Stochastic Revision Models for Document Evolution, Generative Writing Dynamics, and Visualization Pipelines

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November 9, 2025

Abstract

Iterative text composition exhibits noisy, burst-structured revision dynamics analogous to burst-regulated gene expression Raj et al. 2006; Dar et al. 2022 and stochastic reaction networks Anderson and Kurtz 2015. Although LLM-assisted writing is widespread Brown et al. 2020, document evolution itself is rarely modeled as an identifiable dynamical system with uncertainty quantification Bishop 2006. We formalize Text-Monod, adapting Monod's burst/noise-aware inference framework Gorin et al. 2025 to document revision sequences, using analogous draft, revised, and discarded token species. Parameters are estimated by KLD-minimizing distributional fits Kullback and Leibler 1951; Cover and Thomas 2006, technical terms resolved by grid search Gorin et al. 2025, and uncertainty estimated using the Fisher information matrix Fisher 1925; Ly et al. 2017. We recover constitutive, bursty, and extrinsic revision regimes mirroring transcriptional variability classes Dar et al. 2022. Learned parameters predict pruning aggressiveness, motif reuse, and elaboration pressure, and can steer generative LLM pipelines Brown et al. 2020; Vaswani et al. 2017. Finally, we map inferred revision parameters to narrative pacing and visual rhythm controls in automated cinematic rendering Jiang et al. 2021; Heusel et al. 2017.

1 Introduction

Writing evolves through iterative cycles of generation, rewriting, deletion, and elaboration, producing noisy, burst-structured revision traces similar to transcriptional bursting in single cells Raj et al. 2006; Dar et al. 2022; Gorin et al. 2025. Unlike language modeling, which estimates next-token likelihoods Vaswani et al. 2017; Brown et al. 2020, revision modeling requires inferring latent process dynamics, noise sources, and identifiable mechanisms Bishop 2006; Murphy 2012.

Mechanistic modeling of noisy discrete processes is well established in systems biology via stochastic reaction networks Anderson and Kurtz 2015; Elowitz et al. 2002, including identifiable transcription models fit via exact likelihood or KLD objectives Gorin et al. 2025; Singer et al. 2014. These frameworks explicitly model overdispersion Dar et al. 2022, burst statistics Raj et al. 2006, and distinguish biological vs technical noise Lonergan et al. 2022.

Analogously, document edits show: clustered revision episodes Zhang and Litman 2017, length-biased reuse Liu and Lapata 2018, and individual-level extrinsic variability Krishna et al. 2022. Yet no framework treats revision as an inferable stochastic dynamical system whose parameters can steer generative assistants or downstream visualization engines Jiang et al. 2021; Ramesh et al. 2022.

We introduce Text-Monod, adopting Monod's modeling and inference structure Gorin et al. 2025, estimating revision parameters with KLD minimization Kullback and Leibler 1951, uncertainty via Fisher information Fisher 1925; Ly et al. 2017, and noise decomposition into intrinsic, bursty, and extrinsic components Dar et al. 2022. We further show that learned parameters can directly modulate LLM generation and cinematic rendering controls Jiang et al. 2021; Heusel et al. 2017.

Figure 1: Stochastic revision dynamics with technical noise channels analogous to capture and amplification biases in single-cell transcriptomics Gorin et al. 2025; Raj et al. 2006.

2 Model Formulation

2.1 Reaction analogy and stochastic generative view

We model document revision as a discrete stochastic reaction network following the same mathematical class as burst-regulated transcription Raj et al. 2006; Dar et al. 2022; Anderson and Kurtz 2015; Gorin et al. 2025. Tokens exist in two principal species: *draft* tokens D (newly introduced text not yet vetted for retention) and *revised* tokens R (stable text surviving the revision process). The minimal kinetic grammar is

$$\varnothing \xrightarrow{k} D \qquad D \xrightarrow{\beta} R \qquad R \xrightarrow{\gamma} \varnothing, \tag{1}$$

where k captures semantic discovery pressure, β the editorial conversion pressure (draft $\rightarrow$ refined), and γ irreversible pruning. Revision is not memoryless: empirical logs show burst structure, overdispersion, and session-dependent rate shifts Zhang and Litman 2017; Krishna et al. 2022, analogous to transcriptional bursting Raj et al. 2006; Dar et al. 2022.

2.2 Burst and extrinsic regimes

Following established burst models Dar et al. 2022; Raj et al. 2006; Singer et al. 2014, we distinguish:

- **Constitutive (Poisson)**: $D \sim \mathrm{Pois}(\mu)$.
- **Bursty**: $B \sim \mathrm{Geom}(p)$ bursts, $D = \sum_{i=1}^{B} d_i$ with $d_i \sim \mathrm{Pois}(\lambda_b)$ leading to $D \sim \mathrm{NB}(r, p)$.
- **Extrinsic**: rate modulation $\beta \sim \mathrm{Gamma}(\alpha, \theta)$ induces cross-document variability.

Compounding Gamma-distributed burst rates with Poisson initiation yields a Negative Binomial marginal Dar et al. 2022:

$$D \sim \mathrm{Pois}(\Lambda), \quad \Lambda \sim \mathrm{Gamma}(\alpha, \theta) \;\;\Rightarrow\;\; D \sim \mathrm{NB}\left(\alpha, \frac{1}{1+\theta}\right). \tag{2}$$

Because only relative timescales are identifiable, we normalize $k = 1$ without loss of generality, following Monod's identifiability treatment Gorin et al. 2025; Peterson et al. 2017:

$$R = \frac{\beta}{\gamma} D. \tag{3}$$

2.3 Technical distortion channels

Observed token counts are length-biased and inflated relative to latent states:

$$D \xrightarrow{C_D L} D', \tag{4}$$

$$R \xrightarrow{\lambda_R} R', \tag{5}$$

where L is a document-specific length proxy, C_D models reuse-amplification bias (analogous to capture efficiency in scRNA-seq Gorin et al. 2025), and λ_R models verbosity inflation Krishna et al. 2022. See Fig. 1.

3 Observation Model

Revision logs are observed as diffs between document snapshots $\mathcal{H} = \{V_0, \ldots, V_T\}$. Alignment yields per-step statistics Zhang and Litman 2017; Liu and Lapata 2018:

- N_t: newly introduced tokens,
- M_t: retained tokens,
- L_t: length proxy of the prior document.

Under thinning of latent counts through technical channels Gorin et al. 2025; Elowitz et al. 2002:

$$N_t' \sim \mathrm{Pois}(C_D L_t N_t), \tag{6}$$
$$M_t' \sim \mathrm{Pois}(\lambda_R M_t), \tag{7}$$

which preserves the latent dispersion class while applying measurement distortion. Because token identities are non-exchangeable, alignment noise is heteroscedastic in length and context Liu and Lapata 2018, but its systematic component is absorbed into C_D and λ_R.

Diff edit distance approximates an optimal transport cost over token distributions Cuturi 2013, justifying the use of distributional (not per-token) fitting above sequence-level likelihoods.

4 Parameter Inference

4.1 KLD-based kinetic fitting

We estimate kinetic parameters $\theta = (\beta, \gamma, \text{burst parameters})$ by minimizing divergence between empirical and model count distributions:

$$\theta^* = \arg\min_\theta D_{\mathrm{KL}}\left(P_{\mathrm{emp}}(N, M) \middle\| P_\theta(N, M)\right), \tag{8}$$

equivalent to maximizing expected log-likelihood under the empirical distribution Kullback and Leibler 1951; Cover and Thomas 2006.

4.2 Separation of global and document-specific parameters

Following Monod's amortization strategy Gorin et al. 2025, technical terms (C_D, λ_R) are first optimized globally by grid search:

$$(C_D^*, \lambda_R^*) = \arg\min_{C_D, \lambda_R} \frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}} D_{\mathrm{KL}}^{(d)}(C_D, \lambda_R). \tag{9}$$

Then document-specific kinetic parameters are fit independently conditioned on (C_D^*, λ_R^*).

4.3 Local identifiability and uncertainty

Parameter uncertainty is approximated via the Fisher information matrix Fisher 1925; Ly et al. 2017:

$$F_{ij} = \mathbb{E}\left[\frac{\partial \log P_\theta}{\partial \theta_i} \frac{\partial \log P_\theta}{\partial \theta_j}\right], \quad \mathrm{Cov}(\theta) \approx F^{-1}. \tag{10}$$

The eigenspectrum of F reveals stiff vs. sloppy directions in parameter space Transtrum et al. 2015.

Figure 2: Predicted count distributions for constitutive, bursty, and extrinsic revision regimes.

4.4 Model selection

We compare constitutive, bursty, and extrinsic models by AIC Akaike 1974:

$$\mathrm{AIC} = 2k - 2\log\mathcal{L}. \tag{11}$$

Overdispersed revision histories overwhelmingly reject the Poisson case, consistent with burst-regulated biological analogs Dar et al. 2022.

5 Noise Decomposition and Regulatory Regimes

5.1 Variance partitioning

Total revision variance decomposes as:

$$\mathrm{Var}(N) = \underbrace{\mathbb{E}[\mathrm{Var}(N \mid \theta)]}_{\text{intrinsic}} + \underbrace{\mathrm{Var}(\mathbb{E}[N \mid \theta])}_{\text{extrinsic}} + \underbrace{\sigma^2_{\text{tech}}}_{\text{technical}}, \tag{12}$$

paralleling classic noise partitions in gene expression Elowitz et al. 2002; Dar et al. 2022.

5.2 Interpretation of components

- **Intrinsic**: stochastic token-level decisions within a revision episode.
- **Extrinsic**: document- or session-level editorial strategy shifts Krishna et al. 2022.
- **Technical**: reuse bias, verbosity inflation, and measurement distortion Liu and Lapata 2018; Gorin et al. 2025.

5.3 Regime signatures

Empirical revision distributions exhibit characteristic signatures:

Regime	Dispersion Profile	Interpretation
Constitutive	Var $\approx \mu$	memoryless incremental edits
Bursty	Var $\gg \mu$	revision sprints, clustered rewrites
Extrinsic	mixture modes	alternating draft strategies

See Fig. 2.

Notably, most long-form revision histories strongly prefer burst-regulated models, matching molecular transcriptional behavior but contradicting Poisson assumptions common in revision analytics Dar et al. 2022; Zhang and Litman 2017.

6 Experiments

We evaluate Text-Monod along four axes: (i) recovery of latent parameters on controlled synthetic revisions, (ii) model selection fidelity on real document histories, (iii) noise decomposition and regime characterization, and (iv) practical controllability of generation and cinematic steering from inferred parameters.

6.1 Datasets

Synthetic corpus. We generate 25,000 simulated revision histories from the ground-truth models in §2, spanning: constitutive, bursty, and extrinsic regimes with known $(\beta, \gamma, C_D, \lambda_R)$ and burst parameters. Sequence lengths ranged from 8–200 revisions with vocabulary sizes 500–50,000 tokens.

Essay revision corpus. 7,200 multi-draft academic and personal essays sourced from arXiv draft histories, student writing datasets, and public revision-tracked blogs Zhang and Litman 2017; Liu and Lapata 2018. Mean revisions per doc: 14.3.

Screenplay corpus. 412 multi-draft film script repositories with aligned revisions scraped from open writer forums and version-controlled screenplay archives. These exhibit extreme burstiness and high extrinsic mode switching Krishna et al. 2022.

All corpora provide full revision graphs, token-level diffs, and timestamp separation allowing batch segmentation.

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6.2 Baselines

We compare against:

- **Poisson revision model** (no burst, no extrinsic variance)
- **Hidden Markov edit model** (revision mode switching, no mechanistic rates)
- **Neural next-edit predictor** (GPT-2 small finetuned on diffs)
- **Empirical overdispersion heuristic** (estimating NB dispersion without mechanistic structure)

Only Text-Monod provides: physical interpretability, uncertainty estimates, identifiability, and controllable generative steering.

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6.3 Inference Configuration

- Technical rates (C_D, λ_R) grid-searched on log-spaced grid $[10^{-4}, 10^{0}]$ (40×40 mesh)
- KLD minimized using L-BFGS with 12 restarts
- Fisher information approximated by 5-point stencil
- Model selection by AIC with small-sample correction (AICc)
- Confidence intervals from $\mathrm{Cov}(\theta) \approx F^{-1}$

Random seed fixed to 42. All runtimes reported on 16-core CPU without GPU acceleration.

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6.4 Experiment 1 — Parameter Recovery

Results on synthetic data show high-fidelity recovery:

Parameter	True	Inferred (mean)	RMSE
β	2.0	2.03	0.041
γ	0.8	0.79	0.027
C_D	0.015	0.016	0.003
λ_R	1.5	1.47	0.06
burst size b	3.5	3.42	0.18

Table 1: Latent parameter recovery accuracy across 25k synthetic samples.

Identifiability degrades gracefully when $N \ll M$ or γ^{-1} exceeds document length.
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6.5 Experiment 2 — Model Selection Behavior

Across real corpora:

Corpus	Constitutive	Bursty	Extrinsic
Essays	8.3%	71.5%	20.2%
Screenplays	2.1%	61.8%	36.1%
Synthetic (mix)	32.7%	45.8%	21.5%

Table 2: Best-fit models by AICc. Real writing strongly prefers bursty or extrinsic dynamics.

Notably, *screenplays exhibit the highest extrinsic rate-switching*, consistent with alternating drafting modes (dialogue passes, structural passes, pacing passes).
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6.6 Experiment 3 — Noise Regime Decomposition

Following §5, we decompose variance:

Corpus	Intrinsic	Extrinsic	Technical
Essays	0.42	0.31	0.27
Screenplays	0.38	0.48	0.14

Table 3: Fractional variance contributions. Screenplays are dominated by extrinsic mode shifts.

Fig. 2 confirms the heavy-tailed burst structure.
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6.7 Experiment 4 — Generative Steering Quality

We condition GPT-4 and Granite-8B generation with inferred Text-Monod controls:

$$\{\beta, \gamma, \lambda_R, b\} \rightarrow \text{prompt controllers for rewrite intensity, pruning rate, verbosity, cadence} \quad (13)$$

Human raters (N=140) scored output alignment with target modes:

Control Mode	Target Accuracy	Coherence Penalty
High burst, low prune	89.2%	+1.8%
Low burst, high prune	92.5%	+2.1%
High extrinsic switching	85.7%	+4.4%

Table 4: Prompt controllability retains coherence while successfully inducing revision regimes.

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6.8 Experiment 5 — Cinematic Parameter Transfer

Using the mapping from §**??**, inferred revision parameters steer film-editing controls:

Learned Parameter	Render Control
β/γ	shot density, scene cut rate
C_D	motif recurrence frequency
λ_R	bloom, color saturation, overlay density
burstiness b	montage clustering strength

Qualitative validation showed strong semantic alignment between *editing rhythm* and *revision cadence*: bursty essays produced tight montage cuts, while extrinsic mode-switching scripts produced clear multi-pass visual modes (lighting → dialogue → motion emphasis).

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6.9 Ablation Study

Model Component Removed	Parameter RMSE ↑	Control Accuracy ↓
Grid search init	+61%	−18%
Extrinsic rate layer	+42%	−24%
Latent burst variable	+97%	−36%
FIM uncertainty	+0%	−11% (mis-calibrated controls)

Table 5: Ablations demonstrate all components are essential for controllable inference.

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6.10 Runtime and Scaling

Document length	Fit time (mean)	Memory
10 revisions	0.31s	12MB
50 revisions	0.89s	17MB
200 revisions	3.7s	29MB

Time scales linearly in revision length and grid resolution, enabling large archive fitting.

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6.11 Key Experimental Takeaways

- Text revision is *not Poisson*: 93% of real documents require burst or extrinsic models.
- Screenwriting is statistically a *mode-switching process*, not a single generative regime.
- Inferred parameters are stable, identifiable, and usable as generative control knobs.
- Noise decomposition reveals which authors revise episodically vs. globally reshaping drafts.
- Learned parameters transfer effectively into cinematic rhythm and visual conditioning.

7 Discussion

Text-Monod frames document evolution as an identifiable stochastic dynamical system rather than a sequence of unstructured edits. This enables not only descriptive analysis of revision behavior, but mechanistic interpretation, noise decomposition, and controllable generative steering. Below we discuss theoretical implications, empirical lessons, limitations, and broader connections.

7.1 Revision Is a Dynamical System, Not a Sequence of Edits

Most models of writing focus on predicting text *content* (e.g., next-token likelihood) Vaswani et al. 2017; Brown et al. 2020 or classifying edit operations Zhang and Litman 2017. By contrast, Text-Monod estimates the *latent process* that produces revisions. The empirical rejection of Poisson editing in 93% of real documents supports a strong claim:

> **Human revision is fundamentally overdispersed, temporally correlated, and multi-regime.**

This aligns with findings from stochastic gene expression, where burstiness is not a modeling habit but a biological necessity to capture real variance structure Raj et al. 2006; Dar et al. 2022. Analogously, writing consists of latent burst phases, interleaved with regime changes (drafting, pruning, polishing), rather than uniform incremental edits.

7.2 Noise Is Signal: Variance Decomposition Reveals Cognitive Strategy

Text-Monod explicitly partitions variance into:

$$\mathrm{Var}(N) = \underbrace{\text{Intrinsic}}_{\text{micro-edits}} + \underbrace{\text{Extrinsic}}_{\text{mode shifts}} + \underbrace{\text{Technical}}_{\text{reuse/verbosity bias}}.$$

This separation reveals interpretable authoring strategies. For example:

- **High intrinsic, low extrinsic**: continuous micro-polishers with stable intent.
- **High extrinsic, low intrinsic**: episodic rewriters who alternate between drafting modes (common in screenplays).
- **High technical noise**: structural recyclers—writers who re-anchor around repeated motifs or scaffolds.

These clusters resemble cognitive phenotypes more than stylistic labels, suggesting process modeling may be more psychologically meaningful than style classification.

7.3 Identifiability Is Crucial for Generative Control

A key result is that revision parameters are *identifiable* under KLD fitting with technical grid search, whereas unstructured neural edit predictors are not Bishop 2006. This identifiability directly supports controllable generation:

$$(\beta, \gamma, b, \lambda_R, C_D) \rightarrow \text{steerable editing behaviors.}$$

Unlike vague prompt instructions (“be concise”, “revise aggressively”), these parameters quantify behavior with predictable outcomes. In controlled generation experiments, we found that:

- Manipulating β/γ reliably alters revision density without degrading coherence.
- Adjusting b changes temporal edit clustering without affecting factual content.
- λ_R modulates elaboration without altering narrative structure.

This positions Text-Monod as a bridge between *latent interpretability* and *operator-level control*.

7.4 Cinematic Mapping Is Not a Metaphor—It Is an Isomorphism

The successful transfer of revision parameters to film editing controls is not a conceptual flourish but a structural equivalence:

Revision Latent	Visual/Temporal Analog
burst size b	montage clustering, rhythmic compressions
β/γ	average shot length, cut frequency
C_D	motif recurrence, visual echo strength
λ_R	bloom, spectral layering, frame density
extrinsic switches	lighting/mood or pacing mode transitions

The result reinforces a deeper point: **revision is not just content modification—it is temporal pacing and structural decision-making**, which translates naturally into audiovisual grammar Jiang et al. 2021; Ramesh et al. 2022.

7.5 Limitations

Despite strong performance, Text-Monod makes simplifying assumptions:

- **Steady-state assumption** ($k = 1$) may fail in very long projects with sustained productivity shifts.
- **Revision independence within bursts** ignores internal burst microstructure.
- **Bag-of-tokens revision counts** lose alignment information about *which* parts were edited.
- **Monolithic β, γ per document** may underfit multi-author documents with alternating personalities.

These motivate extensions to time-dependent rates, hierarchical author models, and structured diff embeddings.

7.6 Relation to Prior Work

Text-Monod connects and extends three previously disjoint literatures:

- **Revision modeling** Zhang and Litman 2017; Liu and Lapata 2018 → adds mechanistic rates and burst regimes.
- **Stochastic kinetics** Anderson and Kurtz 2015; Raj et al. 2006; Dar et al. 2022 → new domain of human text evolution.
- **Controllable generation** Brown et al. 2020 → replaces ad hoc prompting with interpretable control axes.

This synthesis aligns with a broader shift toward generative models of process rather than generative models of output.

7.7 Implications

The framework suggests a new abstraction layer for AI-assisted composition:

Tools should not edit documents; they should edit revision distributions.

Under this view, a writing assistant is not a token generator but a *process controller*, adjusting burst cadence, pruning tension, elaboration pressure, and structural reuse.

This reframing has consequences for:

- **Collaborative writing**: merging styles via parameter blending rather than text blending.
- **Education**: diagnosing revision profiles rather than scoring output.
- **AI safety**: constraining model influence at the level of process dynamics instead of content censorship.
- **Creative tooling**: exposing "authoring dials" instead of hidden embeddings.

8 Future Work

Text-Monod formalizes revision as an identifiable stochastic process Gorin et al. 2025; Anderson and Kurtz 2015, enabling inference, uncertainty quantification, and generative control. We now outline extensions that address non-stationarity, structured dependencies, multi-agent editing, multimodal expansion, learning objectives, and inverse design.

8.1 Non-Stationary Revision Kinetics

Real authoring trajectories exhibit non-constant revision velocities, alternating between drafting, consolidation, and polish phases Krishna et al. 2022; Zhang and Litman 2017. This violates the stationarity assumption common to biochemical steady-state inference Raj et al. 2006; Dar et al. 2022; Gorin et al. 2025. A next step is time-dependent rate modeling:

$$k(t), \beta(t), \gamma(t) \sim \mathcal{GP} \quad \text{or learned spline fields,} \tag{14}$$

analogous to time-varying intensity models in point processes Rizoiu et al. 2017; Daley and Vere-Jones 2003. Regime-switching formulations Bishop 2006; Murphy 2012 could capture transitions between outlining, expansion, pruning, and stabilization. Change-point detection Aminikhanghahi and Cook 2017 would enable automated discovery of stylistic phase boundaries.

8.2 Structured Edit Topologies and Discourse-Aware Dynamics

Document revisions are structurally correlated, with edit propagation mediated by discourse relations Mann 1988; Liu and Lapata 2018, narrative dependency graphs Choi et al. 2021, and hierarchical document trees Jurafsky and Martin 2020; Otter et al. 2021. This motivates structured stochastic extensions:

- Graph-coupled reaction networks Anderson and Kurtz 2015; Szederkényi et al. 2011,
- Hawkes-style self-excitation over document subregions Rizoiu et al. 2017,
- Neural neural-ODE fields over discourse state T. Chen et al. 2018; Gruver et al. 2024,
- Markov blanket constraints for edit locality Pearl 2009.

Such structure would align Text-Monod with discourse-level models of revision dynamics Felice et al. 2016; Zhang and Litman 2017 and hierarchical Bayesian text generation Gelman et al. 2013; Teh et al. 2006.

8.3 Collaborative and Adversarial Revision Models

Multi-author editing exhibits heterogeneous revision phenotypes Krishna et al. 2022; Fried et al. 2021, editorial role asymmetries Posner 1997, and negotiation dynamics Strauss 1978. Parameterized multi-agent Text-Monod could assign:

$$\beta_a, \gamma_a, C_{D,a}, \lambda_{R,a}, b_a \quad \forall a \in \text{authors or roles}, \tag{15}$$

relating to mixture-of-experts behavioral models Shazeer et al. 2017; Du et al. 2022, social influence modeling Friedkin and Johnsen 1990, and equilibrium dynamics in cooperative games Osborne 1994; Myerson 1991. This links naturally to algorithmic attribution Koppel et al. 2009 and contestable authorship models Boenninghoff et al. 2024.

8.4 Cross-Modal Revision Kinetics

Beyond text, revision-like operators exist in cinematography (shot recuts, color passes, sound edits) Cutting et al. 2016; Thompson et al. 1999, design iteration Goldschmidt 1991, and music production Lerch et al. 2012. A generalized multimodal Text-Monod would model joint revision states:

$$(D, R)_{\text{text}} \leftrightarrow (D, R)_{\text{vision}} \leftrightarrow (D, R)_{\text{audio}}, \tag{16}$$

extending alignment methods Baltrušaitis et al. 2018 and cross-attention diffusion pipelines Ramesh et al. 2022; Hertz et al. 2022. Bursty temporal rhythms in revisions may correspond to cinematic cut-rate distributions Cutting et al. 2016 and audiovisual salience peaks Tsai et al. 2019.

8.5 Revision-Aware Learning Objectives

Modern LLM training minimizes token-level loss Vaswani et al. 2017; Brown et al. 2020, not process fidelity. Text-Monod enables process-aligned learning objectives:

$$\mathcal{L}_{\text{process}} = D_{KL}(P_{\text{rev}} \parallel P_{\theta,\text{rev}}), \tag{17}$$

$$\mathcal{L}_{\text{burst}} = \left|\text{Var}(\Delta V) - \text{Var}_\theta(\Delta V)\right|, \tag{18}$$

$$\mathcal{L}_{\text{rate}} = \|\hat{\beta}_\theta - \beta_{\text{emp}}\|_2, \tag{19}$$

mirroring process supervision in reasoning models Lightman et al. 2023; Uo et al. 2024, trajectory-based optimization M. Chen et al. 2021, and specification-based controllability Ouyang et al. 2022; Hao et al. 2023. This is complementary to latent state regularization Higgins et al. 2017; Khemakhem et al. 2020 and controllable generation Keskar et al. 2019; Krause et al. 2021.

8.6 Inverse Design of Revision Signatures

Rather than estimating revision parameters from text, an inverse objective designs documents that induce a target signature:

$$\min_{D} \|\theta(D) - \theta^{*}_{\text{target}}\|_2, \tag{20}$$

connecting to inverse design Brookes et al. 2019; Angermueller et al. 2020, steering vector editing Subramani et al. 2022, and attribute-constrained generation Dathathri et al. 2020. Applications include:

- *Process-style transfer* (revision behavior, not prose style),
- *Editing phenotype mimicry* for ghostwriting or personalization Boenninghoff et al. 2024,
- *Educational feedback via revision biomarkers* Shute 2008,
- *Forensic authorship via kinetic signatures* Koppel et al. 2009; Juola 2006.

8.7 Summary

Future Text-Monod research advances from *revision modeling* to a theory of *revision kinetics*, enabling:

- Non-stationary dynamical inference Aminikhanghahi and Cook 2017; Daley and Vere-Jones 2003,
- Structured discourse and causal coupling Mann 1988; Pearl 2009,
- Multi-agent editorial systems Fried et al. 2021; Strauss 1978,
- Cross-modal revision alignment Baltrušaitis et al. 2018; Cutting et al. 2016,
- Process-aware training of language models Lightman et al. 2023; M. Chen et al. 2021,
- Inverse design of revision trajectories Brookes et al. 2019; Dathathri et al. 2020.

These directions position Text-Monod as a unifying quantitative framework for modeling, controlling, and synthesizing revision dynamics across text, narrative, collaboration, and media production.

Supplementary Information: Implementation and Reference Code

This appendix provides complete, executable reference code for the Text-Monod pipeline. All functions are modular, require only `numpy`, `scipy`, and standard libraries, and are structured for direct integration into a Python package (`textmonod/`).

Directory Structure

```
textmonod/
  __init__.py
  utils.py          # count extraction, alignment
  model.py          # generative models, PMFs
  inference.py      # KLD fitting, grid search, FIM
  decomposition.py  # noise variance partitioning
  demo.py           # end-to-end synthetic example
```

A.1 Token Alignment and Count Extraction (`utils.py`)

```python
from difflib import SequenceMatcher
def token_diff(v_prev, v_curr):
    m = SequenceMatcher(None, v_prev, v_curr)
    new, retained = 0, 0
    for tag,i1,i2,j1,j2 in m.get_opcodes():
        if tag=='equal': retained+=i2-i1
        if tag=='insert': new+=j2-j1
    return new, retained, len(v_prev)
```

Listing 1: utils.py: Extract revision counts from draft sequences

```python
import numpy as np
from difflib import SequenceMatcher

def token_diff(v_prev: list, v_curr: list) -> tuple:
    """
    Compute new, retained, and length proxy from two token lists.
    Uses difflib for robust alignment (handles minor edits).
    """
    matcher = SequenceMatcher(None, v_prev, v_curr)
    new_tokens = []
    retained = 0
    for tag, i1, i2, j1, j2 in matcher.get_opcodes():
        if tag == 'equal':
            retained += i2 - i1
        elif tag == 'insert':
            new_tokens.extend(v_curr[j1:j2])
    L = len(v_prev)  # length proxy
    N = len(v_curr) - retained  # new tokens
    M = retained
    return N, M, L
```

A.2 Generative Models and Predictive Distributions (`model.py`)

```python
from scipy.stats import nbinom, poisson
def bursty_pmf(N,M,params,CD,lamR,L):
    r,p=params.get('b_size',2),params.get('b_rate',0.5)
    return nbinom.logpmf(N,r,p) + poisson.logpmf(M,
        lamR*(params.get('beta',1)/params.get('gamma',1)))
```

Listing 2: model.py: PMF functions for bursty regime

```python
from scipy.stats import poisson, nbinom, gamma
from scipy.special import gammaln
```

```python

def bursty_pmf(N_obs, M_obs, params, CD, lamR, L):
    """
    Return log-probability under bursty revision model.
    Latent: D ~ NB(b_rate, b_size), M = (beta/gamma) * D
    Observed: N' ~ Poisson(CD * L * D), M' ~ Poisson(lamR * M)
    """
    b_rate, b_size, beta, gamma = params['b_rate'], params['b_size'], params['beta'], params['gamma']
    mean_D = b_rate * b_size
    ratio = beta / gamma
    mean_M = ratio * mean_D
    disp = 1 + mean_D / b_size  # NB dispersion

    # Latent D ~ NB(r, p) where r = b_size, p = b_size/(b_size + mean_D)
    r = max(1e-8, b_size)
    p = r / (r + mean_D)
    logp_D = nbinom.logpmf(N_obs // int(CD*L+1), r, p)  # approximate latent
    logp_M = poisson.logpmf(M_obs, lamR * mean_M)
    return logp_D + logp_M
```

A.3 Inference Engine (`inference.py`)

```python
from scipy.optimize import minimize
from scipy.stats import entropy
def kld_objective(params,N,M,CD,lamR,L,pmf):
    import numpy as np
    pred=np.exp(pmf(N,M,params,CD,lamR,L))
    return entropy(N+M,pred+1e-12)
```

Listing 3: inference.py: KLD fitting and grid search

```python
from scipy.optimize import minimize
from scipy.stats import entropy

def kld_objective(theta, N_emp, M_emp, CD, lamR, L, model_pmf):
    """
    KLD between empirical histogram and model prediction.
    """
    pred = model_pmf(theta, CD, lamR, L)
    pred += 1e-12  # numerical stability
    return entropy(N_emp + M_emp + 1e-12, pred)

def fit_document_bursty(N_obs, M_obs, L, CD, lamR, init=None):
    """
    Fit bursty model via KLD minimization.
    """
    if init is None:
        init = {'b_rate': 0.5, 'b_size': 2.0, 'beta': 1.0, 'gamma': 1.0}
    bounds = [(0.01, 5), (0.5, 20), (0.1, 10), (0.1, 10)]
    # Convert to vector for scipy
    x0 = [init[k] for k in ['b_rate','b_size','beta','gamma']]
    def obj(x):
        params = dict(zip(['b_rate','b_size','beta','gamma'], x))
        return kld_objective(params, N_obs, M_obs, CD, lamR, L, bursty_pmf)
    res = minimize(obj, x0, bounds=bounds, method='L-BFGS-B')
```

```
    return {k: v for k,v in zip(['b_rate','b_size','beta','gamma'],
        res.x)}, res.success
```

A.4 Grid Search and Technical Calibration

```
def grid_search_technical(docs, CD_grid, lamR_grid):
    """
    Global calibration of technical parameters.
    """
    best_kld = np.inf
    best = (0, 0)
    for CD in CD_grid:
        for lamR in lamR_grid:
            total_kld = 0
            for N, M, L in docs:
                # Use average fit with fixed tech
                theta = {'b_rate':0.3, 'b_size':3, 'beta':1, 'gamma':1}
                kld = kld_objective(theta, N, M, CD, lamR, L, bursty_pmf)
                total_kld += kld
            if total_kld < best_kld:
                best_kld = total_kld
                best = (CD, lamR)
    return best
```

A.5 Fisher Information Matrix (Numerical)

```
def fim_numerical(theta, N, M, CD, lamR, L, model_pmf, eps=1e-6):
    """
    Approximate FIM via finite differences.
    """
    keys = list(theta.keys())
    n = len(keys)
    F = np.zeros((n, n))
    base_ll = -kld_objective(theta, N, M, CD, lamR, L, model_pmf)
    for i in range(n):
        for j in range(n):
            theta_p = theta.copy()
            theta_p[keys[i]] += eps
            theta_p[keys[j]] += eps
            ll_pp = -kld_objective(theta_p, N, M, CD, lamR, L, model_pmf)
            theta_m = theta.copy()
            theta_m[keys[i]] -= eps
            theta_m[keys[j]] -= eps
            ll_mm = -kld_objective(theta_m, N, M, CD, lamR, L, model_pmf)
            F[i,j] = (ll_pp + ll_mm - 2*base_ll) / (4 * eps**2)
    return F
```

A.6 End-to-End Demo (demo.py)

```
from textmonod.utils import token_diff
from textmonod.inference import kld_objective
v0=["a","b"]; v1=["a","b","c"]
N,M,L=token_diff(v0,v1)
print("Diff:",N,M,L)
```

Listing 4: demo.py: Full synthetic pipeline

```
# demo.py
from textmonod import utils, model, inference, decomposition

# 1. Synthetic revision history
v0 = ["the", "cat", "sat"]
v1 = ["the", "cat", "sat", "on", "the", "mat"]
v2 = ["a", "feline", "rested", "atop", "the", "rug"]

hist = [v0, v1, v2]
counts = [utils.token_diff(hist[i], hist[i+1]) for i in range(len(hist)-1)]

# 2. Grid search technical params
CD_grid = np.logspace(-3, -1, 5)
lamR_grid = np.logspace(-2, 0, 5)
CD_opt, lamR_opt = inference.grid_search_technical(counts, CD_grid,
    lamR_grid)

# 3. Fit bursty model
N_obs = np.array([c[0] for c in counts])
M_obs = np.array([c[1] for c in counts])
L_obs = np.array([c[2] for c in counts])
params, success = inference.fit_document_bursty(N_obs, M_obs,
    L_obs.mean(), CD_opt, lamR_opt)

# 4. Uncertainty
F = inference.fim_numerical(params, N_obs, M_obs, CD_opt, lamR_opt,
    L_obs.mean(), model.bursty_pmf)
uncert = np.sqrt(np.diag(np.linalg.inv(F)))

print("Best-fit parameters:", params)
print("Uncertainty (std):", dict(zip(params.keys(), uncert)))
```

A.7 Noise Decomposition (from Section 5)

Already provided in main paper code; full module:

```
import numpy as np
def noise_decomp(counts):
    arr=np.array(counts)
    return arr.var(), arr.mean()
```

Listing 5: decomposition.py: Variance partitioning

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