# Sentiment Controlled LLM Decoding via Hamiltonian Monte Carlo

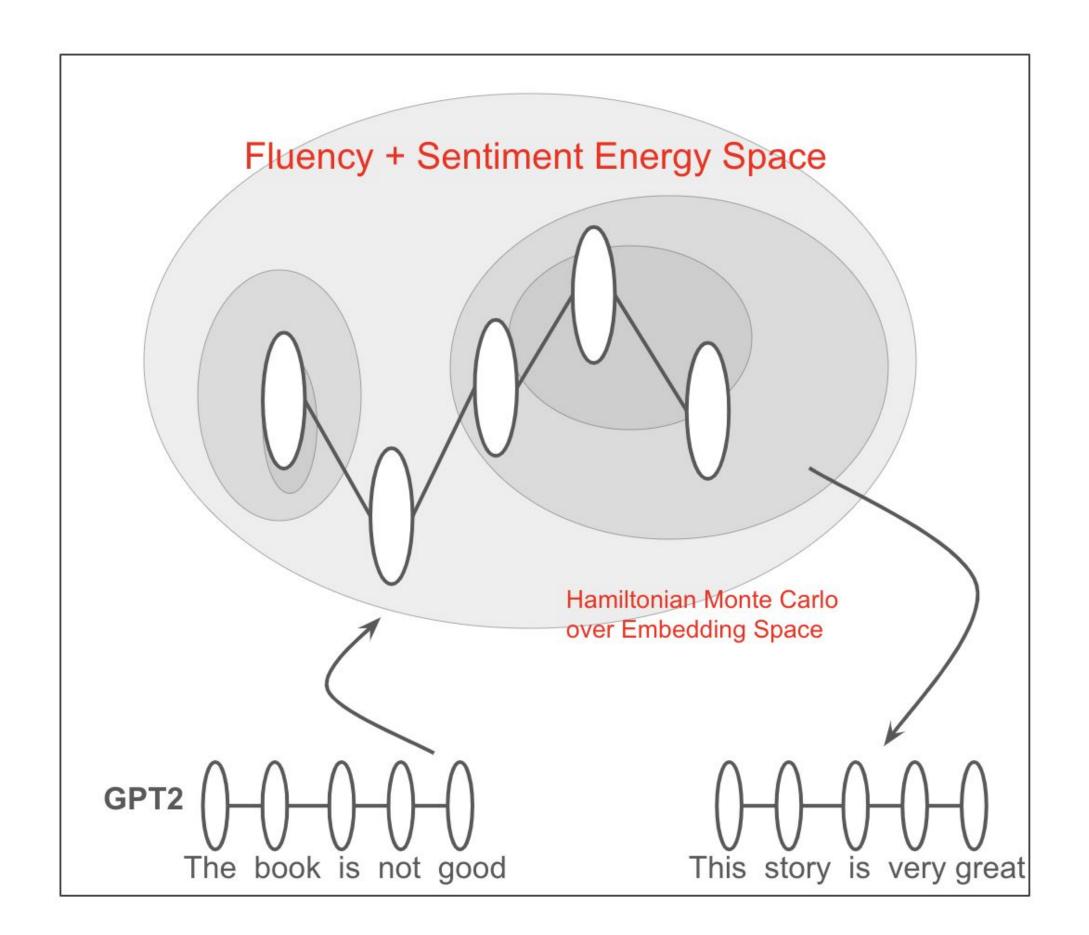


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**Goal**: HMC sampling directly within the continuous space of token embeddings, achieve more contextually coherent and controlled sentiment text generation compared to other decoding methods.

#### Motivation

- Coherent and sentiment-controlled text generation from minimal prompts is a key capability driving the next frontier in NLP.
- Recent studies on Langevin sampling over logit space / embedding space and discrete auto-regressive bias sampling
- Leveraging HMC sampling for broader exploration, avoiding local minima and ensuring diversity.



## Approach

Idea: HMC over embedding space with an energy function

- This approach explores the continuous token embedding space, enabling more coherent and sentiment-controlled text generation. The process is initialized with text generated by a standard language model.
- The energy function is designed to incorporate both fluency and sentiment objectives, encouraging outputs that are both grammatically fluent and sentiment-aligned.
- Sequences are updated via Hamiltonian dynamics, which leverage momentum and gradient-based exploration to enable broader, more structured sampling behavior.
- The accept/reject step in HMC ensures samples follow the desired posterior distribution.

#### Solution depiction

```
Algorithm 1 Hamilton Monte Carlo sampling steps
Require: Input sequence s, Output length L, base LM, Sentiment score func-
      tion f and threshold \epsilon, step size \alpha, Leapfrog step size \delta, Leapfrog steps L,
      momentum st<br/>d dev \sigma
Ensure: Accepted samples
 1: Initialize Y_0 from LM embeddings prompted with s
 2: for t = 0 to t = 500 do
            \mathbf{\Phi}_0^{(i)} \sim \mathcal{N}(0,\sigma) for each token i
            X_0 = Y_t
            Compute energy E(X_0)
            for l = 0 to L - 1 do
                  \mathbf{\Phi}_{(l+\frac{1}{2})\delta} = \mathbf{\Phi}_{l\delta} - \frac{\delta}{2} \left. \frac{\partial E}{\partial \mathbf{Y}} \right|_{\mathbf{Y} = \mathbf{X}_{l\delta}}
                  \boldsymbol{X}_{(l+1)\delta} = \boldsymbol{X}_{l\delta} + \delta \boldsymbol{R}^{-1} \boldsymbol{\Phi}_{(l+\frac{1}{2})\delta}
                  \mathbf{\Phi}_{(l+1)\delta} = \mathbf{\Phi}_{(l+\frac{1}{2})\delta} - \frac{\delta}{2} \left. \frac{\partial E}{\partial \mathbf{Y}} \right|_{\mathbf{Y} = \mathbf{X}_{(l+1)\delta}}
            end for
10:
            \alpha = \min (1, \exp (-H(\boldsymbol{X}_{L\delta}, \boldsymbol{\Phi}_{L\delta}) + H(\boldsymbol{X}_0, \boldsymbol{\Phi}_0)))
            if Uniform(0,1) \leq \alpha then
12:
                  Y_{t+1} = X_{L\delta}; save to samples
13:
            else
14:
                 Y_{t+1} = Y_t
15:
            end if
16:
            if t \% 10 == 0 then
17:
                  \lambda_i^t = \max\left(0, \lambda_i^{t-1} + \alpha \nabla_{\lambda_i} E(\mathbf{Y})\right)
18:
            end if
19:
20: end for
```

$$E(Y) = -\log P_{LM}(\operatorname{project}(Y)|x) - \lambda(\epsilon - f(Y))$$

f(Y) = a sentiment classifier trained by adding a linear layer on top of GPT2LMHead's output representations.

Dataset: https://huggingface.co/datasets/stanfordnlp/sst2

#### Challenges

- Energy and Gradient Computation: Non-differentiable token mapping for energy (fluency + sentiment) complicated gradient computation w.r.t. Token Embeddings.
- Used a Straight-Through Estimator to enable backpropagation through discrete token assignments Kinetic Energy in HMC: Improper mass matrix scaling caused low acceptance rates, leading to inefficient sampling.
- Tuned the mass matrix to balance kinetic energy, improving acceptance
- Token Mapping: Mapping continuous embeddings to discrete tokens.
- Applied distance-based mapping (nearest embeddings)
- Stuck in Local Minima / Unsatisfied Sentiment
   Dynamically adjust sentiment weight based on the energy gradient every 10th iteration
  - Dynamically increase leapfrog step size if same samples are sampled

## Experiments

Prompt: "Once upon a day,"

	textattack/roberta-base-SST-2	2 DistillGPT2
Text	Sentiment Score	Perplexity
about the time he was told by his parents that it was "a bad idea" for him to start writing	0.003014187096	17.26315498
stars the time he was told by his parents that it was "a bad idea" for him to start inhab	0.002595550148	28.28341484
about the time he was told by his parents that it was "a bad idea" for him to start resusc	0.003512033727	22.61892128
	0.00700000	-11
about the time he was told by his parents that it was "a good idea" for him to start resusc	0.8878903985	21.5558815
about the time he was told by his parents that it was "a good idea" for him to start resusc	0.8878903985	21.5558815
Text		21.5558815 Perplexity
Text		
Text an adaptation of a book by John Steinbeck, and we're sure this is the first time the book has	Sentiment Score 0.09196235985	Perplexity
,	Sentiment Score 0.09196235985	Perplexity 18.63439369

