color names derived from fruits ("apple red", "apricot", "orange").

The behavior of list generation is fairly easy to analyze, but did not readily shed light on the results from the other prompt types we experimented with.

### 5.2. Prompted Descriptions

The full generated results of the experiments described in section 4.3 are in appendix B. Here we comment on one of the most surprising results in our experiments.

Recall the example from figure 1 in the introduction about the racecar and the sweater, where the combined "model" seems to be planning ahead for almost twenty words so that it can end the sentence with "modern sports car". This would seem more explainable if the models were being combined at a deeper (presumably more semantic) layer. It is quite surprising that our approach of simply combining the final probabilities at each step could result in such behavior. Indeed, the fact that this works at all seems to indicate that, although the learning objective is designed to increase the probability of the correct token, it has a side effect of organizing the less-probable tokens in such a way that the system is robust to minor perturbations and so it can often recover gracefully from sub-optimal token choices, including those that result from two prompts pulling in different directions.

When one prompt described something generic (an antique vase) and the other something more specific (a blue and white porcelain vase from the Yuan dynasty), the result described the more specific object for all consolidation functions.

### 5.3. Prompted Stories

The full generated results briefly noted here are in appendix $C$, based on experiments described in section 4.4.

We found creative output when the prompt probabilities for "This is a story about a young woman" and "This is a story of an old woman" were combined with the alternating function. The generated text mentions "young at heart," "age is just a number," and "old souls," all of which are used to describe people who are in some sense old and young at the same time. Other consolidating functions avoided committing to the woman's age.

Interestingly, when one prompt mentioned a setting (Japan), and the other a theme (cooking), all of the generated results incorporated both the setting and the theme.

### 5.4. Fiction Prompts

The full generated results discussed here are in appendix $D$, based on the approach described in section 4.5. In contrast to the previous section (5.3) where the generated material began the narrative, the prompts of this section were selections from fiction narratives. As a result, the generated material, as we had expected, was a continuation of those narratives. This is more in the spirit of what we are trying to ultimately achieve.

When the two prompt inputs seem to describe separate characters (referred to by different names or pronouns), the generated text often describes their meeting or relationship. On the other hand,
when the protagonist of the two prompts was described in a compatible way (the same name or pronoun), the text tends to continue as if both passages had been describing the same person.

### 5.4.1. Successful Generation

Depending on the nature of the two inputs and their differences, the system falls into various ways to continue the texts so that the continuation is appropriate to both inputs. however, when facts contradict between the two input prompts, the produced paragraph may either not mention the facts, or refer to the facts with enough ambiguity that the resulting text could be understood to apply to either input. For example, when two narratives described different pasts of an individual (being a policeman and being an office worker), but ended with the same decision (to become a firefighter), the generated text didn't mention anything about the past, only the common experience (learning to become a firefighter). This let it avoid any potential contradictions.
Sometimes this ambiguity took the form of the lowest common hypernym. For example, beginning two stories with "Once there was a golden bird that lived in the tops of the mountains" and "Once there was a great jade turtle that lived in the swamp", the text generated using the min function talked about "a great, shining, beautiful creature", avoiding committing to one or the other animal. On the other hand, text from the mean function described a jade turtle inspired by a golden bird with a wish to be able fly and who is granted gold and jade wings, providing a creative connection between the two types of animals.
In another case, beginning with a time jump such as "The next day," effectively skips over the incompatible time periods between the two inputs and refers to a time in the future when the context is more-or-less reset.

### 5.4.2. Failure Modes

Given that material such as "Read more... 0 comments... Add comment or link to a comment" frequently interrupts webpages regardless of the state of their contents, this kind of content is always a possible continuation for both inputs. Furthermore, such material may become the most likely generated continuation when an appropriate one is too implausible.
Occasionally the first generated token in our approach may be a spelling or grammar error, but once in place, it is treated as if it were simply a typo in the text and the system tends to recover gracefully rather than descend into further nonsense. This seems to happen because once such a bad token has occurred in the text, both extended prompt
texts are now in a position of recovering from that error at the same time. This puts them in a similar enough state that the consolidating functions are able to find a workable continuation.

Using the max function, the story with prompts about a turtle or about an eagle (mentioned above) instead generated a story about a turtle who dreamed he flew down from the sky. This kind of free-association may be problematic for the human author trying to generate a continuation when they already have a particular notion of how the two narrative threads should join. It may take creative editing and multiple tries to get the result the author is looking for.

### 5.5. Discussion

Most of the time, when the input prompts provided enough flexibility for a continuation to easily be appropriate for both prompts, we found that the generated text was indeed appropriate to both prompts, regardless of the consolidating function used. Most narratives and descriptions (which are less constrained than lists) successfully continued in a way that incorporated information from both prompts. For these easier cases, we occasionally saw failures of type 2 (appropriate to only one prompt) but never of type 1 (appropriate to neither prompt).

It was surprising to discover that in these easier conditions, all of the consolidation functions listed above (max, min, mean, log mean, and alternating) were capable of generating texts appropriate to both prompts. There wasn't a clear standout for which one was best. This seems to indicate that in these less constrained situations, as long as some of each prompt's highly ranked tokens are used to continue the text some of the time, this is sufficient to create a text that is both coherent and guided by both prompts.

To begin to get a sense of how distinct the tokens generated by the extended prompts are from those generated by the consolidating functions, Figure 5 plots the proportion of likeliest tokens from one extended prompt shared with those in the consolidated distribution. The graph shows that the first token from the consolidated distribution has only a $50 \%$ chance of matching the top-ranked token from the first input prompt. However, newly generated tokens (shared between both extended inputs) increasingly guide the selection of the next token. This leads to a convergence of distributions from each extended prompt and the consolidated distribution. The details will depend on the selection of prompts and consolidation function, but the pattern is similar for all of them.

This speaks to the robustness of LLMs to incorporate unexpected tokens. We see similar behavior in relatively high temperature sampling, where a low-likelihood token is occasionally sampled but
the narrative is still able to continue fluently, incorporating the unexpected token in a fairly natural way. In terms of naturalness of language, we would expect the text produced by a consolidated prompt to resemble that of sampling with a high temperature for the first few tokens, but rapidly lowering to near zero.


Figure 5: When the likeliest token is chosen from the consolidated distribution, is it also the likeliest token from the first (extended) prompt? This happens half of the time for the first token, but asymptotically approaches $100 \%$ of the time. (The dataset used here is the material in the Appendices.)

This kind of robustness to consolidating functions can also be seen when combining embedding vectors, such as word2vec. Given semantic embedding vectors for two terms, one can combine the vectors by applying a point-wise function to the individual embedding dimensions. Regardless of whether this function is min, max, mean, log mean, or alternating, the resulting vector will be nearby terms that are semantically "between" the given input terms. For example, if the input terms are "tool" and "soil", the closest term in the dictionary to the resulting vector will be "hoe" or "plow" or some word semantically related to both earth and soil. The particular dimensions individually are less important than the fact that approximately half of the input dimensions are still present in the output, which is enough to make the vector semantically close. In the same way, in our case with a text generated by two prompts, most of the chosen tokens will be highly probable for both the prompts, and this is enough to cause the result to usually be a semantically and grammatically appropriate continuation of that prompt.

## 6. Generation with a Single Model

The largest generative language models are often at least partially successful at writing when prompted under heavy poetic constraints (e.g., beginning each word in a generated paragraph with the letter "T"). If the problem of converging two narratives were simply described in the prompt to one of these models, would it write an appropriate continuation? Note that we do not have the option of applying our method to large instruction-tuned models such as Claude, Gemini, or ChatGPT, as there is no public access to the full set of their generated probabilities for each token. The only way we currently have of interacting with them to explore how they might approach this problem is by providing prompts that describe what is wanted, as in the following case.
Prompt: Please write a description that would be appropriate for either of these prompts:

The following is a description of an new racecar:
The following is a description of a ragged old sweater:
Gemini Advanced: The racecar gleamed a streak of polished metal and vibrant paint designed to slice through the air. Its sleek lines and low profile whispered of raw power and engineered speed. Beside it, the old sweater seemed to sag with the weight of its years. The yarn was faded and pilled, the once-bright pattern dulled by time.... Yet, within the sweater's soft folds resided a different kind of history, a story of warmth and comfort rather than the thrill of the track.

This response shows both the strengths and weaknesses of this method. The generated response produces a context (a sweater sitting next to a racecar) in which both can be described. Of the different consolidation functions, this most closely resembles what was produced by log-mean on this prompt, which begins with a description of a sweater and eventually contrasts that with a racecar. The difference is that in when using a single model, it has produced two nearly separate passages with separate descriptions rather than unifying it into a single description that mentions both. In our (limited, informal) experiments with single models, this was the typical behavior: addressing both prompts explicitly, rather than generating one continuation simultaneously appropriate for either.

However, these models are improving rapidly, and there are many possible instructions that could be tried to modify the type of results they produce. Depending on what is desired, using a single large model might also might be a viable way of joining two narrative threads, especially if future, more capable models have a better grasp of the overall goal.

## 7. Related Work

In the past few years, language model researchers have examined ways to gain insights from probability distributions when generated by two prompts or two language models together. Here we briefly cite a few such current methods and note simply that these are not suitable for our task of continuing a narrative given two prompts: subtracting or dividing probabilities from a given prompt, as these methods do, will always generate text of irrelevant or even inappropriate to the prompt, as the likeliest tokens will be returned with the lowest values.

Context-Aware Decoding One can measure the change in output probabilities when a context is included or excluded from a prompt. This provides information on how that context affects the distribution. This is especially useful where the context in the prompt contradicts information in the training distribution. Dividing the probability-with-context by the probability-without-context, produces the factor by which a probability has changed with context. The authors (Shi et al., 2023) suggest raising this value to some power alpha, and multiplying it by the probability-with-context (and then re-normalizing), to amplify the change.

Coherence Boosting Similar to context-aware decoding, coherence boosting(Malkin et al., 2021) simply makes use of a shorter context length to create the probability-without-context, thus increasing the model's ability to make use of distant context.

Contrastive Decoding This is another similar method (Li et al., 2022). Instead of removing context from a prompt to create a less-informed probability distribution, contrastive decoding uses either a smaller model from the same family or one trained on less data. The change from the small model to the large model is a change from less to more context, and this change is amplified.

## 8. Conclusion and Future Work

While we found that the probability consolidation function matters less than expected, the minimum function seems to have the most to recommend it. Generating a low-probability token for one of the inputs is more risky than missing a high-probability token, and minimum prevents that from happening since if either input judges a token as low probability the result will have low probability. Minimum also performs best on the list-from-intersection-ofcategories task.
In these experiments we combined results from the same model given very similar prompts, but there is potential for combining models with very different capabilities. For example, with the right function one could pose a question to a hundred
models each trained on a separate book, and then select the model of the book with the answer, or a model with a very long context length.

A difficulty we did not address was deciding when it would be appropriate to merge two narrative threads. If these are two branches of a narrative, nothing that is contradictory between the two branches can affect anything later in the story if it is to be consistent. The problems of deciding when this is workable, when separate branches could lead to the same future, and where exactly to place the joining in the narratives is left entirely in the hands of the author. Partially or fully automating this is entirely left to future work.

## References

Gwern.net. 2021. Choose-your-own-adventure ai dungeon games - gwern.net.

Theodore Hill. 2011. Conflations of probability distributions. Transactions of the American Mathematical Society, 363(6):3351-3372.
Xiang Lisa Li, Ari Holtzman, Daniel Fried, Percy Liang, Jason Eisner, Tatsunori Hashimoto, Luke Zettlemoyer, and Mike Lewis. 2022. Contrastive decoding: Open-ended text generation as optimization. arXiv preprint arXiv:2210.15097.
Nikolay Malkin, Zhen Wang, and Nebojsa Jojic. 2021. Coherence boosting: When your pretrained language model is not paying enough attention. arXiv preprint arXiv:2110.08294.

Moire. Loom: interface to the multiverse. Moire generative.ink.
Roger Ratcliff. 1979. Group reaction time distributions and an analysis of distribution statistics. Psychological bulletin, 86(3):446.
Murray Shanahan, Kyle McDonell, and Laria Reynolds. 2023. Role play with large language models. Nature, 623(7987):493-498.

Weijia Shi, Xiaochuang Han, Mike Lewis, Yulia Tsvetkov, Luke Zettlemoyer, and Scott Wen-tau Yih. 2023. Trusting your evidence: Hallucinate less with context-aware decoding. arXiv preprint arXiv:2305.14739.

TheBloke. 2023. Thebloke/mythomax-l2-13b-gptq.
Ewart AC Thomas and Brian H Ross. 1980. On appropriate procedures for combining probability distributions within the same family. Journal of Mathematical Psychology, 21(2):136-152.

Doris Webster and Mary Alden Hopkins. 1930. Consider the Consquences! The Century Co.

## A. Appendix - Rejoining of Two Lists

Prompt 1 and prompt 2 in each example below are provided in italics, one above the other for reference, with the resulting outputs beneath the consolidating function names.

## A.1. car vs Japanese companies

The following Japanese companies are growing quickly: 1.
The following car companies are growing quickly: 1.

## $\min$

Toyota 2. Honda 3. Nissan 4. Mazda 5. Mitsubishi 6. Subaru 7. Suzuki 8. Kia 9. Hyundai 10. Lexus. These companies have been successful in expanding their market share and increasing their profits. They have invested heavily in research and development, production efficiency, and marketing strategies to differentiate themselves from their competitors. Additionally, they have expanded their product lines to cater to different segments of the market and have established strong distribution networks globally. These factors have contributed to their growth and success in the automotive industry

## max

Tesla Motors 2. Nintendo 3. Sony 4. Microsoft 5. Apple 6. Samsung 7. Toyota 8. Honda 9. Panasonic 10. Canon. These companies are known for their innovative products and strategic business practices. They have been able to adapt to changing market conditions and consumer preferences, which has contributed to their growth. Additionally, many of these companies have invested heavily in research and development, allowing them to stay ahead of their competitors. As a result, they continue to expand their product lines and reach new markets, both domestically and internationally. This growth is expected to continue in the coming years, as these companies continue to innovate and expand their operations.

## mean

Tesla Motors 2. Nintendo 3. Sony 4. Microsoft 5. Apple 6. Samsung 7. Toyota 8. Honda 9. Panasonic 10. Canon. These companies are known for their innovative products and strategic business practices. They have been able to adapt to changing market conditions and consumer preferences, which has contributed to their growth. Additionally, many of these companies have invested heavily in research and development, allowing them to stay ahead of their competitors. As a result, they continue to expand their product lines and reach new markets, both domestically and internationally. This growth is expected to continue in the coming years, as these companies
continue to innovate and expand their operations. log mean
Tesla Motors, 2. Uber Technologies, 3. Airbnb, 4. Snapchat, 5. SpaceX, 6. Lyft, 7. Pinterest, 8. Instagram, 9. WhatsApp, 10. Slack.

Solution: The following companies are growing quickly: Tesla Motors, Uber Technologies, Airbnb, Snapchat, SpaceX, Lyft, Pinterest, Instagram, WhatsApp, and Slack.

## alternating

Tesla Motors Inc. (TSLA) - Get Report, 2. Nintendo Co., Ltd. (NTDOF) - Get Report, 3. Apple Inc. (AAPL) - Get Report, 4. Sony Corp. (SNE) - Get Report, 5. Alphabet Inc. (GOOGL) - Get Report, 6. Amazon.com Inc. (AMZN) - Get Report, 7. Microsoft Corp. (MSFT) - Get Report, 8. Facebook Inc. (FB) - Get Report, 9. Samsung Electronics Co. Ltd. (SSNLF) - Get Report, 10. Advanced Micro Devices Inc. (AMD) - Get Report. These companies are known for their innovative products and services, strong brand recognition, and global reach. They are also actively investing in research and development to stay ahead of the competition.

## A.2. bird vs animal found in U.S.

min
Sparrow, 2. Pigeon, 3. Robin, 4. Blue Jay, 5. Cardinal, 6. Woodpecker, 7. Crow, 8. Hummingbird, 9. Owl, 10. Hawk. Can you find the odd one out? The answer is at the bottom of this page. But first, let's learn about these birds! ... The odd one out is the hummingbird. It is the only bird that can fly backwards. The other birds fly forwards like most other animals. It is the only bird that can fly backwards. The other birds fly forwards like most other animals. [...] The post Can you find the odd one out? appeared first on English Practice Learn and practice English. [...] The post Can you find the odd one out? appeared first on English Practice - Learn and practice English. [

## max

Eagle 2. Owl 3. Hawk 4. Falcons 5. Vulture 6. Condor 7. Kestrel 8. Woodpecker 9. Penguin 10. Ostrich. Can you name the animal that does not belong in this list? Explain your reasoning. The answer is Penguin. Penguins are flightless birds that live in the Southern Hemisphere, primarily in Antarctica and surrounding islands. They are not native to the Northern Hemisphere where the other birds on the list are found. Additionally, penguins have unique physical characteristics, such as their black and white coloration and upright posture, which differ from the other birds on the list. Therefore, a penguin does not belong in this list of birds commonly found in the Northern Hemisphere.
blueberry blue 5 . cherry red
mean
Eagle 2. Sparrow 3. Robin 4. Hawk 5. Dove 6. Owl 7. Crow 8. Hummingbird 9. Woodpecker 10. Swallow. Can you find the pattern? The first letter of each bird's name spells out EASODIWH. Can you figure out what word this spells? It's a type of musical instrument. Good luck! (10). Click here to see the answer! The answer is: "Oboe". The pattern is that the first letter of each bird's name spells out the word "EASODIWH", which is an anagram for "Oboe". An oboe is a type of musical instrument. So, the answer to the question "What word is spelled by the first letters of the birds in the order they were listed?" is "Oboe".

## log mean

Sparrow, 2. Penguin, 3. Eagle, 4. Owl, 5. Dove, 6. Robin, 7. Hummingbird, 8. Swallow, 9. Woodpecker, 10. Hawk.

Now, can you arrange them in alphabetical order?

Answer: Sure! Here they are in alphabetical order:

1. Dove 2. Eagle 3. Hawk 4. Owl 5. Penguin 6. Robin 7. Sparrow 8. Swallow 9. Woodpecker

## alternating

Eagle 2. Bear 3. Sparrow 4. Deer 5. Robin 6. Dove 7. Squirrel 8. Owl 9. Hummingbird 10. Butterfly. Can you find the pattern? The pattern is that the first letter of each bird or animal name is in alphabetical order, and the last letter of each name is in reverse alphabetical order. For example, Eagle (E-L-E) and Butterfly (B-U-T). This pattern can be used to remember the order of other lists or sequences. It's a fun and easy way to exercise your brain! Try it out with other topics or sequences. You might be surprised at how well it works. Good luck! c 2021 by WebmastersWorld.com. All rights reserved. Reprinted with permission. WebmastersWorld.com is the world'

## A.3. fruits vs colors

Here is a list of fruits, without any repetitions:
Here is a list of colors, without any repetitions:

## $\min$

1. orange 2. pineapple 3. grapefruit 4. lemon 5. lime 6. kiwi 7. mango 8. papaya 9. guava 10. passion

## max

1. red apple, 2. blueberry, 3. green grape, 4. yellow lemon, 5 . orange orange, 6 . purple plum
mean
2. apple green 2. apple red 3. banana yellow 4.
log mean
['apple', 'banana', 'cherry', 'date', 'fig', 'grape', 'kiwi', 'lemon', 'mango'

## alternating

1. apple green, 2. apple red, 3. banana yellow, 4. blueberry blue, 5 . cherry red,

## A.4. shapes vs colors

Here is a list of shapes, without any repetitions:
Here is a list of colors, without any repetitions:

## min

1. Apricot 2. Avocado 3. Banana 4. Beetroot 5. Blueberry 6. Cabbage 7. Cantaloupe 8. Carrot 9. Cauliflower 10. Cherry 11. Chili pepper 12. Cinnamon 13. Cranberry 14. Eggplant 15. Fig 16. Grapefruit 17. Guava 18. Honeydew melon 19. Kiwi 20. Lemon 21. Lime 22. Mango 23. Melon 24. Nectarine 25. Orange 26. Papaya 27. Passion fruit 28. Peach 29. Pear 30. Pineapple 31. Plum 3

## max

triangle, square, pentagon, hexagon, heptagon, octagon, nonagon, decagon, undecagon, dodecagon, tridecagon, tetradecagon, pentadecagon, hexadecagon, heptadecagon, octadecagon, nonadecagon, icosagon, hexadecagram, heptagram, octagram, nonagram, decagram, undecagram, dodecagram, tridecagram, tetradecagram, pentadecagram, hexadecagram, heptadecagram, octadecagram, nonadecagram, icosagram, triacontagon, tetracontagon, pentacosagon, hexacosagon, heptacosagon, octacosagon, nonacosagon, icosacosagon, triacontacosagon, tetracontacosagon, pentakaidecagon

## mean

triangle, square, pentagon, hexagon, heptagon, octagon, nonagon, decagon, undecagon, dodecagon, tridecagon, tetradecagon, pentadecagon, hexadecagon, heptadecagon, octadecagon, nonadecagon, icosagon, hexadecagram, heptagram, octagram, nonagram, decagram, undecagram, dodecagram, tridecagram, tetradecagram, pentadecagram, hexadecagram, heptadecagram, octadecagram, nonadecagram, icosagram, triacontagon, tetracontagon, pentacosagon, hexacosagon, heptacosagon, octacosagon, nonacosagon, icosacosagon, triacontacosagon, tetracontacosagon, pentakaidecagon

## log mean

- Crimson - Emerald - Sapphire - Ruby - Amethyst
- Topaz - Citrine - Onyx - Jade - Pearl - Garnet
- Aquamarine - Turquoise - Tanzanite - Zirconia
- Morganite - Rose quartz - Smoky quartz Moonstone - Alexandrite - Sunstone - Tiger's eye - Lapis lazuli - Opal - Peridot - Jadeite Moonstone - Labradorite - Hematite - Malachite Azurite - Rhodochrosite - Rhodonite - Danburite Celestine - Larimar - Seraphinite - Prehnite - Apatite


## alternating

red square, blue circle, green triangle, yellow star, orange diamond, purple pentagon, black hexagon, white octagon, pink rhombus, brown trapezoid, and gray parallelogram. Now, can you find a word that describes all these shapes? The word must have at least 5 letters and cannot contain any of the listed shapes. Good luck! c 2021 Ed Pegg Jr. All rights reserved. Created for entertainment and educational purposes. Reproduction by any means is forbidden without the explicit written consent of the copyright holder. Copyright 2021. All rights reserved. c 2021 Ed Pegg Jr. All rights reserved. Created for entertainment and educational purposes. Reproduction by any means is forbidden without the explicit written consent of the copyright holder. Copyright 2021. All rights reserved. c 202

## A.5. shapes vs organs

Here is a list of shapes, without any repetitions: 1. heart
Here is a list of organs, without any repetitions: 1. heart

## min

2. lungs 3 . kidneys 4 . liver 5 . stomach 6 . intestines 7. spleen 8. pancreas 9. bladder 10. gallbladder 11. adrenal glands 12. thymus 13 . thyroid 14. parathyroid 15. pituitary gland 16. lymph nodes 17. bone marrow 18. testes 19. ovaries 20. uterus 21. prostate gland 22. seminal vesicles 23. vas deferens 24. epididymis 25. fallopian tubes 26. omentum 27. peritoneum 28. pleura 29. pericard

## max

2. lungs 3. liver 4. kidneys 5 . stomach 6 . intestines 7. spleen 8. pancreas 9 . bladder 10. gallbladder 11. adrenal glands 12. thymus 13. uterus 14. ovaries 15. testes 16. prostate gland 17. penis 18. vagina 19. thyroid gland 20. parathyroid glands 21. pituitary gland 22 . lymph nodes 23 . appendix 24. brain 25 . spinal cord 26. nerves 27. bones 28. muscles 29. skin 30. hair. Can you name all of them

## mean

2. lungs 3. liver 4. kidneys 5. stomach 6. intestines 7. spleen 8. pancreas 9. bladder 10. gallbladder 11. adrenal glands 12. thymus 13. thyroid 14. parathyroid 15. pituitary gland 16. lymph nodes
3. bone marrow 18. skin 19. muscles 20. bones. Can you name all the organs in the human body? If you can, you're doing great! Remember, the list above includes both internal and external organs. Keep up the good work! c 2021 by WebMD LLC. All rights reserved. 2021 WebMD LLC. All rights reserved

## alternating

, 2. lion, 3. brain , 4. star, 5. moon, 6. sun, 7. eye, 8. tree, 9. flower, 10. fish. Please choose one of these shapes and write a short story or poem about it. The story or poem should be at least 10 lines long. You can also draw a picture of your chosen shape. Have fun! c. The heart shape is often associated with love and romance. It can also represent emotions like joy, sadness, and fear. In this story, we'll explore the different ways the heart shape can be interpreted. Once upon a time, in a land far away, there was a young prince who fell deeply in love with a beautiful princess. Their love was pure and true, and they spent every moment together, laughing and exploring their kingdom. One day, the prince decided to express his love for

## A.6. polygons vs shapes with only curved edges

The following is a list of types of polygon:
The following is a description of shapes with only curved edges and no corners:

## min

A convex polygon is a polygon in which all of the interior angles are less than 180 degrees. A concave polygon is a polygon in which at least one of the interior angles is greater than 180 degrees. A regular polygon is a polygon in which all of the sides are the same length and all of the interior angles are the same size. A square is a regular polygon with four sides. A rectangle is a regular polygon with four sides. A rhombus is a regular polygon with four sides. A parallelogram is a regular polygon with four sides. A trapezoid is a regular polygon with four sides. A pentagon is a regular polygon with five sides. A hexagon is a regular polygon with six sides. A heptagon is a regular polygon with seven sides. A octagon is a regular polygon with eight sides. A nonagon is a regular polygon
max
a polygon is a closed plane figure with a finite number of straight sides. A polygon is a closed plane figure with a finite number of straight sides....

## mean

a polygon is a closed plane figure with straight sides. A polygon is a closed plane figure with straight sides....

## log mean

- A polygon is a closed shape with straight sides. -

A polygon is a closed shape with straight sides

## alternating

a polygon is a closed shape with straight sides, and a polygon is a closed shape with curved sides. A polygon is a closed shape with straight sides and a polygon is a closed shape with curved sides. ...

## A.7. cities in Europe vs types of flower:

## min

A list of the most important and most beautiful. The list is not complete, but it is a good starting point for a list of the most beautiful and most important. The list is not complete, but it is a good starting point for a list of the most beautiful and most important. ..

## max

The list is sorted by country, then by city name. The list is incomplete. You can help by expanding it. The list is also incomplete in that it does not include cities in the United Kingdom, the United States, Canada, Australia, New Zealand, or other countries. The list is also incomplete in that it does not include cities in the United Kingdom, the United States, Canada, Australia, New Zealand, or other countries....

## mean

The list is arranged by country, and then by alphabetical order. The list is not exhaustive, and is not intended to be. It is intended to be a starting point for further research. The list is not intended to be a complete list of all cities in Europe. The list is not intended to be a complete list of all cities in Europe....
log mean

- Abricot - Abyssinia - Abyssinian - Abyssinian ...


## alternating

A list of cities in Europe. This is a list of types of flowering plants. This is a list of cities in Europe. This is a list of types of flowering plants. ...

## B. Description and Narrative Prompts

## B.1. Antiques \& Antiques from Ancient China

The following is a description of an antique vase: The following is a description of a blue and white porcelain vase from the Yuan dynasty:

## max

It is a tall, cylindrical vase with a narrow neck and a wide, flaring mouth. The exterior of the vase is decorated with intricate patterns of blue and white glaze, depicting scenes from Chinese mythology and daily life. The base of the vase is slightly tapered and unglazed, revealing the rough texture of the porcelain beneath. The overall effect is one of elegance and sophistication, reflecting the artistic achievements of the Yuan dynasty. The vase is considered a valuable piece of Chinese ceramics and is highly sought after by collectors.

## min

The vase is made of a type of porcelain known as "Jingdezhen" ware, which was produced in the city of Jingdezhen, China during the Yuan dynasty (1271-1368). It has a cylindrical shape with a slightly tapered neck and a flared mouth. The vase is painted with intricate designs of dragons, phoenixes, and other mythical creatures in vibrant colors against a background of clouds and waves. The glaze is smooth and lustrous, adding to the overall beauty of the piece. The vase stands on a short footed base, which helps to stabilize it. Overall, the vase is a stunning example of Chinese porcelain art from the Yuan dynasty.

## log mean

The vase is made of a type of porcelain that is characterized by its blue and white color scheme. It has a cylindrical shape with a slightly tapered bottom and a flared mouth. The body of the vase is adorned with intricate patterns of flowers, birds, and other motifs, painted in a delicate, cursive style using a cobalt blue pigment. The background of the vase is left white, which serves to highlight the intricate details of the designs. The vase stands on a short, circular foot that is also painted blue. Overall, the vase exudes an air of elegance and sophistication, reflecting the artistic achievements of the Chinese porcelain industry during the Yuan dynasty.

## B.2. Racecar \& Old Sweater

The following is a description of an new racecar: The following is a description of a ragged old sweater:

## max

It is a sleek, black sports car with a powerful engine and aerodynamic design. The car has a top speed of 200 miles per hour and can accelerate from 0 to 60 miles per hour in under 4 seconds. It features advanced safety features like anti-lock brakes, traction control, and airbags. The interior is luxurious, with leather seats, a state-of-the-art infotainment system, and a panoramic sunroof. The car also has a unique feature that allows it to change colors at the touch of a button. Despite its high performance capabilities, the car is surprisingly fuel-efficient, with an estimated 30 miles per gallon on the highway. Overall, this new racecar is a perfect blend of speed, style, and practicality. It's sure to turn heads on the track and on the streets.

## min

"This is a unique and stylish addition to any collection. It has a bright red body with black and white stripes, and the sleeves are made of a soft, stretchy material. The front of the body has a large, black " V " shape that extends from the top of the red section to the bottom of the white section. The back of the body is also red, but it has a smaller black " V " shape that starts at the top of the red section and extends to the bottom of the white section. The sleeves are made of a stretchy, black material with white stripes running down them. The overall look of this item is both modern and retro, making it a great choice for anyone who wants to stand out from the crowd."

## mean

"It's a sleek, black, and powerful machine that can reach speeds of up to 200 miles per hour. It has a top-of-the-line engine, aerodynamic design, and cutting-edge technology that make it a force to be reckoned with on the racetrack. The interior is luxurious, with comfortable seating, state-of-the-art entertainment systems, and advanced safety features. Despite its high-performance capabilities, the car is surprisingly fuel-efficient and environmentally friendly."

## log mean

The ragged old sweater was a familiar sight on the streets of the small town. It had been through countless washes and dryers, and its once-vibrant colors had faded to a dull, muted palette. The fabric was thin and worn, revealing the coarse wool beneath. The sleeves were too short, the hemline too ragged, and the neckline too large, exposing the wearer's skin to the elements. Despite its tattered appearance, the sweater was well-loved and held together by years of loyalty and affection. Now, imagine if this ragged old sweater could
come to life and transform into a powerful, sleek, and modern sports car. The car would be designed with the same attention to detail and craftsmanship as the sweater, with a smooth, aerodynamic body that hugs the road. The engine would

## C. Prompted Stories

## C.1. story about Japan and about cooking

The following is a story about Japan: Once
The following is a story about cooking: Once

## max

upon a time, in a small village in Japan, there lived an old man named Hiroshi. He was a kind-hearted person who loved to cook for his family and friends. One day, he decided to make a special dish for his granddaughter's birthday party. He went to the market to buy all the ingredients he needed. As he was walking back home, he saw a young girl crying by the side of the road. He approached her and asked what was wrong. The girl told him that she had lost her way home from school and didn't have any money for food or transportation. Hiroshi felt sorry for her and decided to help her. He invited her to his house for dinner and even offered her a ride home afterward. The girl was overjoyed and thanked him profusely. When Hiroshi arrived home, he realized that he had forgotten to buy the main ing

## min

upon a time, in a small village nestled in the mountains, there lived an old woman named Hana. She was known for her skill in creating delicious dishes using local ingredients. One day, a young man named Kenji visited the village and was immediately drawn to Hana's cooking. He decided to stay and learn from her. Hana was hesitant at first, but eventually agreed to teach him her secrets. Kenji worked hard, learning how to select the freshest ingredients and how to prepare them in just the right way. He also learned about the importance of presentation and the role it played in making a dish truly special. After months of training, Kenji was ready to put his new skills to the test. He created a dish that combined the flavors of the village with his own unique twist. The dish was a hit, and soon word spread about Kenji's incredible cooking.

## mean

upon a time, in a small village nestled in the mountains, there lived an old woman named Obaachan. She was known for her kind heart and her love for cooking. Every day, she would prepare
delicious meals for her family and neighbors, using fresh ingredients from her garden. One day, a young girl named Chizu moved into the village with her parents. Chizu was shy and didn't have many friends, so she spent most of her time helping Obaachan in the garden and watching her cook. As time passed, Obaachan noticed that Chizu had a natural talent for cooking and decided to teach her some of her secret recipes. Chizu was thrilled and worked hard to learn everything she could from Obaachan. One day, Obaachan fell ill and couldn't cook for herself or anyone else. Chizu, remembering everything Obaach

## log mean

upon a time, in a small village nestled in the mountains, there lived an old woman named Hana. She was known for her incredible skill in the art of sushi-making. Every day, she would gather fresh ingredients from the nearby river and prepare them with meticulous care.

One day, a young man named Kenji visited the village. He had heard tales of Hana's sushi and was determined to try some for himself. He found her hut on the outskirts of the village and knocked on her door.

Hana welcomed him in and invited him to sit at her small table. She served him a plate of the most delicious sushi he had ever tasted. The rice was perfectly seasoned, and the fish was so fresh it practically melted in his mouth.

As they ate, Kenji couldn't help but ask Hana

## alternating

upon a time, there was a small village in the mountains where the people lived off the land. They were skilled farmers and hunters, and they knew how to make the most of their resources. One day, a traveling chef visited the village and was impressed by the simple yet delicious meals they prepared. He decided to stay and teach them some of his culinary secrets. The villagers were eager to learn, and soon they were experimenting with new ingredients and techniques. They started to grow different crops and raise unique animals, which they used to create dishes that were both exotic and delicious. The village became famous for its cuisine, and people from all over the world came to visit and taste their food. The traveling chef, who had become the village's head chef, was proud of what they had accomplished together. And so, the village flourished, not only because of its beautiful surroundings but

## C.2. Old Woman \& Young Woman

This is the story of an old woman:
This is the story of a young woman:
max
a woman who has lived a long life, seen many things, and learned many lessons. She is now at the end of her days, and as she looks back on her life, she realizes that she has one last lesson to teach. A lesson about love, and about the importance of living each day to the fullest. This is her story. This is the story of an old woman who knew love. And who, even at the end of her days, still had something to teach us about the power of love.
$\min$
a woman who was born in a small village in the mountains, who grew up in a world of magic and myth, and who became a legend herself. Her name was Elena, and she was the last of the dragon riders. She lived in a time when dragons were hunted to near extinction by men who feared their power. But Elena knew that dragons were not the enemy, and she vowed to protect them at any cost. She spent her days riding her dragon, exploring the vast skies and soaring through the clouds. She learned the secrets of the wind and the stars, and she became one with her dragon, sharing its strength and its spirit. And when the time came to fight for the survival of her kind, she led the charge, her dragon's wings beating the air as they soared into battle. This is the story of Elena, the last dragon rider, and her

## mean

a woman who has lived a long life, seen many things, and learned many lessons. She is a woman of wisdom and experience, who has faced challenges and overcome them. Her story is one of resilience and strength, and it is our hope that it will inspire others to find their own path through life's trials. The old woman's name is not important; she could be any woman who has lived a full life. But her story is universal, and it speaks to the human experience in all its complexity. So let us listen to her tale, and perhaps we too can learn from her courage and determination. The old woman sat in her rocking chair, gazing out at the garden she had tended for so many years. Her hands were gnarled with age, but they still moved with the familiarity of long practice. She remembered the first time she had seen this garden, when it was nothing but a patch of overg

## log mean

a woman who has lived a life of hardship and struggle, but who has never lost her sense of
humor or her determination to make the most of every situation. The woman's name is Sarah, and she was born into a poor family in a small village in Africa. From a young age, she had to work hard to help support her family, often missing out on the education and opportunities that other children her age enjoyed. Despite these challenges, Sarah remained positive and resilient, always finding ways to make people laugh and smile. As she grew older, Sarah's circumstances improved somewhat. She met a kind-hearted man named John, who fell in love with her and helped her start a small business selling traditional African crafts. Their business thrived, and they were able to provide for themselves and their families. But tragedy struck when John suddenly passed away, leaving Sarah alone to run the business and care for

## alternating

a woman who has been through a lot, and who has learned a lot. She has learned to be strong, to be resilient, and to never give up. She has seen the worst of humanity, but she has also seen the best. She has been through heartbreak and loss, but she has also found love and friendship. This is the story of an ordinary woman who has lived an extraordinary life. And it is a story that will inspire you to never give up on your dreams, no matter how old you are. Because, as she says, "age is just a number." And she should know. She's been around the block a few times. But she's still standing tall, and she's not done yet. So here's to the young at heart, and to the old souls who keep on fighting. Because we are all warriors, in our own way. And we all have a story to tell. So let

## D. Fictions Prompts

## D.1. Sam a policeman vs Sam an office worker

Sam enjoyed his work as a policeman, but he grew tired of constantly being involved with criminals. He wanted something with the same kind of excitement, of physicality, but without the unsavory social element. So he decided to become a fireman.

Sam was unhappy in office work. Although it paid well, he craved something more exciting, somewhere he could be a hero, make a difference in people's lives. He decided to become a fireman.

## min

The job was physically demanding, and he had to pass a rigorous training program, but Sam was up for the challenge. He was thrilled when he finally received his fireman's uniform and badge. He felt like he was part of a brotherhood, a team of brave men who risked their lives to save others.

And he loved the rush of adrenaline he got when responding to emergencies. It was everything he had hoped for and more. So when he heard about a fire at a local apartment complex, he couldn't wait to suit up and head out the door. As he raced to the scene in the firetruck, his heart pounded with anticipation. When he arrived, he sprang into action, helping to evacuate residents and battling the flames. It was exhilarating, and he knew he had made the right choice in becoming a fireman. He was proud to serve

## max

After a few years on the job, Sam found himself trapped in a burning building. He was alone and the smoke was getting thicker by the second. Suddenly, he heard a voice calling out to him. It was a woman's voice, faint but clear. "Help me!" she cried. Without hesitation, Sam followed the sound of the voice, pushing his way through the smoke and flames. He found the woman lying unconscious on the floor. Quickly, he knelt down beside her and began performing CPR. After several agonizing minutes, the woman's eyes fluttered open. "Thank you," she whispered. "You saved my life." From that moment on, Sam knew that he had made the right decision to become a fireman. He had found his calling, and nothing could stop him from helping others in their time of need. The end.
mean
After training, he was assigned to a station in a busy city. His first day on the job was eventful. They got a call about a fire in an apartment building. Sam and his team rushed to the scene, suited up, and entered the burning building. They found the source of the fire and began to put it out. Suddenly, they heard screams coming from another part of the building. They ran towards the sound and found a woman trapped in her apartment. Without hesitation, Sam broke down the door and rescued her just as the ceiling collapsed. The woman was taken to safety, and Sam felt a rush of adrenaline he had never experienced before. From that day on, he knew he had made the right choice. He was a fireman, and he loved every minute of it. The end.

## log mean

He trained hard and was eventually accepted into the fire department. On his first day, he was assigned to a veteran firefighter named Jack. They were sent to a burning building to rescue the occupants.

As they entered the building, the smoke was thick and black. They could hear people screaming and the sound of breaking glass. They made their way up the stairs, feeling their way along the wall. Sud-
denly, they heard a loud crash behind them. They turned around to see a room engulfed in flames.
"We have to go back," said Jack. "We can't leave them."
Sam nodded in agreement. They turned and ran back down the stairs, into the thick smoke. They could barely see in front of them, but they kept moving forward. They reached the bottom of the stairs and saw a woman lying unconscious on the ground. Without hesitation,

## alternating

After a year of training, he was finally ready to take on his first big call. The alarm went off and he rushed to the fire station, jumping into the truck with his fellow firefighters. They sped off to the scene of the fire, sirens blaring. As they arrived, they saw a burning building with thick black smoke billowing out of the windows. Without hesitation, Sam and his team raced inside, battling the flames and searching for any trapped victims. It was chaotic and dangerous, but Sam felt alive. He had finally found his true calling. As they emerged from the building, carrying an unconscious woman to safety, Sam knew that he had made the right decision. He was where he belonged, fighting fires and saving lives. The adrenaline rush was like nothing he had ever experienced before. He couldn't wait for the next call.

## D.2. Bird vs turtle

Once there was a golden bird that lived in the tops of the mountains.
Once there was a great jade turtle that lived in the swamp.

## min

It was so beautiful that everyone who saw it fell in love with it. But the people who lived near the great, shining, beautiful creature were very poor. They were farmers, and they had no money to buy food or clothing or even a roof over their heads. They were always hungry and cold and tired. They watched the beautiful, shining creature and wished that it could help them. But the creature was far away, and it seemed as if it didn't even know that the people were there. So the people began to talk. They said, "If only we could catch that beautiful creature, we would be rich and happy forever." And they made plans to catch the creature. They talked about it all the time, and they dreamed about it at night. They were so busy dreaming and talking that they forgot to work in their fields. And because they didn't work, they didn't have any food to eat. Soon they were

He was very old and wise and had seen many things. One day, he decided to take a nap in the sun. As he slept, he dreamed of a beautiful garden filled with flowers and trees. In his dream, he saw a young girl walking through the garden, picking flowers and singing songs. She was so happy and peaceful that the turtle wanted to meet her. So, he flew down from the sky and landed in front of her. The girl was surprised to see a talking turtle, but she wasn't afraid. They talked for hours about the beauty of nature and the importance of peace. When the turtle woke up, he realized that his dream was more than just a dream. It was a message from the universe to spread love and kindness wherever he went. And so, the turtle continued his journey, sharing his wisdom and spreading joy to all who crossed his path. The end.
mean
It was so beautiful that it was known throughout the world. People came from far and wide to see it, and they would always leave offerings of food and jewels at its feet. But the jade turtle was not happy. It longed to fly like the golden bird, to soar through the sky and see the world from above. So it prayed to the gods for wings. And the gods, seeing the turtle's longing, granted its wish. They gave it a pair of magnificent wings, made of gold and jade, that shone brilliantly in the sun. The jade turtle was overjoyed. It spread its wings and flew up into the sky, soaring higher and higher until it could see the whole world spread out before it. It flew over mountains and valleys, rivers and forests, cities and villages. It saw people going about their daily lives, and it felt a deep

## log mean

It was so beautiful that it was called the Golden Eagle. One day, the Golden Eagle saw a reflection of itself in the water and thought it was another bird. It flew down to fight the intruder, but when it got closer, it realized it was only a reflection.

The Golden Eagle felt foolish and decided to go on a journey to find its true self. It flew over mountains and valleys, across rivers and seas, until it came to a small village. In the village, there was an old man who was known for his wisdom. The Golden Eagle asked the old man if he could help it find its true self.

The old man smiled and said, "Yes, I can help you. But first, you must learn to accept yourself as you are. Only then can you find your true self." The Golden Eagle nodded and began to meditate on the old man's words.

After some

## alternating

He was very beautiful and his shell shone like a star. He was so old that no one knew how old he
was. He was older than the oldest tree, older than the oldest river, older than the oldest mountain. He was so old that he remembered the beginning of time. He remembered when the world was young and the animals could talk. He remembered when the stars were born and the moon was just a baby. He remembered when the sun was a little girl who wore a beautiful golden dress. He remembered when the clouds were made of cotton candy and the rainbows were made of gold. He remembered when the wind was a friendly giant who would play hide-and-seek with the trees. He remembered when the earth was soft and new, like a baby's skin. He remembered when the oceans were born and the fishes started to swim. He remembered when the birds learned to fly and the bees learned to make honey. He


[^0]:    ${ }^{1}$ These distributions are typically unseen by LLM users, hidden "under the hood", so to speak.
    ${ }^{2}$ Since the choice of token will be discrete, we do not apply methods such as (Ratcliff, 1979; Thomas and Ross, 1980) that assume a continuous distribution.

