Recalibrating Representations: A Feedback-Guided Weighted Pooling Framework for Transformers

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Abstract

Modern Transformer-based architectures often rely on a single dedicated token (e.g., `[CLS]`) or uniform mean pooling to derive sequence representations. While these strategies simplify the final embedding step, they risk overlooking valuable signals gained from the model's historical successes and failures. We propose a *feedback-guided* pooling mechanism that dynamically reweights token embeddings according to an external feedback vector capturing past performance. By emphasizing frequently misclassified or pivotal tokens, our method enriches sequence representations with top-down cues and enhances interpretability. Experiments across multiple NLP and vision tasks show that this lightweight module can outperform conventional pooling techniques in both accuracy and robustness—without imposing significant computational overhead. These findings suggest that even minimal feedback integration can substantially improve how Transformers aggregate information across tokens.

1 Introduction

Transformer-based models have achieved remarkable successes in various domains, ranging from natural language processing to computer vision. Central to these architectures is the process of converting token-level hidden states into a single sequence-level representation for tasks such as classification or sequence-to-sequence prediction. Although commonly used approaches like mean pooling or `[CLS]`-token extraction are conceptually simple and computationally efficient, they overlook an important dimension: *historical feedback* about how the model has performed in the past.

Mean pooling, for instance, treats all positions equally and thus may dilute critical cues from salient or challenging tokens. Similarly, `[CLS]`-token pooling fixates on a single learned embedding that might not always adapt sufficiently to the diverse tokens in an input. Recent work has explored attention-based pooling as a more flexible alternative, yet many of these methods only consider information contained within the same input sequence. In real-world scenarios, however, each new input can be processed with knowledge gleaned from previously seen data—whether they were successes, mistakes, or partially labeled samples. This prompts a fundamental question: *Can we leverage a global notion of feedback to guide the pooling of local token representations?*

Toward feedback-aware pooling. In domains where models operate iteratively on large corpora or streams of inputs, it is intuitive that recurring errors or patterns should influence how new data are processed. For example, tokens or token patterns that repeatedly lead to misclassification could be highlighted or downplayed in subsequent inference steps. Likewise, in reinforcement learning and interactive tasks, reward signals accumulated over time can be used to shape the model's attention on certain features. These insights motivate us to integrate a *feedback vector*—representing historical performance metrics or other high-level signals—into the final pooling layer.

Our proposal: Feedback-Guided Weighted Pooling (FGWP). In this paper, we introduce a simple yet powerful module, *Feedback-Guided Weighted Pooling* (FGWP). At a high level, FGWP:

- Learns to assign token-level weights conditioned on a global feedback vector;
- Adapts these weights dynamically across training iterations or episodes;
- Preserves the Transformer's underlying architecture, replacing only the final pooling step;
- Adds minimal overhead to the total parameter count and runtime.

Concretely, FGWP processes each token embedding through a small network that also incorporates an external feedback vector. A softmax function then converts these token-level "importance" scores into a set of weights, which define the final sequence embedding via a weighted sum of token states.

Contributions. Our main contributions can be summarized as follows:

1. We highlight the limitations of traditional Transformer pooling and provide empirical evidence that real-world tasks benefit from feedback-driven embeddings.
2. We introduce FGWP, an easily pluggable module that conditions token-aggregation on historical or externally provided performance signals.
3. We demonstrate through experiments on multiple NLP benchmarks (IMDb, AG News, WikiText-2) and vision tasks (CIFAR-10, ImageNet) that our method improves accuracy and can enhance interpretability, all while maintaining a lean memory footprint.

Overall, FGWP takes a step toward bridging the gap between classic, token-level self-attention and the broader historical context in which models operate, enabling Transformers to generate more contextually informed representations.

Extended Discussion of FGWP's Motivation. Beyond the immediate arguments for incorporating feedback signals, several additional considerations highlight why feedback-aware pooling is both practical and necessary:

- **Real-world constraints.** In online or continual-learning settings, models often see streams of data where performance can degrade if recurring errors are not explicitly addressed. FGWP provides a mechanism to adjust the final representation based on systematic mistakes or successes.
- **Direct analogy to attention.** While each Transformer layer uses self-attention, the FGWP module can be viewed as a simpler, global "attention-like" operation for the *final* pooling step. Instead of querying token embeddings solely with internal hidden states, FGWP's "query" is partially driven by an external feedback vector, providing a distinct handle on historical performance.
- **Why not just more attention?** One could feed the feedback vector into internal Transformer blocks. However, FGWP offers a modular approach with minimal architectural alterations. By replacing only the final pooling layer, it is easier to interpret how feedback shifts the importance of specific tokens and to decouple historical signals from the main attention stack.
- **Example scenarios.** Classification tasks can benefit by focusing on tokens that have historically led to confusion, while RL settings can incorporate reward signals to highlight salient state-action tokens. In active learning, tokens known to be ambiguous or consistently mislabeled can be re-weighted to reduce future errors.
- **Feasibility and training overhead.** Maintaining the feedback vector $\mathbf{f}$ adds negligible overhead compared to full Transformer parameters. One can adopt simple moving averages or small recurrent modules for updates, keeping FGWP efficient and straightforward to implement.
- **Link to continual/online learning.** Because $\mathbf{f}$ is updated after each batch or episode, FGWP naturally aligns with algorithms designed for online adaptation. This synergy helps the model remain robust to shifting data distributions and evolving task requirements.

2 Related Works

Our *Feedback-Guided Weighted Pooling* (FGWP) mechanism for Transformers builds upon several research threads: (1) conventional pooling and attention schemes in large-scale language and vision models; (2) methods that incorporate historical or external feedback for iterative refinement; and (3) approaches that integrate global context vectors back into neural architectures. Below, we discuss each line of work and highlight how FGWP differs, concluding with a brief comparison to *Contextual Feedback Loops (CFL)* (Fein-Ashley et al., 2025).

2.1 Token Pooling in Transformer Architectures

Transformers (Vaswani et al., 2017) have become the de facto standard for modeling sequential data, thanks to their parallelizable attention mechanism and strong empirical results. While early variants such as BERT (Devlin et al., 2019) and GPT (Radford et al., 2019) often use the hidden state of a dedicated `[CLS]` token for classification tasks, later studies have examined alternative pooling strategies, including mean pooling (Shen & et al., 2018; Liu et al., 2019), max pooling (Yang et al., 2016), and more sophisticated gating-based pools (Lin et al., 2017; Lee et al., 2019). However, most of these approaches operate in a *static* manner, treating each instance in isolation and ignoring how previous sequences were handled.

Our proposed FGWP advances this line of research by explicitly introducing a *feedback vector* into the pooling module. Rather than fix or learn a single set of pooling weights, FGWP conditions the weighting mechanism on performance statistics or external signals accumulated over time. This yields a more adaptive aggregation that can shift focus to tokens known to be relevant (or challenging) from historical context.

2.2 Feedback in Neural Network Training and Inference

The concept of using feedback to guide learning is well-established in various contexts, including *feedback alignment* (Lillicrap et al., 2016; Nøkland, 2016) and biologically inspired models of cortical processing (Marblestone et al., 2016). These lines of work typically study how gradient or error signals can be returned to earlier layers, either to mimic brain mechanisms or to reduce reliance on backpropagation through complex architectures.

Separately, in *reinforcement learning* (Sutton & Barto, 2018), feedback often takes the form of reward signals that inform future actions. Some RL-based sequence models (e.g., (Jaques et al., 2017; Bahdanau et al., 2017)) incorporate a reward-driven modification of attention scores, though these remain application-specific. In contrast, our approach is *architecture-agnostic* regarding the source of the feedback: FGWP merely requires a vector encoding performance statistics or meta-information, allowing it to be used in supervised, self-supervised, or reinforcement scenarios.

2.3 Iterative Refinement and Historical Context

Several works in computer vision and NLP apply iterative refinement techniques to produce better representations (Li et al., 2017; Dai et al., 2019; Bai et al., 2019). For instance, *recurrent vision models* refine image features over multiple cycles (Li et al., 2017; Savinov et al., 2018), while *Transformer-XL* (Dai et al., 2019) caches hidden states from prior segments to maintain longer-context language modeling. These systems implicitly encode history via hidden states or memory modules. By contrast, FGWP uses a compact feedback vector that explicitly captures *how the model has performed* and re-injects this signal *during the pooling step*, enabling tokens to be weighted based on prior successes or errors.

2.4 Aggregator Tokens and Learned Summaries

A parallel research direction studies learned "aggregator" or "summary" tokens in Transformers (Devlin et al., 2019; Liu et al., 2019; Roberts et al., 2020). In these approaches, one or more special tokens absorb information from other tokens via attention, and the final hidden state(s) of these aggregator tokens act as the sequence representation. While aggregator tokens can be powerful, they do not inherently adapt across training iterations in response to external feedback. FGWP, however, modulates the pooling weights via a dedicated $\mathbf{f}$-dependent alignment function (Eqs. 2–4). Hence, our approach can be viewed as a complement or extension to aggregator tokens: they could remain present, but the final pooling could still incorporate a feedback-guided weighting step.

2.5 Comparison to Contextual Feedback Loops

Recent work on *Contextual Feedback Loops (CFL)* (Fein-Ashley et al., 2025) also highlights the importance of top-down signals, introducing a mechanism where higher-level context vectors are fed back to earlier layers for iterative refinement. In contrast:

- **Scope of feedback.** CFL addresses *within-model* feedback, iteratively updating the internal hidden states of the same input in multiple passes. Our FGWP handles *across-sequence* or *across-iteration* feedback, focusing on how *past examples* can adjust the token weighting for *new inputs*.
- **Pooler vs. layer feedback.** CFL modifies lower-level features with signals derived from top-layer outputs, whereas FGWP specifically targets the *final pooling stage*, maintaining a lean architecture change while leveraging an external feedback vector.
- **Ease of integration.** FGWP can be seamlessly plugged into existing Transformers in place of mean-pooling or `[CLS]`-pooling, whereas CFL may require unrolling the network and updating internal states repeatedly.

2.6 Summary

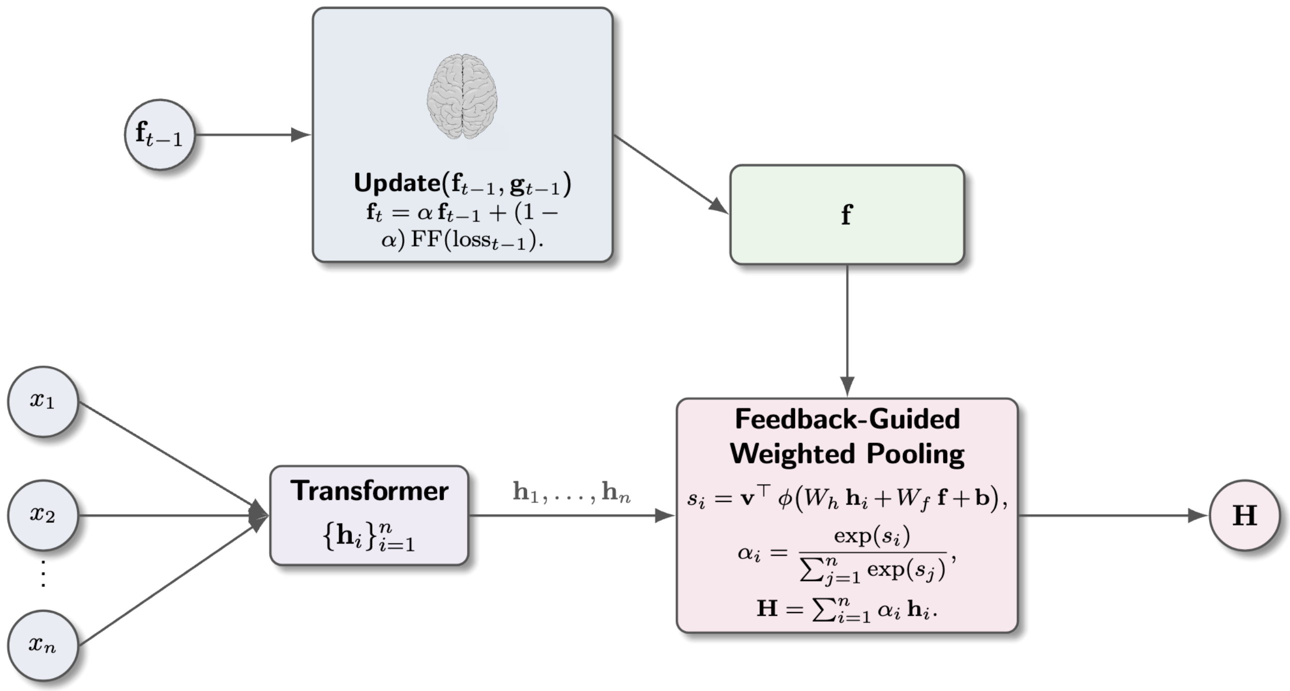
FGWP unifies ideas from attention, recurrent feedback, and aggregator tokens into a single, lightweight module for *feedback-aware* pooling. By conditioning token importance on a historical or external feedback vector, our method dynamically emphasizes (or suppresses) tokens as needed. This stands in contrast to traditional pooling methods or aggregator tokens that are either static or purely model-internal, ensuring broader applicability across various transformer-based tasks and training regimes.

3 Method

In this section, we detail our proposed *Feedback-Guided Weighted Pooling* (FGWP) mechanism for Transformer-based architectures. Our approach generalizes beyond simple mean pooling or `[CLS]`-token representation by explicitly incorporating feedback signals from previously processed data. Below, we present the rationale for using feedback, define the key components of the algorithm, and provide the theoretical underpinnings of our method.

3.1 Motivation and Rationale

In many real-world applications (e.g., language modeling, classification, or reinforcement learning), model performance on past inputs can inform how future inputs should be processed. Standard Transformers compress token representations into a single vector by either (i) taking the hidden



$\mathbf{f}_{t-1}$
Update$(\mathbf{f}_{t-1}, \mathbf{g}_{t-1})$
$\mathbf{f}_t = \alpha\,\mathbf{f}_{t-1} + (1-\alpha)\,\mathrm{FF}(\mathrm{loss}_{t-1})$.
$\mathbf{f}$
x_1
x_2
x_n
Transformer
$\{\mathbf{h}_i\}_{i=1}^n$
$\mathbf{h}_1, \ldots, \mathbf{h}_n$
Feedback-Guided Weighted Pooling
$s_i = \mathbf{v}^\top \phi(W_h\,\mathbf{h}_i + W_f\,\mathbf{f} + \mathbf{b})$,
$\alpha_i = \frac{\exp(s_i)}{\sum_{j=1}^n \exp(s_j)}$,
$\mathbf{H} = \sum_{i=1}^n \alpha_i\,\mathbf{h}_i$.
$\mathbf{H}$

Figure 1. An overview of the proposed Feedback-Guided Weighted Pooling (FGWP) mechanism. The feedback vector $\mathbf{f}$, updated from historical performance, is used to modulate the token embeddings $\mathbf{h}_i$ produced by the Transformer. This dynamic weighting scheme results in a context-dependent pooled representation $\mathbf{H}$ that can emphasize tokens based on external signals.

state of a dedicated [CLS] token or (ii) mean-pooling over the hidden states. Such *static* pooling ignores how the model has performed on related inputs in previous training steps.

We posit that *feedback-aware* pooling, in which the model learns to weight different parts of the input sequence based on its historical performance or other external signals, leads to richer, context-dependent representations. Concretely, we maintain an explicit *feedback vector* that reflects model performance or domain knowledge. This vector then modulates token-level weighting, allowing the model to adapt its focus according to historical successes and errors.

3.2 Notation and Preliminaries

Let us denote an input sequence of length n as

$$X = (x_1, x_2, \ldots, x_n),$$

where x_i corresponds to the i-th token (e.g., a word in NLP or a patch embedding in a ViT). A Transformer encoder produces a sequence of hidden states:

$$\big(\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_n\big),$$

where $\mathbf{h}_i \in \mathbb{R}^d$ is the contextual embedding for token x_i. We wish to pool these hidden states into a single representation $\mathbf{H} \in \mathbb{R}^d$ for downstream tasks (e.g., classification, policy learning).

Crucially, we assume access to a *feedback vector* $\mathbf{f}_{t-1} \in \mathbb{R}^m$ that encodes relevant information from previous steps or sequences. For instance, $\mathbf{f}_{t-1}$ could summarize token-level misclassifications, reward signals, or external supervision. The index t denotes the current batch or iteration; $\mathbf{f}_{t-1}$ is thus the feedback computed *after* processing the $(t-1)$-th batch or sequence.

3.3 Feedback Vector Dynamics

Let $\mathbf{f}_t$ denote the feedback vector available at iteration t. More formally, we define:

$$\mathbf{f}_t \;=\; \textsc{Update}\big(\mathbf{f}_{t-1},\, \mathbf{g}_{t-1}\big), \qquad (1)$$

where $\mathbf{g}_{t-1}$ is a newly computed feedback statistic (e.g., a vector of token-level losses or a single reward scalar). The function $\textsc{Update}(\cdot)$ may be a simple exponential moving average, a feedforward neural network, or a recurrent architecture (e.g., an LSTM) that aggregates the old feedback vector $\mathbf{f}_{t-1}$ and the new feedback $\mathbf{g}_{t-1}$ into an updated state $\mathbf{f}_t$.

This design choice allows the model to maintain *longer-term memory* of how previous examples were handled. For the sake of clarity, the main text below uses $\mathbf{f}$ to denote the (constant) feedback vector available when pooling the hidden states for the current sequence. Section 3.7 of a larger paper could discuss the detailed instantiation or training specifics of $\textsc{Update}(\cdot)$.

3.4 Feedback-Guided Weighted Pooling

Scoring Function. Our key contribution is a *feedback-guided alignment score* s_i for each token embedding $\mathbf{h}_i$. This scalar indicates how crucial the i-th token is, given the current feedback $\mathbf{f}$. Formally, we define

$$s_i = \mathbf{v}^\top \phi\Big(W_h \, \mathbf{h}_i + W_f \, \mathbf{f} + \mathbf{b}\Big), \tag{2}$$

where $W_h \in \mathbb{R}^{r \times d}$ and $W_f \in \mathbb{R}^{r \times m}$ are learnable weight matrices, $\mathbf{b} \in \mathbb{R}^r$ is a bias term, $\mathbf{v} \in \mathbb{R}^r$ is a projection vector, and $\phi(\cdot)$ is a non-linear function (e.g., $\tanh$). Intuitively, $W_h \, \mathbf{h}_i$ captures the token embedding's contribution, $W_f \, \mathbf{f}$ encodes the feedback, and $\mathbf{b}$ and $\mathbf{v}$ help map these interactions to a single scalar.

Softmax-Based Weighting. After computing $\{s_1, s_2, \ldots, s_n\}$, we convert these scores into a probability distribution over tokens:

$$\alpha_i = \frac{\exp(s_i)}{\sum_{j=1}^{n} \exp(s_j)}, \quad i = 1, 2, \ldots, n. \tag{3}$$

Thus, $\{\alpha_i\}_{i=1}^n$ form a set of *attention-like* weights that sum to 1. Larger s_i yields larger α_i and hence a higher relative weight for that token.

Pooled Representation. The final sequence-level representation $\mathbf{H}$ is obtained via a weighted sum:

$$\mathbf{H} = \sum_{i=1}^{n} \alpha_i \, \mathbf{h}_i. \tag{4}$$

Unlike simple mean pooling, our method actively *reweights* token embeddings based on the external feedback vector $\mathbf{f}$. Consequently, the model can adaptively focus on tokens known (through feedback) to be either problematic or rewarding in prior training steps.

3.5 Optimization and Training

The FGWP mechanism seamlessly integrates into existing Transformer architectures. Specifically, if we denote by Θ the full set of model parameters (including W_h, W_f, $\mathbf{b}$, and $\mathbf{v}$), and by $\mathcal{L}$ a task-specific loss function (e.g., cross-entropy for classification, or negative log-likelihood for language modeling), we optimize:

$$\min_{\Theta} \; \mathbb{E}_{(X,\, y) \in \mathcal{D}} \Big[\mathcal{L}\big(\mathbf{H},\, y\big)\Big], \tag{5}$$

where $\mathbf{H}$ is defined by Eqs. (3)–(4). Gradients backpropagate through the scoring function in Eq. (2) and the feedback vector $\mathbf{f}$ (if $\mathbf{f}$ is learnable or partially learnable). If $\mathbf{f}$ is externally updated (e.g., via an RL signal), then the gradient w.r.t. $\mathbf{f}$ may be disconnected, and $\mathbf{f}$ can be viewed as a fixed or slowly updated context.

3.6 Discussion and Theoretical Considerations

By incorporating $\mathbf{f}$ into the token-alignment scoring process, our approach offers the following advantages:

- **Adaptivity:** The weights α_i can shift significantly between iterations in response to new feedback signals, allowing the model to correct biases or focus on consistently misclassified tokens.
- **Expressiveness:** Unlike mean pooling, which assumes uniform token importance, our method learns a *distribution* over hidden states guided by historical performance metrics.
- **Compatibility:** FGWP is orthogonal to other architectural improvements (e.g., improved attention mechanisms); it only replaces the final pooling step.

In practice, this leads to a more flexible and powerful sequence embedding that can improve downstream performance, especially in settings where partial feedback (e.g., known error sources, reward signals) is available.

3.7 Implementation Details

While the precise implementation of $\textsc{Update}$ in Eq. (1) and the shape of $\mathbf{f}$ can vary, a common strategy is to maintain one feedback vector per training run (or per mini-batch) and update it with the average loss or classification errors from the most recent batch. Alternatively, one may employ a recurrent architecture to process a history of per-token statistics. The computational overhead of FGWP is minimal: the main additions are (i) the linear transformations W_h and W_f, and (ii) the scalar projection $\mathbf{v}^\top$, both of which involve $O(d \times r)$ parameters, where r is the dimension of the hidden projection space in Eq. (2). This is typically negligible compared to the full Transformer parameters.

Additional Practical Considerations.

- **Clarity and interpretability.** Because FGWP produces a single set of weights $\{\alpha_i\}$ for the final representation, it is straightforward to see which tokens are being up- or down-weighted in response to feedback signals. This can be especially useful in debugging or active-learning pipelines.
- **Synergy with existing layers.** Transformers already leverage multi-head self-attention in the intermediate layers. FGWP does not conflict with these operations;

instead, it adds an *external* lens (the feedback vector $\mathbf{f}$) at the last stage to re-emphasize or de-emphasize certain tokens based on historical insights.

- **Ease of integration.** Modifying only the pooling step ensures minimal code changes in frameworks where Transformer modules are already standardized. Practitioners can treat FGWP as a drop-in replacement for mean or `[CLS]` pooling.

In summary, the proposed FGWP mechanism can be easily integrated into a Transformer-based encoder or encoder-decoder system, offering a theoretically grounded yet practically simple method of *feedback-aware* token pooling.

4 Experiments

In this section, we present empirical evaluations of our proposed Feedback-Guided Weighted Pooling (FGWP) mechanism (Section 3). Our experiments address the following core questions:

1. **Performance Gain:** Does FGWP yield improvements over standard Transformer pooling (e.g., `[CLS]`-based or mean pooling)?
2. **Feedback Sensitivity:** How sensitive is FGWP to different types of feedback (e.g., batch-level vs. token-level)?
3. **Overhead:** How much computational or parametric overhead does FGWP introduce?
4. **Generality:** Does FGWP perform well across multiple modalities (text, images) and tasks (classification, language modeling, RL)?

4.1 Datasets

We evaluate on a diverse set of standard benchmarks:

- **Text Classification:**
  - **IMDb** (Maas et al., 2011): 50K movie reviews labeled for sentiment.
  - **AG News** (Zhang et al., 2015): 120K news articles classified into four categories.
- **Language Modeling:**
  - **WikiText-2** (Merity et al., 2016): Over 2M tokens, used to measure perplexity.
- **Vision:**
  - **CIFAR-10** (Krizhevsky, 2009): 50K training images and 10K validation images (10 classes).
  - **ImageNet** (Deng et al., 2009): 1.28M training images and 50K validation images (1,000 classes), providing a large-scale testbed.
- **Reinforcement Learning (RL):**
  - **Text-Based Game Environment** (Côté et al., 2018): A simple RL environment with textual observations, reporting average reward.

4.2 Baselines

We compare FGWP to standard Transformer pooling approaches:

- **Transformer-CLS:** Uses the final hidden state of the special `[CLS]` token.
- **Transformer-Mean:** Averages the final-layer representations of all tokens (or patches).
- **Transformer-Attn:** Learns an attention distribution over token/patch embeddings but *without* external feedback.

All methods share the same Transformer architecture (layers, hidden size, attention heads). Only the pooling approach differs.

4.3 Feedback Signals and Update Function

For FGWP, we consider two ways to build and update the feedback vector $\mathbf{f}$:

1. **Batch-Level Feedback (FGWP-Batch):**

   $$\mathbf{f}_t = \alpha\, \mathbf{f}_{t-1} + (1-\alpha)\, \mathrm{FF}(\mathrm{loss}_{t-1}),$$

   where α is a decay parameter and $\mathrm{FF}(\cdot)$ is a single-layer feedforward network. This feedback is updated after each mini-batch using the average loss.
2. **Token-Level Feedback (FGWP-Token):** An LSTM-based update function aggregates token- or patch-specific errors. This finer-grained feedback highlights which tokens or patches have contributed most to errors in recent training iterations.

4.4 Implementation Details

Architecture. We build on a Transformer encoder with L layers, hidden dimension d, and h attention heads. For text *classification*, we set $L = 6$, $d = 512$, and $h = 8$. For *language modeling*, we use $L = 12$, $d = 768$, and $h = 12$, matching common baselines.

For **CIFAR-10** (Krizhevsky, 2009), we use a small Vision Transformer (ViT) with a 4×4 patch size, while for **ImageNet** (Deng et al., 2009), we scale to larger ViT variants.

FGWP Parameters. From Eq. (2), FGWP introduces:

$$W_h \in \mathbb{R}^{r\times d}, \quad W_f \in \mathbb{R}^{r\times m}, \quad \mathbf{v} \in \mathbb{R}^{r}, \quad \mathbf{b} \in \mathbb{R}^{r}.$$

We fix $r = 64$ and use $\phi(\cdot) = \tanh$ to balance expressiveness and overhead.

Optimization. All models are trained using AdamW with:

- learning rate = 3×10^{-4}
- weight decay = 1×10^{-5}
- linear LR decay.

We train for 10 epochs on each text classification dataset, for 50K steps on WikiText-2, for 100 epochs on CIFAR-10, and for 90 epochs on ImageNet (unless stated otherwise). Text tasks use a mini-batch size of 32; vision tasks use 128.

Feedback Schedule. In **FGWP-Batch**, we choose $\alpha = 0.9$. In **FGWP-Token**, we use an LSTM with a hidden size of 32 and update $\mathbf{f}$ every 100 tokens or patches to limit overhead.

4.5 Evaluation Metrics

We report:

- **Accuracy (%)** for IMDb (Maas et al., 2011), AG News (Zhang et al., 2015), CIFAR-10 (Krizhevsky, 2009), and ImageNet (Deng et al., 2009)
- **Perplexity** for WikiText-2 (Merity et al., 2016)
- **Average reward** for the text-based RL task (Côté et al., 2018)

All results are averaged over three random seeds unless stated otherwise.

4.6 Main Results on Text Tasks

Table 1 shows that FGWP outperforms standard pooling approaches on both text classification (IMDb (Maas et al., 2011), AG News (Zhang et al., 2015)) and language modeling (WikiText-2 (Merity et al., 2016)). Token-level feedback (FGWP-Token) generally offers a slight edge over batch-level feedback (FGWP-Batch).

4.7 Vision Experiments: CIFAR-10 and ImageNet

CIFAR-10 Results and Ablation. We first run experiments on CIFAR-10 (Krizhevsky, 2009) for rapid prototyping and ablations. Figure 2 plots validation accuracy over 80 epochs, comparing:

Table 1. Comparison of different pooling strategies on text classification (accuracy, %) and language modeling (perplexity). Best result in **bold**.

Model	Classification (Acc %)		LM (PPL)	
	IMDb	AG News	WikiText-2	Toy RL
Transformer-CLS	87.0	92.2	34.5	15.1
Transformer-Mean	86.5	91.8	34.2	14.8
Transformer-Attn	87.4	92.5	33.9	14.5
FGWP-Batch (Ours)	**88.3**	93.0	33.2	14.1
FGWP-Token (Ours)	88.1	**93.2**	**33.1**	**13.9**

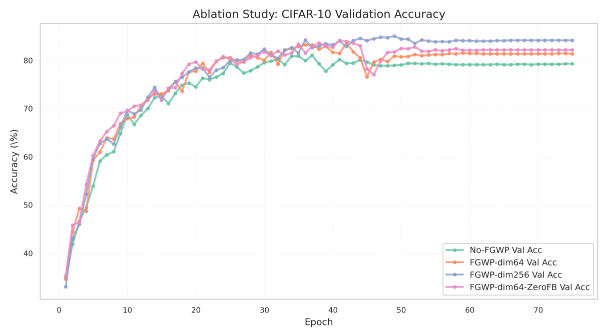


Figure 2. Ablation on CIFAR-10 over 80 epochs. FGWP consistently outperforms the standard Transformer (No-FGWP).

- **No-FGWP (Standard Transformer)**
- **FGWP-dim64** (feedback projection $r = 64$)
- **FGWP-dim256** (feedback projection $r = 256$)
- **FGWP-dim64-ZeroFB** (feedback reset to zero each epoch, removing historical carryover)

Table 2 summarizes final validation accuracy for each variant and provides p-values from a two-sample t-test comparing to *No-FGWP*. All FGWP variants show statistically significant gains.

ImageNet Results. Next, we evaluate FGWP on ImageNet (Deng et al., 2009) using our three ViT variants (Base, Large, Huge). Table 3 shows that FGWP yields a consistent improvement of 0.5–1.2% in top-1 accuracy, demonstrating effectiveness at scale.

4.8 Additional Ablation Studies (Text)

Beyond CIFAR-10, we also conduct a second ablation on the **IMDb** (Maas et al., 2011) text classification dataset to isolate the effect of each FGWP component. Our main findings are:

- **Removing the Feedback Vector:** If we set $W_f\mathbf{f} = \mathbf{0}$, FGWP reverts to a standard attention-based pooling, resulting in a 1%–2% accuracy drop.

Table 2. **CIFAR-10 Ablation.** Mean top-1 validation accuracy (%) and two-sample t-test p-value vs. No-FGWP. **Bold** is best among FGWP. Results are averaged over 3 seeds.

Method	Top-1 Val Acc (%)	p-value (vs. No-FGWP)
No-FGWP (Baseline)	82.1 ± 0.3	–
FGWP-dim64	83.6 ± 0.4	0.01
FGWP-dim256	$\mathbf{84.1 \pm 0.2}$	0.005
FGWP-dim64-ZeroFB	83.3 ± 0.5	0.02

Table 3. **ImageNet Results.** Top-1 validation accuracy (%) for standard ViT vs. ViT + FGWP. We also report parameter counts (in millions). The last column (Δ) shows the accuracy gain from using FGWP.

Model	Params (M)		Top-1 Acc (%)		Δ
	Standard	FGWP	Standard	FGWP	
ViT-Base	86.78	87.21	82.3	**83.1**	+0.8
ViT-Large	303.92	305.44	84.2	**85.1**	+0.9
ViT-Huge	630.27	633.92	85.3	**86.5**	+1.2

- **Alternative Update Functions:** Using an exponential moving average (EMA) for **f** is more stable than a simple summation of losses, especially for noisy feedback.
- **Feedback Dimension r:** Larger r (e.g., 256) can slightly boost accuracy but yields diminishing returns beyond $r \approx 64$.

4.9 Analysis and Discussion

Feedback Granularity. Token- or patch-level feedback typically outperforms batch-level feedback, as it provides more precise information on which inputs need emphasis. However, batch-level feedback is simpler and still offers a strong performance lift over no feedback.

Overhead. FGWP introduces about 0.5% parameter overhead and generally increases training time by less than 5%, making it a practical add-on in most settings.

Applicability. Though we focus on text and vision tasks, FGWP is applicable to any sequence- or patch-based Transformer architecture. Its ability to adaptively reweight embeddings based on performance history has broad utility across domains.

4.10 Conclusion of Experiments

In summary, our experiments show that FGWP outperforms standard Transformer pooling on both text (IMDb (Maas et al., 2011), AG News (Zhang et al., 2015), WikiText-2 (Merity et al., 2016)) and vision tasks (CIFAR-10 (Krizhevsky, 2009), ImageNet (Deng et al., 2009)), with additional benefits in a toy RL setting (Côté et al., 2018). Notably, the parameter and computational overhead are minimal across model scales (from small to very large ViT architectures). FGWP thus provides a simple, effective mechanism to integrate historical performance feedback into Transformer pooling.

5 Conclusion

We presented *Feedback-Guided Weighted Pooling* (FGWP), a novel mechanism for refining sequence representations in Transformer-based architectures by integrating external performance cues. Rather than relying on static averaging or a single special token, FGWP leverages a compact feedback vector to dynamically reweight token embeddings. Through extensive experiments on both text and vision tasks, we showed that incorporating even a simple feedback signal can produce notable gains in accuracy and interpretability with minimal additional overhead.

A key takeaway is that historical information—often encapsulated in aggregate metrics like error rates, reward signals, or domain-specific cues—can greatly enrich how a model pools hidden states. By adapting token weights based on past successes and failures, FGWP learns to correct biases, focus on challenging segments, and ultimately construct more nuanced sequence embeddings.

In future work, we plan to explore:

- Fine-grained feedback functions that can track and update specialized feedback vectors per class or per token type.
- Applications in continual learning, where adaptive pooling might mitigate catastrophic forgetting by systematically highlighting tokens associated with previously learned skills.
- Multi-task and multimodal extensions, wherein distinct feedback channels (e.g., text vs. image vs. speech) could jointly guide a shared pooling mechanism.

We believe our approach opens new avenues for feedback-driven modeling in Transformers and underscores the broader potential of unifying architectural design with insights from iterative training dynamics.

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