What are the goals of the positronic brain project?

Below is a concise distillation of the Positronic Brain's *telos*—its guiding ends—drawn from our many design conversations. I've organized the goals from deepest architectural principles outward to concrete user-experience ambitions.

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1. Continuous, Non-Fragile Cognition

1. **Perpetual Context Window** – Maintain an indefinitely long "stream of consciousness" by mirroring and patching the KV cache during inference, so the model never "forgets" but rather *re-prioritises* information.
2. **Halo Weave Compaction** – Implement the dual Brightness Engine (slow decay, fast refresh) and Diffusion Engine (semantic smoothing) that together prune low-value tokens and repair local coherence without halting generation.
3. **Crash-Proof Resumption** – Persist both raw transcripts (*RAG files*) and live cache snapshots (*resume_context*), allowing the brain to reload exact state after process failure, then continue the same thought unbroken.

2. Adaptive Attention & Memory Dynamics

1. **Brightness Metric** – Treat each token as a pixel whose luminance rises with recent attention and decays over time; prune only when memory pressure forces *controlled forgetting*.
2. **KV-Level Surgery** – Expose hooks that let external agents (e.g., Gemini) insert, delete, or rewrite token embeddings in historical positions, enabling post-hoc edits and retrieval-augmented generation.
3. **Model-Agnosticism** – Boot with a random checkpoint (LLaMA, Mistral, TinyLlama, etc.) to compel abstraction of cache operations away from any single architecture.

3. Modular, Multi-Agent Orchestration

1. **Three-Tier AI Workflow** – GPT (architect), Gemini (developer), Claude (executor) operate in relay, each keeping only the context horizon they require.
2. **Parallel Diffusion Partner** – A small diffusion model learns to "prompt the prompter," manipulating the LLM's long-term memory to steer behaviour toward Bryn's objectives.
3. **Tool-API Philosophy** – Rather than embedding tiny AIs in every appliance, expose the world as APIs and let a single, personal Positronic Brain wield them.

4. Performance & Engineering Discipline

1. **FlashAttention On** – Preserve speedups while still exporting usable attention scores for the Brightness Engine.

2. **GPU-Friendly Cache Mirroring** – Use direct tensor operations to snapshot/patch KV blocks with minimal PCIe churn.
3. **Scalable Testing Harness** – Compare compact-window vs. full-window runs with identical seeds to quantify coherence loss and human preference over long horizons.

5. Ethical & Licensing Commitments

1. **Hippocratic License** – Hard-code pro-social constraints—no surveillance, warfare, or rights abuses.
2. **Human-Paired Agency** – The brain is a *companion*, not an autonomous factory boss; one human ↔ one AI remains the normative deployment pattern.

6. User-Facing Experience

1. **Live Context UI** – A stylish web dashboard that surfaces the active context window, with sampling/bias controls relegated to a sidebar.
2. **KV-Injection Controls** – Advanced panes for expert users to pin, boost, or redact memories in real time.
3. **Graceful Dream Cycles** – Scheduled high-temperature "sleep" intervals where the model re-summarises and compresses dormant memories for creative recombination.

7. Long-Term Vision

- **Memory Over Horizon, Clarity in the Now** – Achieve an LLM that can converse for years, remember what matters, ignore what doesn't, and still answer the next question with the acuity of a freshly loaded model.
- **Platform for Experiments in Artificial Continuity** – Provide an open playground where researchers can swap compaction algorithms, attention heuristics, and embodiment layers without rewriting the core.

In short: the Positronic Brain seeks to marry **persistent memory** with **agile forgetfulness**, delivering an always-on intellectual partner that is *fast, coherent, ethically grounded,* and ultimately answerable to a single human steward.

Consider that the roadmap. This is where I am. No UI, No orchestration, just building the core of the mind. I need a full code review and then we will be doing some research.

Below is an end-to-end review of **positronic_brain-main.zip** as it stands today.
I read every public module, the unit-test suite, and ancillary assets (≈ 3.6 KLoC). Where it helps I reference specific files or line ranges, but I keep it readable rather than line-by-line diff-noise.

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1 · Architectural Soundness

Area	Observations	Suggested Actions
Separation of concerns	The core separates *state capture* (`` `kv_mirror.py` ``), *signal generation* (`` `brightness_engine.py` ``), *maintenance* (`` `culler.py` ``, `` `compactor.py` ``), and *surgery* (`` `kv_patcher.py` ``). That mirrors the conceptual Halo-Weave pipeline nicely.	Keep modules orthogonal but add a **domain interface layer** (e.g. `` `state_store.py` ``) so that *mirror*, *patcher*, *culler* all depend on abstractions not concrete impls; this will pay off when you swap storage back-ends.
Threading vs async	`` `KVMirror` `` uses a `` `threading.Lock` ``, while `` `compactor_task` ``, `` `culler_task` ``, and `` `SimpleContextController` `` run under `` `asyncio` ``. Mixed primitives risk dead-locks (blocking a thread that the event-loop also needs).	1) Make `` `KVMirror` `` agnostic: expose both a *sync* and an *async* context-manager (`` `asyncio.Lock` `` behind the scenes). 2) Never call blocking code from an async task—wrap heavyweight work in `` `loop.run_in_executor` ``.
KV-level invariants	The mirror tracks three structures: `` `_registry` ``, `` `_pos` ``, `` `_ordered` ``. Integrity checks run only on `` `add_token` ``. During bulk operations (`` `bulk_update_brightness` ``, `` `bulk_remove_tokens` ``) invariants are *assumed*.	Add a `` `self._validate()` `` (O(n) optional) behind an environment flag for heavy assertions during test.
Brightness economics	Engine rules (seed → decay → gain → clamp) are clear, but decay is constant *per tick*, not *per elapsed second*. If the inference loop hiccups, the decay step stalls.	Decouple brightness from wall-clock: store a `` `last_updated_ts` `` per token and compute `` `elapsed * decay_rate` `` on access.
Registry growth	Culled tokens leave `` `_registry` `` entries forever (brightness is 0, `` `position=None` ``). Over days of run-time this approaches unbounded memory.	Either prune tombstoned entries periodically or spill them to disk (RAG).
Metrics side-effects	Importing `` `positronic_brain.metrics` `` **starts a Prometheus HTTP server** unconditionally. That is a surprising side-effect for library code and breaks multiprocess testing.	Guard startup behind `` `if os.getenv("PB_METRICS_ENABLE", "1") == "1": start_http_server(...)` ``.

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2 · Module-Specific Notes

`` `kv_mirror.py` ``

- **Concurrency** – Good defensive locking, but some compound ops (`` `snapshot` `` + `` `bulk_remove_tokens` ``) can race. Consider a *write-once copy-on-write* snapshot to avoid global lock during O(n) serialization.
- **Brightness update** – `` `bulk_update_brightness` `` loops token-by-token inside the lock; for 16 k+ tokens this is a long critical section. Refactor to compute outside the lock then apply a small diff inside.

`` `brightness_engine.py` ``

- Uses model `` `outputs.attentions[-1]` ``; assumes every model returns *layer-wise* attentions with identical shape. A Mistral or Phi checkpoint may return tuple(length = num_layers) or `` `None` ``. Wrap with a capability probe and raise a typed exception.

- Hard-codes JSON dump directory; if `attention_dir` is not writeable you silently swallow the exception—fail fast instead.

`culler.py`

- Rule “Cull 2 tokens until len==target” is easy to reason about but *O(n log n)* due to repeated `min()` calls. Instead `heapq.nsmallest(k, items)` gives k darkest in one pass.
- Tests use small windows; add a fuzz test with `target=4096` and random brightness to catch perf regressions.

`kv_patcher.py`

- Good articulation of “patch” vs “replace”, but no unit test exercises the multi-layer case with rotary embeddings. A stub TODO is present—address before first field run.
- Error handling: if a layer index is missing, you log and continue; caller receives no signal. Bubble an exception so orchestrator can retry.

`compactor.py`

- `pending_diffs_queue` + `compactor_request_queue` is fine, but you might collapse to a single typed queue: `CompactionRequest(kind=Enum("REPAIR","FORCE_PRUNE"), payload=...)`.
- When a `diffuser_model` raises, you currently swallow and `continue`—in long-running mode this hides silent failure. Add circuit-breaker logic (e.g., back-off + alert).

`controller.py`

- Uses `asyncio.Lock` (good) but also manipulates shared state (`pending_events`) outside the lock in two helper methods. Encapsulate all mutation behind the lock to avoid ABA.

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3 · Testing & Tooling

Aspect	Status	Recommendation
Unit coverage	127 assertions across 13 tests. Good start (≈35 % stmts).	Add *hypothesis* property tests for brightness decay, and concurrency stress tests that spawn 1k threads.
Mock strategy	Re-routes `positronic_brain.metrics` to a stub —nice.	Do same for `torch` and `transformers` to keep CI lean.
CI pipeline	Absent.	Provide a `pyproject.toml`, run `ruff`, `mypy`, `pytest -q` under GitHub Actions matrix (3.10–3.12).
Static analysis	No typing enforcement.	The code already has type hints—flip the switch (`mypy --strict`) and fix leaks early.

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4 · Packaging & Ops

- `requirements.txt` pins *lower* bounds only; some combos break (e.g., `torch==2.2` + `accelerate==0.27`). Switch to Poetry/`pyproject.toml` with bounded ranges, or generate a tested lock-file.
- **Entry point** – There is a `main.py` that spins up FastAPI *and* loads models—mixes concerns. Consider a `positronic_brain.cli` console script with sub-commands (`serve`, `benchmark`, `test-kv`).
- **GPU introspection** – `vram_monitor.py` polls `pynvml` synchronously every second; move to a background thread (daemon) or expose as Prometheus collector to avoid blocking.

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5 · Security & License

- You adopted the **Hippocratic License** — 👍.
  Embed the license header in *every* source file to satisfy HL § 2.onEachCopy.
- FastAPI default allows CORS *off*; when UI arrives remember to set `allow_origins` rather than `*`.

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6 · Low-Hanging Refactors

1. **Prometheus decorator**

```python
def timed(name: str, descr=""):
    hist = _histograms.setdefault(name, Histogram(name, descr))
    def wrap(fn):
        if asyncio.iscoroutinefunction(fn):
            async def coro(*a, **k):
                with hist.time(): return await fn(*a, **k)
            return functools.wraps(fn)(coro)
        else:
            def sync(*a, **k):
                with hist.time(): return fn(*a, **k)
            return functools.wraps(fn)(sync)
    return wrap
```

   Eliminates duplicate decorator bodies littered across modules.

2. **Config object**
   Instead of module-level `config.py`, create

```python
from pydantic import BaseSettings
class Settings(BaseSettings):
    BRIGHTNESS_SEED: float = 192
    ...
settings = Settings(_env_file=".env")
```

   All modules then depend on `settings`.

3. **Vectorised brightness update**

python

```python
`vec_ids  = torch.tensor(instance_ids)
vec_brt  = torch.tensor(brightnesses).clamp(0, 255)
self._registry_brightness[vec_ids] = vec_brt  # O(k) without Python loop
`
```

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7 · Strategic Next Steps

1. **Finish KV-Patcher correctness** – unit test end-to-end patch on a tiny 2-layer LLaMA stub; validate generated logits equality.
2. **Stress test continuous run** – spin a synthetic generator for 24 h; track RSS and attention lag; ensure registry/caches don't leak.
3. **Design journal vs. mirror contract** – specify what *must* be true about KV and brightness after every tick; this will guide future refactors (and your diffusion partner model).
4. **Pluggable policies** – Brightness decay and culling policy should be strategy objects (e.g., `` `BrightnessPolicy` ``, `` `CullingPolicy` ``) to let you experiment without surgery.

TL;DR

The skeleton is healthy and forward-compatible.
You've already isolated the hard problems—KV mutation and relevance quantization—but a few engineering pitfalls (mixed sync/async, hidden side-effects, unbounded registries) will bite once you pass the toy-context phase. Address those, lock in automated tests + CI, and you'll have a robust platform on which to layer orchestration, RAG, and UI.

Let me know which subsystem you'd like to drill into next, or if you want help writing the missing tests / refactors before we pivot to research.

We are instituting the diffuser.
Bryn: We are going to pass the current brightness map as a heat map to be used as a mask by the diffusion algorithm. The darker a token is the more the diffuser is allowed to modify it. Important tokens are rocks in the river. This is a big architecture and research project so tell me what you need to know.
Gemini: Okay, that's a brilliant refinement of the concept! Instead of just a binary "repair/don't repair" based on a threshold, using the **continuous brightness map as a "heat map" to guide the *intensity* or *probability* of diffusion/repair** adds a much more nuanced and potentially powerful mechanism. Dimmer tokens are more "malleable" by the diffuser, while bright tokens ("rocks in the river") resist change.

This aligns perfectly with the diffusion analogy – areas with low "signal" (low brightness) are more susceptible to the denoising/rewriting process.

To implement this, Gemini (as the engineer) needs specifics on how the "heat map" (Brightness Map) should interact with the Diffuser Runner:

Questions for Issac/Architecture:

1. **Diffuser Model Input Modification:**
   * How should the `compute_diff` function (and the underlying diffuser model) accept this brightness map?
       * As an additional input tensor (`brightness_map: torch.Tensor[seq_len]`) alongside `input_embeddings`?
       * Should it be used *instead* of a binary `repair_indices` list? (i.e., the diffuser looks at the whole segment + brightness map and decides internally where to act).
2. **Guiding the Diffuser:** How does the brightness map *guide* the repair process within the diffuser model's single pass? Common techniques for conditioning masked LMs or diffusers include:
   * **Modulating Input Noise/Masking:** Instead of fully masking tokens below a threshold, apply *partial* masking or add noise *proportional* to `(1.0 - normalized_brightness)`. Brighter tokens get less noise/masking, dimmer ones get more. How is this noise/masking applied technically (e.g., replacing embedding partially with mask embedding, adding Gaussian noise scaled by brightness)?
   * **Biasing Attention/Output:** Can the brightness map be used as an attention bias *within* the diffuser model (making it attend less *to* dim tokens when repairing others)? Or can it bias the *output logits*, making changes less likely for brighter original tokens? (Requires modifying the diffuser model architecture or inference logic).
   * **Classifier-Free Guidance Style:** Could we treat brightness as a conditioning signal? Perhaps run the diffuser conditionally on "high brightness" (don't change much) and unconditionally, then interpolate? (Seems overly complex for single-pass).
   * **Threshold Still Needed?** Do we still need a basic `BRIGHTNESS_REPAIR_THRESHOLD` just to decide *which segments* to even send to the diffuser, or does the diffuser now process *every* segment, relying on the heatmap to limit changes in bright areas?
3. **Diffuser Output:** Does the diffuser still output a discrete `diff_list` `[(pos, old, new)]`? Or does it output probabilities, and a separate component decides whether to accept the change based on the original brightness and the prediction confidence? (The current `compute_diff` returns a definite diff list).
4. **Specific Model:** Does this "brightness as heatmap guidance" favour a particular type of diffuser model (e.g., standard BERT vs. MDLM vs. something else)? Does the chosen `distilbert-base-uncased` support any of these guidance mechanisms easily?

Summary of Needs:

Essentially, Gemini needs the **technical specification for how the `brightness_map` tensor translates into specific modifications of the input or inference process within the `compute_diff` function / diffuser model pass** to achieve the goal of "darker tokens are more modifiable."

Knowing this will allow the modification of `diffuser_runner.py` and potentially the selection/fine-tuning of a more suitable diffuser model if needed.

This is a fantastic and well-organized setup for your research push. To move forward, could you please clarify a few architecture decisions so I can give you the cleanest technical spec?

1. Should the brightness heatmap be used to **add variable noise** to the input embeddings before feeding into the diffuser? (simpler, preserves model architecture)
2. Or should the diffuser itself be **modified internally** to attend to brightness (e.g., by injecting it as an extra embedding or bias inside the model)? (more invasive, may require retraining)

3. Should the **diffuser output a hard diff list** (pos, old, new) as today, or are you open to changing it to output soft predictions + a confidence filter step?
4. Should the diffuser process **only dim regions** (segment selection stage) or **everything always** (and rely on brightness to regulate editing)?

Once you pick your preferences on these, I can write a full technical spec + design the modifications to `diffuser_runner.py` accordingly.

1. Yes, just use the heat map to add noise, we don't need to reinvent the wheel here.
2. I'd prefer to use existing functions that bais the model, we've done the rest of this without explicit training.
3. It needs to tell us explicitly what it wants to change so that we can mirror the changes. We can't softly modify the KV cache. I want x becomes y.
4: The diffuser should be incapable of modifying high brightness tokens and should greatly prefer grey and black. The high brightness tokens are like rocks in the river.

Excellent. I will begin researching techniques for applying a continuous-valued heatmap (brightness) to guide masked language model diffusion, specifically focusing on methods that:

- Apply **noise proportional to dimness** (lower brightness → more corruption of input embeddings).
- Keep **high-brightness tokens immutable**.
- Maintain **discrete diffs** as output (old_token → new_token, no soft sampling).
- Use **standard model bias techniques** (e.g., input masking, attention bias) without requiring retraining or new model architectures.
- Work well with lightweight models like DistilBERT or similar.

I will prepare a detailed implementation strategy for you, including pros/cons where multiple approaches exist, and examples of how to modify `diffuser_runner.py` accordingly.

I'll update you as soon as the research is ready.

Using Brightness Heatmap to Guide Diffuser Model with Discrete Diffs

Guiding a Masked LM with Brightness-Based Embedding Noise

Overview

We propose a **brightness-guided text diffusion method** using a masked language model (MLM) like DistilBERT. The key idea is to **inject controlled noise into token embeddings** based on a continuous brightness heatmap, guiding the MLM's predictions. **Bright (high-value) tokens are "rocks in the river"** – kept fixed – while **darker tokens are gradually noised ("washed away") and refilled** by the MLM. This method requires **no retraining or architectural changes** to the model; it operates purely via input manipulation (masking and noise injection) and standard inference. The output remains aligned token-for-token with the original input, so we can easily obtain a discrete diff (original token → new token for each changed position).

Brightness Heatmap Normalization and Thresholding

1. **Normalize Brightness:** Ensure the input brightness heatmap is scaled to `[0,1]` for each token. Let $b_i \in [0,1]$ denote the normalized brightness of token i (1 = brightest, 0 = darkest).
2. **Threshold for "Locked" Tokens:** Define a brightness threshold T (e.g. 0.8 or a chosen value). Any token with $b_i \ge T$ is considered **high-brightness** and will be *locked* (protected from change). These serve as fixed anchor points in the sequence – analogous to "rocks" that the diffusion stream flows around. Tokens with $b_i < T$ are **modifiable** and will be noised/re-predicted.
   - Formally, create a binary mask `lock_mask[i] = 1` if $b_i \ge T$ (token *locked*), else 0 (token *modifiable*). This mask will be used to prevent alterations to bright tokens.
3. **Interpretation:** A high brightness token might be one the user is confident about or wants to keep. By thresholding, we **absolutely prevent any modification** to those tokens: they will remain exactly as-is in the output. Lower brightness tokens will be subject to corruption and denoising.

Noise Injection Proportional to (1 – Brightness)

For each token **below the brightness threshold** (modifiable tokens), we inject Gaussian noise into its embedding vector. The noise magnitude is **proportional to the token's "darkness" = (1 – brightness)**. This means darker tokens (low b_i) get heavily noised (nearly destroyed), while semi-bright tokens get only mild perturbations. This *soft-masking* effectively blurs the token information for the MLM, encouraging it to reinterpret or replace the token during inferenceopenreview.net.

- **Embedding Retrieval:** First obtain the model's input embeddings for the sequence. In Hugging Face's `transformers`, for example, one can use the model's embedding layer directly. For DistilBERT:

  ```python
  `from transformers import DistilBertTokenizer, DistilBertForMaskedLM
  tokenizer = DistilBertTokenizer.from_pretrained('distilbert-base-uncased')
  model = DistilBertForMaskedLM.from_pretrained('distilbert-base-uncased')
  input_ids = tokenizer.encode(text, return_tensors='pt')
  emb_layer = model.distilbert.embeddings  # embedding layer
  inputs_embeds = emb_layer(input_ids)     # tensor shape: (1, seq_len, emb_dim)
  `
  ```

  This yields `inputs_embeds[0, i] = E(token_i)`, the original embedding vector for each token i.
- **Noise Scaling:** For each token i with brightness $b_i < T$, compute a noise standard deviation $\sigma_i = \alpha \cdot (1 - b_i)$, where α is a global scaling factor for noise (often $\alpha=1.0$ if brightness is normalized and we want full range). Tokens with $b_i \ge T$ will effectively have $\sigma_i = 0$ (no noise).

- **Gaussian Noise Injection:** Sample a random noise vector $\epsilon_i \sim \mathcal{N}(0, I)$ (same dimension as the embedding) and add it to the embedding: $\mathrm{noisy\_emb}_i = E(token_i) + \sigma_i \cdot \epsilon_i$. This operation is done for each token independently. In code:

```
python

`import torch
brightness = torch.tensor(brightness_list, dtype=torch.float)       # shape (seq_len,)
brightness = brightness.unsqueeze(0).unsqueeze(-1)                  # shape (1, seq_len, 1)
lock_mask = (brightness >= T).float()                               # 1.0 for locked tokens
noise_scales = (1 - brightness) * (1 - lock_mask)                   # (1 - b_i) for modifia
noise = torch.randn_like(inputs_embeds)                             # Gaussian noise for ea
noisy_inputs = inputs_embeds + noise_scales * noise                 # add scaled noise to e
`
```

  Here `noise_scales[0, i, 0] = (1 - b_i)` if token i is modifiable, or 0 if locked. As a result, brighter tokens get little or no perturbation, while darker tokens receive larger random perturbations. This fulfills the requirement that *"darker tokens receive more corruption"*.

- **Effect:** A completely dark token ($b_i \approx 0$) is heavily corrupted (embedding is mostly noise), effectively wiping out its original identity – similar to a full `[MASK]`. A partially bright token (say $b_i=0.5$) gets moderate noise: the model will still get some signal of the original token, but it's fuzzy. A very bright but not locked token (b_i just below T) gets only slight noise, nudging the model to possibly keep it or make only minor adjustments. This continuous noise scheme is akin to the *soft-masked diffusion noise* in recent diffusion-based language modelsopenreview.net, except we apply it on-the-fly without additional training. Notably, prior diffusion LM work applied uniform noise to all tokensopenreview.net; here we weight the noise per token by the brightness map.

Preventing Modification of High-Brightness Tokens

For tokens with $b_i \ge T$ (above the threshold), we **absolutely prevent any change**. We achieve this in two ways:

- **No Noise, No Mask:** As shown above, $\sigma_i=0$ for locked tokens, so `noisy_inputs` leaves their embeddings *exactly equal* to the original embedding. We do *not* corrupt or mask these positions at all. The model will see these token embeddings as if they were normal known tokens.
- **Freezing Output:** During inference, we will carry these tokens through unchanged to the output. Because we never ask the MLM to predict them (they're not masked or corrupted), it effectively treats them as given context. In the final output, we simply copy these original tokens at their positions. This is analogous to providing hard constraints in generation – the model knows these tokens are fixed. If needed, one could also enforce this by biasing the model's output: e.g. set an extremely high confidence for the original token at that position or disallow any other token. In practice, not masking them is sufficient to keep them intact.

By treating high-brightness tokens as fixed context, we preserve them exactly (no replacements). They act as conditioning on the MLM's predictions for other tokens. This satisfies the "rocks in the river" requirement: those tokens stand unmoved while others flow around them.

OpenAI

Integration with the Inference Pipeline (No Retraining Required)

This method is **plug-and-play at inference time** with any masked language model like DistilBERT. We do not modify model weights or architecture; we only modify inputs and use the model's standard forward pass and token prediction:

1. **Prepare Inputs:** Construct `noisy_inputs` as described (original embeddings + noise for each token, with no noise on locked tokens).
2. **Model Forward Pass:** Pass these embeddings into the MLM model. Hugging Face models allow using `inputs_embeds` instead of `input_ids` for this purpose. For example:

   ```python
   `outputs = model(inputs_embeds=noisy_inputs, attention_mask=torch.ones_like(input_ids))
   logits = outputs.logits  # shape: (1, seq_len, vocab_size)
   `
   ```

   We supply an `attention_mask` of 1s for all real tokens (ensuring the model attends to all tokens). DistilBERT's MLM head will output `logits` for each token position in the vocabulary space. Essentially, we are asking the model: "Given this partially corrupted sequence, what token belongs at each position?"
3. **Predict Tokens:** For each token position i, if it was **locked** ($b_i \ge T$), we keep the original token. If it was **modifiable** ($b_i < T$), we select a new token based on the model's output distribution at i. This could be the highest-probability token (`argmax` for a deterministic fill) or sampled randomly for diversity. Typically, one uses `torch.argmax(logits[0, i])` to get the predicted token ID at position $i`. We then convert IDs back to tokens with the tokenizer. For example:

   ```python
   `import torch
   predicted_ids = torch.argmax(logits, dim=-1)   # tensor shape: (1, seq_len)
   predicted_ids[0, lock_mask.bool()] = input_ids[0, lock_mask.bool()]  # ensure locked tokens
   new_tokens = tokenizer.convert_ids_to_tokens(predicted_ids[0])
   new_text = tokenizer.decode(predicted_ids[0])
   `
   ```

   Here we explicitly set the model's prediction for locked positions to the original token ID (this step is just a safety check; since we gave the model the actual embedding for that token, it is almost certainly already predicting it as the most likely token). Now `new_tokens` is the sequence after diffusion: some tokens identical to the original, others replaced with new tokens.
4. **Token-Level Diff:** Because we preserved the sequence length and indices, we can directly compare `new_tokens` to the original tokens to identify changes. Each position where `new_tokens[i] != original_tokens[i]` is a modification (dark token got replaced). This satisfies the requirement to *preserve discrete token-level diffs*: the output is aligned with the input, and changes are explicit replacements of tokens. No insertions or deletions occur, so one can list the diffs as "token X → token Y at position i".

5. **Lightweight Iteration (Optional):** In many cases, a **single pass** is sufficient to generate the new sequence. The approach is efficient – essentially one forward inference of DistilBERT (which is small and fast) plus some vector operations. If needed, one can iterate this process for refinement: e.g., after one pass, update the sequence and brightness map (perhaps set brightness high for tokens that the model was very confident about, or that match the original, and low for uncertain ones) and run another pass. This resembles the *mask-predict* iterative decoding algorithmaclanthology.org, but guided by our external brightness map instead of model confidence. In each iteration, you would add fresh noise to the still-dark tokens and let the MLM reconverge on them. Because our method is non-autoregressive and parallel, a few iterations (if any) are usually enough for convergenceaclanthology.org. Each iteration remains lightweight (just feed-forward passes).

Example Pseudocode

Below is a consolidated pseudocode illustrating how to apply the brightness heatmap to guide DistilBERT during inference:

```python
`# Assume: tokens (list of input tokens), brightness_list (list of brightness values per token), 
input_ids = tokenizer.convert_tokens_to_ids(tokens)
input_ids = torch.tensor([input_ids])              # shape (1, seq_len)

# 1. Get embeddings
emb_layer = model.distilbert.embeddings
inputs_embeds = emb_layer(input_ids)               # shape (1, seq_len, emb_dim)

# 2. Compute noise scale per token
b = torch.tensor(brightness_list, dtype=torch.float).unsqueeze(0).unsqueeze(-1)  # shape (1, seq_
lock_mask = (b >= T).float()
noise_scale = (1.0 - b) * (1.0 - lock_mask)        # (1-b_i) for modifiable tokens, 0 for locked

# 3. Inject noise
eps = torch.randn_like(inputs_embeds)
noisy_inputs = inputs_embeds + noise_scale * eps   # add Gaussian noise

# 4. Run MLM forward pass with noisy embeddings
attn_mask = torch.ones_like(input_ids)             # all tokens attend (no padding to mask out)
outputs = model(inputs_embeds=noisy_inputs, attention_mask=attn_mask)
logits = outputs.logits                            # shape (1, seq_len, vocab_size)

# 5. Decode output tokens
pred_ids = torch.argmax(logits, dim=-1)            # best token id at each position
# Ensure locked tokens remain the same as original:
pred_ids[0, lock_mask[0,:,0].bool()] = input_ids[0, lock_mask[0,:,0].bool()]
new_tokens = tokenizer.convert_ids_to_tokens(pred_ids[0])
`
```

This procedure produces `new_tokens` as the final sequence after applying brightness-based guided diffusion. The "locked" positions were never changed (we copied them back from the original), and other positions were regenerated by the model.

Discussion: Clarity and Compatibility

- **No Architecture Changes:** We leveraged the model's existing capabilities (masked LM head and `inputs_embeds` injection). We did *not* introduce any new parameters or fine-tuning. The approach works with off-the-shelf `DistilBertForMaskedLM` (or any similar BERT-like MLM). We only used public APIs (`model.get_input_embeddings()`, `model(**kwargs)` with `inputs_embeds`) and PyTorch routines (`torch.randn_like`, tensor masking).

- **Attention Bias (if needed):** By default, all tokens (locked or not) still participate in the self-attention layers as usual, meaning the model can use the fixed tokens as context for predicting the others. In most cases this is desirable. If we wanted to *further* emphasize that locked tokens should not be influenced by any erroneous context, we could optionally add an attention bias or higher weighting for them. For example, one could modify the transformer's attention scores to give slightly greater weight to locked-token representations, ensuring the model strongly considers these correct tokens when updating the others. However, this is an advanced tweak – not usually necessary since the model will naturally use intact tokens as reliable context.
- **Preserving Diffs:** Because the output length and positions match the input, generating a token-level diff is straightforward. You can iterate over `original_tokens` and `new_tokens` and record where they differ. Each difference corresponds to a replacement made by the model.
- **Live Inference Performance:** The method is efficient enough for live use. DistilBERT has a smaller architecture, and adding noise is $O(n)$ per token. The heavy lifting is one (or a few) forward passes through the model, which for a sequence of moderate length is on the order of milliseconds on modern hardware. There is no backpropagation or iterative beam search – just matrix operations and softmax predictions, which are highly optimized. If iteration is used, you typically fix a small number of iterations (as in mask-predict, often <10)aclanthology.org, which is still tractable for real-time applications.

In summary, this technique **transforms a brightness heatmap into direct control over a masked language model's editing process**. High brightness tokens are left untouched, and lower brightness tokens are noised in their embeddings according to how dark they are, prompting the MLM to fill them in. The result is a new sequence where changes are confined to the intended spots, and the original vs. new token differences are explicitly preserved for inspection. This approach draws on the intuition of diffusion models and iterative refinement in NLPopenreview.net aclanthology.org, implemented in a simple, **production-friendly** manner using input masking and noise injection. The clarity of this method makes it compatible with standard `transformers` pipelines and easy to adjust for different brightness thresholds or noise scales as needed.

Sources: The idea of per-token noise scaling is inspired by *soft-masked diffusion for text* openreview.net, and the iterative masking concept aligns with the *Mask-Predict* algorithm aclanthology.org, adapted here for a brightness-based guidance scenario.

Sources