Scaling Diffusion Language Models via Adaptation from Autoregressive Models

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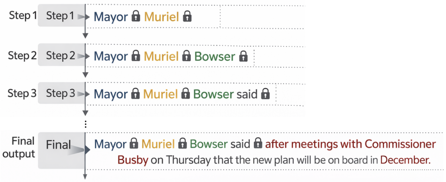
Motivation: Comparison of AR and DLM

Autoregressive LLM (AR)



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+ **Abundant pretrained models** and mature training infrastructure.

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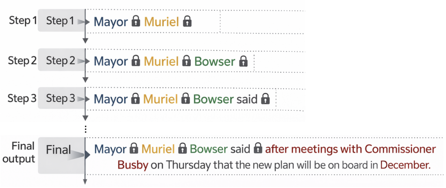

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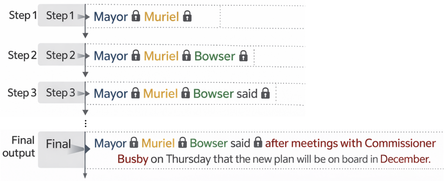

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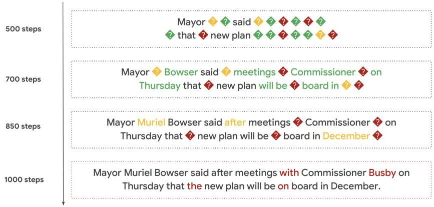

Figure adapted from Shi et al., "Simplified and Generalized Masked Diffusion for Discrete Data".

+ **Controllable and parallel** generation.

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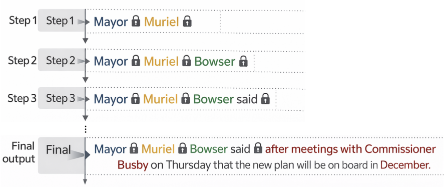

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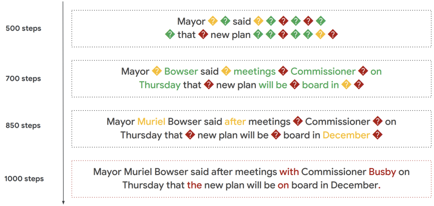

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- − **Relatively small model size** limits the competitiveness of DLMs compared to AR models.

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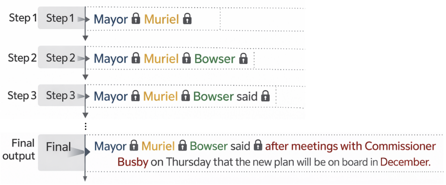

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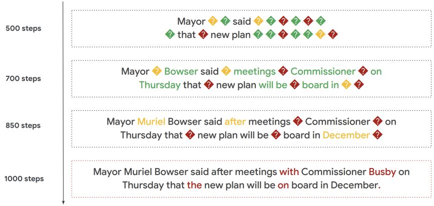

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- **Controllable and parallel** generation.
- **Relatively small model size** limits the competitiveness of DLMs compared to AR models.

Solution: Adapt large pretrained AR LLMs to diffusion, combining the **scalability** of AR models with the **flexibility** of diffusion.

Motivation: Challenges of Adaptation

- **AR:** Trained with causal masking on clean token sequences, predicting the next token at each step.
- **DLM:** Trained with bidirectional context on noisy sequences, predicting denoised tokens at arbitrary positions.

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Key challenge: Mismatched training objectives and input distributions.

Preliminaries: Continuous Diffusion Models

- **Clean data:** $\mathbf{x}_0 \sim p_{\text{data}}(\mathbf{x}_0)$
- **Terminal noise:** $\mathbf{x}_T \sim \mathcal{N}(0, \mathbf{I})$
- **Noisy state at time** t**:** $\mathbf{x}_t \sim q(\mathbf{x}_t)$

Forward Process:

$$q(\mathbf{x}_{1:T} \mid \mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t \mid \mathbf{x}_{t-1}), \quad q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) = \mathcal{N}\left(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I}\right)$$

which gradually corrupts clean data $\mathbf{x}_0$ into increasingly noisy variables.

Reverse Process:

$$p_\theta(\mathbf{x}_{0:T}) = p_\theta(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t),$$

which learns to iteratively denoise $\mathbf{x}_t$ to reconstruct $\mathbf{x}_0$.

Training Objective (ELBO).

$$-\log p_\theta(\mathbf{x}_0) \ \leq \ \mathbb{E}_{q(\mathbf{x}_1|\mathbf{x}_0)}[-\log p_\theta(\mathbf{x}_0 \mid \mathbf{x}_1)] + D_{\mathrm{KL}}(q(\mathbf{x}_T \mid \mathbf{x}_0) \,\|\, p_\theta(\mathbf{x}_T)) + \mathcal{L}_T,$$

where

$$\mathcal{L}_T = \sum_{t=2}^{T} \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)}[D_{\mathrm{KL}}(q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0) \,\|\, p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t))],$$

which enforces consistency between the true and learned reverse transitions at intermediate timesteps.

Preliminaries: Discrete Diffusion Models

In discrete denoising models, each token is a one-hot vector:

$$\mathbf{x}_t \in \{0,1\}^K$$

Forward Process:

$$q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) = \mathrm{Cat}(\mathbf{x}_t; \mathbf{Q}_t^\top \mathbf{x}_{t-1})$$

Absorbing diffusion transition:

$$\mathbf{Q}_t = (1-\beta_t)\mathbf{I} + \beta_t \mathbf{1}\mathbf{m}^\top$$

- With probability $1-\beta_t$: token unchanged
- With probability β_t: token $\rightarrow$ `[MASK]`

The marginal distribution at time t has a closed form:

$$q(\mathbf{x}_t \mid \mathbf{x}_0) = \alpha_t \mathbf{x}_0 + (1-\alpha_t)\mathbf{m}, \quad \alpha_t = \prod_{i=1}^{t}(1-\beta_i).$$

Model: Continuous-time Discrete Diffusion Process

Consider dividing $[0, 1]$ into T intervals ($T \to \infty$). For $0 \leq s < t \leq 1$:

Forward Process

$$q(\boldsymbol{x}_t \mid \boldsymbol{x}_s) = \frac{\alpha_t}{\alpha_s}\boldsymbol{x}_s + \left(1 - \frac{\alpha_t}{\alpha_s}\right)\boldsymbol{m}.$$

Backward Process

$$q(\boldsymbol{x}_s \mid \boldsymbol{x}_t, \boldsymbol{x}_0) = \begin{cases} \dfrac{\alpha_s - \alpha_t}{1 - \alpha_t}\boldsymbol{x}_0 + \dfrac{1 - \alpha_s}{1 - \alpha_t}\boldsymbol{m}, & \text{if } \boldsymbol{x}_t = \boldsymbol{m}, \\ \boldsymbol{x}_0, & \text{if } \boldsymbol{x}_t \neq \boldsymbol{m}. \end{cases}$$

Approximate the true backward transition using a denoising model:

$$p_\theta(\boldsymbol{x}_s \mid \boldsymbol{x}_t, f_\theta(\boldsymbol{x}_t)),$$

where $f_\theta(\boldsymbol{x}_t)$ approximates $\boldsymbol{x}_0$.

Define a similar form of backward transition:

$$p_\theta(\boldsymbol{x}_s \mid \boldsymbol{x}_t) = \frac{\alpha_s - \alpha_t}{1 - \alpha_t} f_\theta(\boldsymbol{x}_t) + \frac{1 - \alpha_s}{1 - \alpha_t}\boldsymbol{m}.$$

$f_\theta(\cdot)$ is implemented by a neural network (e.g., a Transformer).

Model: Continuous-time Discrete Diffusion Process

At each timestep, the KL term simplifies to:

$$D_{\mathrm{KL}}(q(\boldsymbol{x}_s \mid \boldsymbol{x}_t, \boldsymbol{x}_0) \parallel p_\theta(\boldsymbol{x}_s \mid \boldsymbol{x}_t)) = -\frac{\alpha_s - \alpha_t}{1 - \alpha_t} \delta_{\boldsymbol{x}_t, \boldsymbol{m}} \boldsymbol{x}_0^\top \log f_\theta(\boldsymbol{x}_t).$$

As $T \to \infty$, the continuous-time loss becomes:

$$\lim_{T \to \infty} \mathcal{L}_T = \int_0^1 \frac{\alpha_t'}{1 - \alpha_t} \mathbb{E}_{q(\boldsymbol{x}_t \mid \boldsymbol{x}_0)} \left[\delta_{\boldsymbol{x}_t, \boldsymbol{m}} \boldsymbol{x}_0^\top \log f_\theta(\boldsymbol{x}_t) \right] dt.$$

Following prior work, choose $\alpha_t = 1 - t$. This gives a simple weight $\frac{-\alpha_t'}{1-\alpha_t} = \frac{1}{t}$. The formulation extends independently to a sequence of N tokens:

$$\mathbf{x}_t = [\boldsymbol{x}_t^1, \ldots, \boldsymbol{x}_t^N].$$

During training, sample $t \sim \mathcal{U}(0, 1)$ and optimize:

$$\mathcal{L}_t^{1:N} = \frac{1}{t} \mathbb{E}_{q(\mathbf{x}_t \mid \mathbf{x}_0)} \left[-\sum_{n=1}^{N} \delta_{\boldsymbol{x}_t^n, \boldsymbol{m}} (\boldsymbol{x}_0^n)^\top \log f_\theta(\mathbf{x}_t^{1:N})_n \right].$$

Model: Unifying Language Modeling Objectives

AR LLM:

$$\mathcal{L}_{\text{AR}}^{1:N} = -\sum_{n=1}^{N} (\mathbf{x}_0^n)^\top \log f_\theta\left(\mathbf{x}_0^{1:n-1}\right)_{n-1}$$

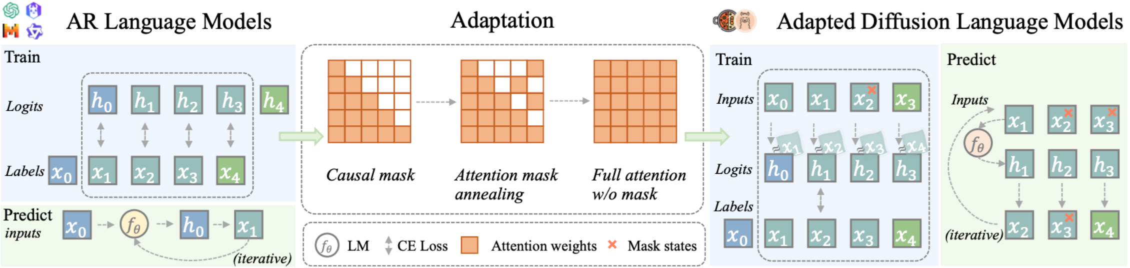
DLM:

$$\mathcal{L}_t^{1:N} = \frac{1}{t}\,\mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)}\left[-\sum_{n=1}^{N} \delta_{\mathbf{x}_t^n,\boldsymbol{m}}\,(\mathbf{x}_0^n)^\top \log f_\theta\left(\mathbf{x}_t^{1:N}\right)_n\right]$$

Key differences:

- Reweighting $\frac{1}{t}$: importance over noise levels.
- Mask indicator: predicts only corrupted tokens.
- Noisy, bidirectional context vs. clean, causal attention.

Model: Adaptation



- **Attention Mask Annealing:** causal → bidirectional attention.
- **Shift Operation:** preserve AR target shifting to align diffusion denoising.
- **Time-Embedding-Free Architecture:** reuse AR architecture; noise level encoded implicitly.

Experiment: Adaptation Setup

Models

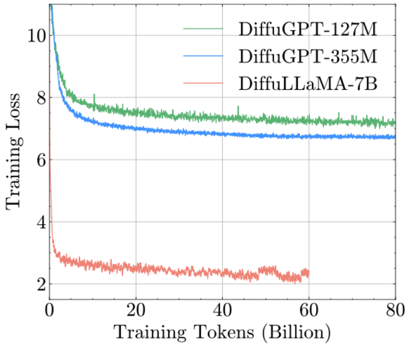
- **DiffuGPT:** GPT-2 base $\rightarrow$ diffusion
- **DiffuLLaMA:** LLaMA-2-7B $\rightarrow$ diffusion

Data

- DiffuGPT: 30B tokens from FineWeb
- DiffuLLaMA: 60B tokens from SlimPajama + Starcoder

Training

- Full-parameter finetuning (fp16)
- Sequence packing of length 2048 + logits shifting
- Attention mask annealing for GPT-2 and bi-directional for LLaMA



Training loss vs. total tokens for different model sizes.

Experiment: Evaluation Setup

Tasks:

- Reading comprehension and long-range dependency
- Commonsense and math reasoning
- Text and code infilling

Category	**Datasets**	**Metric**
QA / Completion	TriviaQA, LAMBADA	Exact Match (Accuracy)
Common Sense	HellaSwag, Wino, SIQA, PIQA	Accuracy
Math	GSM8K	Accuracy
Infilling	ROCStories	ROUGE-1/2/L
Code Infilling	HumanEval	pass@1

Experiment: Evaluation Setup (Metrics I: Exact Match / Accuracy)

Datasets: TriviaQA (reading comprehension), LAMBADA (last word prediction), GSM8K (math reasoning)

Definition:

$$\mathrm{EM} = \mathbf{1}\left[\mathrm{normalize}(\hat{y}) = \mathrm{normalize}(y^{\star})\right]$$

- String-level exact match after normalization (case, punctuation, articles).
- Dataset score = average EM over all samples.

Key details:

- QA and math tasks have well-defined final answers.
- Avoids ambiguity from paraphrases.

For GSM8K, only the final numeric answer is evaluated (not intermediate reasoning).

Experiment: Evaluation Setup (Metrics II: Multiple-Choice Reasoning)

Datasets: HellaSwag, WinoGrande, SIQA, PIQA

Evaluation Protocol:

- Each question has a prompt and several candidate choices.
- For each choice c, compute the **token-averaged negative log-likelihood**:

$$\text{Score}(c) = \frac{1}{|c|} \sum_{i \in c} - \log p(x_i \mid \text{prompt})$$

- Select the choice with the lowest score.
- Metric = accuracy (fraction of correct choices).

Key details:

- Length normalization avoids bias toward shorter options.
- Same scoring applies to AR and diffusion models.

Experiment: Evaluation Setup (Metrics III: Infilling and Code Evaluation)

Text Infilling: ROCStories

- Task: fill missing spans in short stories.
- Metric: ROUGE-1 / ROUGE-2 / ROUGE-L.

- ROUGE-1: unigram overlap
- ROUGE-2: bigram overlap
- ROUGE-L: longest common subsequence

Code Infilling: HumanEval

- Task: fill missing code so that unit tests pass.
- Metric: pass@1.

$$\text{pass@1} = \frac{\#\{\text{programs passing tests}\}}{\#\{\text{problems}\}}$$

Experiment: Results (Benchmark performance)

Model	Size	Type	QA	Word	CommonSense Reasoning				Math	Infilling	
			TriQA	Lamb.	HSwag	Wino.	SIQA	PIQA	GSM8K*	ROCStories	Code
GPT2-S	127M	AR	4.0	25.9	29.9	48.5	35.7	62.1	44.8	(7.8/0.8/7.4)	(1.6)
SEDD-S	170M	DD	1.5	12.4	30.2	50.1	34.4	55.6	45.3	11.9/0.7/10.9	0.7
DiffuGPT-S	127M	DD	2.0	21.6	<u>33.4</u>	<u>50.8</u>	<u>37.0</u>	57.7	<u>50.2</u>	<u>13.7/1.4/12.6</u>	0.3
GPT2-M	355M	AR	6.7	37.7	38.3	50.7	37.7	67.4	45.6	(8.6/0.9/8.2)	(2.6)
SEDD-M	424M	DD	1.8	23.1	31.5	49.0	35.4	56.1	53.5	13.1/1.4/12.2	0.5
DiffuGPT-M	355M	DD	3.8	30.3	37.2	<u>52.6</u>	<u>39.0</u>	59.6	<u>61.8</u>	<u>18.7/2.7/17.0</u>	<u>2.9</u>
Plaid1B	1.3B	CD	1.2	8.6	39.3	51.3	32.3	54.5	32.6	12.1/1.1/11.2	0.1
LLaMA2	7B	AR	45.4	68.8	74.9	67.1	44.8	78.3	58.6	(11.6/2.1/10.5)	(1.7)
DiffuLLaMA	7B	DD	**18.5**	**53.9**	**58.7**	**56.4**	**43.2**	**63.3**	<u>**63.1**</u>	<u>**23.3/5.5/21.2**</u>	<u>**15.5**</u>

Note: SEDD and Plaid are prior state-of-the-art DLMs. Bold denotes the best DLM result; underlined values outperform the corresponding AR base model.

+ DiffuGPT and DiffuLLaMA consistently outperform **prior SOTA DLMs**.
+ DiffuGPT and DiffuLLaMA excel at **global reasoning** like math, code, and infilling tasks.
− DiffuLLaMA still lags behind LLaMA2 on some benchmarks. The paper believes this gap is primarily data-limited

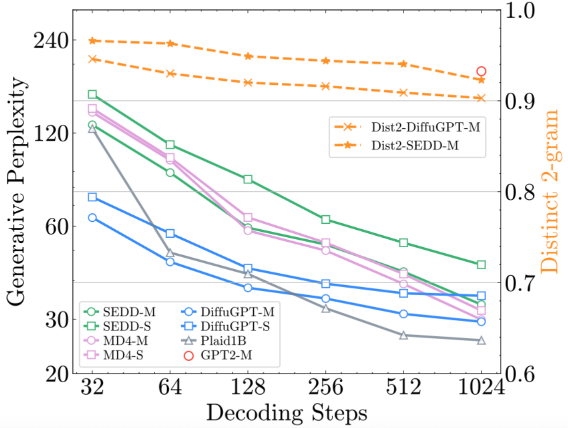
Experiment: Results (Unconditional Generation)

- **Quality: Perplexity (PPL).** Given a generated sequence $x_{1:N}$, an external evaluator (GPT-2 Large) assigns token probabilities $p(x_{1:N}) = \prod_{i=1}^{N} p(x_i \mid x_{<i})$. Then

$$\mathrm{PPL} = \exp\left(-\frac{1}{N}\sum_{i=1}^{N}\log p(x_i \mid x_{<i})\right)$$

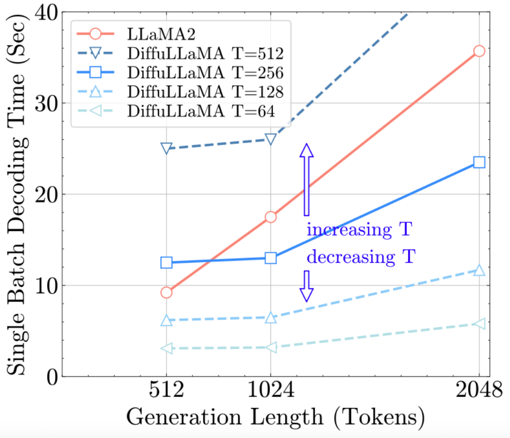
- **Diversity: Distinct-2** measures the fraction of **unique 2-grams** (bigrams) in the generated text.

$$\text{Distinct-2} = \frac{\#\{\text{unique 2-grams}\}}{\#\{\text{total 2-grams}\}}$$



Experiment: Results (Inference Speed)

- Decoding time mainly scales with the number of **diffusion steps** T.
- Diffusion inference offers an explicit knob (T) to control latency and quality.



Accommodation

Is it worth reading? Yes!

- Provides a clear comparison between DLMs and AR LLM objectives.
- Serves as a useful reference for model formulations and evaluation metrics in diffusion-based text generation.

Is it worth implementing? Yes!

- Proposes a simple and practical way to align AR and diffusion objectives via engineering tricks.
- Demonstrates promising empirical results, with room for further scaling and optimization.