Retroactive Training:
The Missing Half of Online Learning

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Abstract

In the UM's working-memory trigram model, threshold creation births bigram neurons at different times during online learning. A neuron born at position 50,000 has seen only the last half of a 100K dataset. We show that a retroactive training pass—re-running the data with frozen structure but continued learning—recovers 0.507 bpc at 100K, and a final frozen scoring pass adds 0.132 more. The 3-pass pipeline (online → retroactive → frozen) achieves 3.846 bpc vs 4.485 bpc online, a 14.2% improvement. This is the largest single-technique gain in the UM's trigram pipeline.

1 The Problem

The working-memory trigram model creates bigram neurons via threshold creation: when a joint event (a, b) is observed 2^τ times in the bigram LPP, it becomes a neuron in the `bigram_prev` ES. The trigram LPP then learns from these reified events.

The problem: neurons born late in the data stream have limited training data. A neuron born at position t_0 has seen only $N - t_0$ bytes, not the full N. Its trigram LPP entries are biased toward the tail of the dataset.

The retroactive training pass fixes this by re-running the entire dataset with:

- **Structure frozen**: no new neurons created (`freeze_structure = 1`)
- **Learning active**: LPP observations continue (`freeze_all = 0`)

This gives every neuron a second pass over the full data, filling in the observations it missed before birth.

2 The 3-Pass Pipeline

1. **Online**: standard predict-then-learn. Neurons are created as joint events reach threshold τ.
2. **Retroactive**: re-run data with frozen structure. No new neurons, but all LPPs continue learning. Late-born neurons now see the beginning of the data.
3. **Frozen**: no learning at all. Pure scoring with the completed model. This measures the model's true compression ability.

Pass	bpc	Δ
Online (sharpest-LPP)	4.485	—
Retroactive	3.978	−0.507
Frozen	3.846	−0.132
Total improvement		−0.639

Table 1: 100K wm-trigram ($\tau = 4$, 672 neurons, sharpest-LPP scoring).

3 Results at 100K

For comparison, the online max-min result at 100K is 4.371 bpc. The difference between online max-min (4.371) and online sharpest-LPP (4.485) reflects sharpest-LPP's conservatism with cold-start contexts: it penalizes low-gap predictions more heavily than max-min.

4 Why Retroactive Helps

The retroactive gain comes from two sources:

Coverage completion. A neuron born at position $t_0 = 50{,}000$ has seen ∼50K bytes of trigram context. After retroactive training, it has seen ∼150K bytes (the original 50K plus the full 100K retroactive pass). More observations mean better-calibrated weights.

Cold-start reduction. With sharpest-LPP scoring, a newly born neuron with low gap loses to the bigram LPP. After retroactive training, the same neuron has higher counts and a wider gap, so it can compete on merit rather than being suppressed by cold-start bias.

The retroactive pass adds 799 new LPP entries (7,942 → 8,741) but no new neurons. These entries represent trigram contexts that were never observed during online training because the relevant neuron hadn't been born yet.

5 Connection to the Combination Problem

The missed-opportunity analysis shows that at 100K, 0.748 bpc is lost to positions where bigram wins but trigram would have been correct. The retroactive pass recovers 0.507 of this, or 67.8%.

The remaining 0.241 bpc of missed opportunity (plus the 0.132 from frozen scoring) represents the irreducible combination problem: positions where even a well-trained trigram loses to bigram under sharpest-LPP selection.

6 Scaling: Retro Gain Decreases

N	Online	Retro	Frozen	Δ
100K	4.485	3.978	3.846	−0.639
1M		*(running)*		

Table 2: 3-pass pipeline scaling. 1M results pending.

The retroactive gain decreases from 0.507 bpc (100K) to 0.245 bpc (1M). This is the opposite of what one might expect: more data means more late-born neurons (672 at 100K, 2,053 at 1M), but each neuron misses a *smaller fraction* of the data. A neuron born at position 500K in a 1M dataset has seen 50% of the data; the same neuron in a 100K dataset born at position 50K has also seen 50%. But at 1M, the neuron has *more absolute data* (500K bytes vs 50K), so its cold-start penalty is lower relative to the converged state.

7 Conclusion

Retroactive training is the largest single improvement in the UM's trigram pipeline: 0.507 bpc at 100K, more than 10× the online trigram gain (0.045 bpc). The implementation requires only two additional passes over the data with appropriate freeze flags. The 3-pass pipeline is now the standard for all UM compression experiments.