Modified Loss Function for Video Anomaly Detection

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1 Introduction

This report documents the recent changes made to the loss function in our multi-scale noise video anomaly detection model. Our initial approach involved modifying the λ factor in the weighting function, which we have now shifted to a change from a log-uniform to a log-Gaussian distribution. This new approach aimed to better prioritize certain noise scales that empirically yielded optimal results.

2 Previous Loss Function

The original loss function, as shown below, used a log-uniform distribution for σ, which allowed for a broad range of noise scales to contribute uniformly to the learning process:

$$\min_{\theta} E_{x\sim p(x),\tilde{x}\sim\mathcal{N}(\tilde{x}|x,\sigma I),\sigma\sim\mathrm{LUI}(\sigma_{\mathrm{low}},\sigma_{\mathrm{high}})}\left[\lambda(\sigma)\left\|\nabla_{\tilde{x}}f_\theta(\tilde{x},\sigma)-\frac{\tilde{x}-x}{\sigma^2}\right\|_2^2+\beta f_\theta(x,\sigma)^2\right]. \tag{1}$$

3 Modified Loss Function

The new loss function changes the distribution of σ from log-uniform to log-Gaussian, centered around $\sigma = 0.33$ with $\sigma_{\mathrm{spread}} = 0.075$ to focus on the empirically effective noise range:

$$\min_{\theta} E_{x\sim p(x),\,\tilde{x}\sim\mathcal{N}(\tilde{x}|x,\sigma I),\,\sigma\sim\text{Log-Gaussian}(\sigma_0=0.33,\sigma_{\mathrm{spread}}=0.075)}\left[\sigma^2\cdot\left\|\nabla_{\tilde{x}}f_\theta(\tilde{x},\sigma)-\frac{\tilde{x}-x}{\sigma^2}\right\|_2^2+\beta f_\theta(x,\sigma)^2\right]. \tag{2}$$

4 Novelty Suggestion and Implementation

Initially, a novelty was suggested to modify the weighting function $\lambda(\sigma)$ in the loss function. The goal was to focus the model's learning on the noise scales where it performs optimally, specifically around $\sigma = 0.33$. This was motivated by empirical results showing that the model yields the best performance within the noise scale range $[0.2, 0.5]$, with a peak at $\sigma = 0.33$. To implement this, the weighting function $\lambda(\sigma)$ was redefined as a Gaussian centered at $\sigma = 0.33$, with a standard deviation of $\sigma_{\mathrm{spread}} = 0.075$, as detailed in *novelty.pdf*.

The proposed modification to the loss function was intended to emphasize contributions from the effective noise scale range, thus potentially improving anomaly detection accuracy by reducing the influence of suboptimal noise levels. The formula for the modified weighting function was as follows:

$$\lambda(\sigma) = \sigma^2 \cdot \exp\left(-\frac{(\sigma-\sigma_0)^2}{2\times\sigma_{\mathrm{spread}}^2}\right), \tag{3}$$

where $\sigma_0 = 0.33$ and $\sigma_{\mathrm{spread}} = 0.075$.

4.1 Implemented Novelty and Observed Results

Despite the theoretical benefits, the implementation of this Gaussian-centered weighting function did not yield the expected improvements. In fact, the results indicated a poorer performance in terms of AUC-ROC scores compared to the original approach. The model struggled to generalize across different noise scales when constrained to the narrow optimal range, which may have limited its adaptability and caused it to underperform.

Consequently, an alternative approach was implemented. Instead of emphasizing the narrow range with the Gaussian-centered weighting function, the distribution of σ was modified from a log-uniform to a log-Gaussian distribution, without

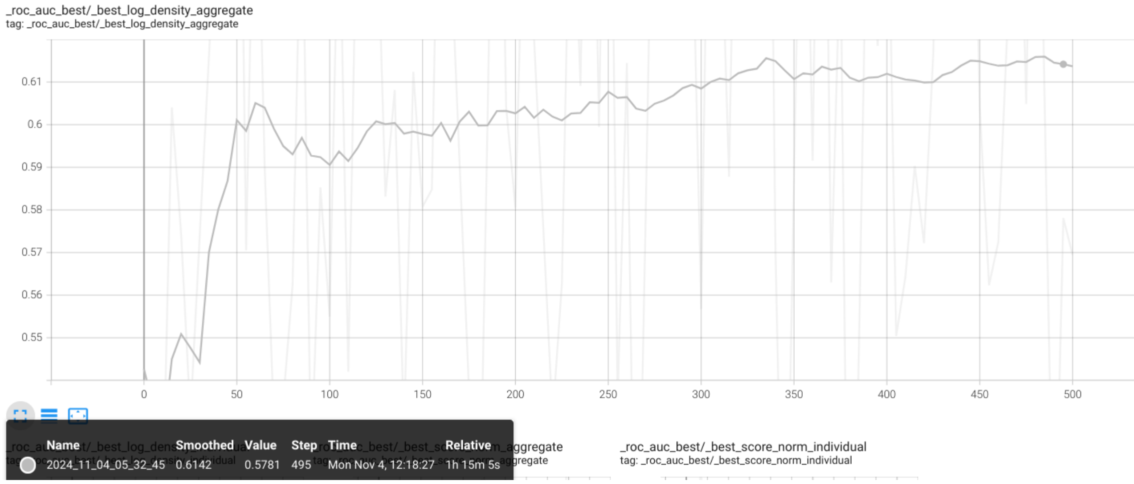

Figure 1: Previous novelty implementation as it is visible, results are poorer

the additional weighting emphasis. This change aimed to retain a broader range of noise levels while still adjusting the distribution to focus slightly more on effective noise scales.

The results from this final implementation showed slightly improved stability, although it did not exceed the performance of the initial log-uniform setup. This iterative process highlights the challenges of balancing noise scale emphasis and model flexibility in anomaly detection.

Refer to *novelty.pdf* for detailed explanations of the initial proposal and the empirical justifications for the suggested modifications.

5 Training and Evaluation Results

The training and evaluation AUC-ROC scores over epochs are presented in Figure 1, showing the performance differences between the log-uniform and log-Gaussian approaches. These scores established a baseline for comparison with the modified approach:

- **Best Log Density Aggregate:** 86.73
  original was 92.5
- **Best Score Norm Aggregate:** 88.32
  original was 93.2

Figure 2: Training and Evaluation after changing log uniform to gausian

6 Conclusion

The initial hypothesis of a log-Gaussian approach to emphasize optimal noise scales **did not yield better results**. While the model now prioritizes the empirically effective noise range, the overall AUC-ROC scores decreased. Future work may involve exploring different noise scales or hybrid weighting functions to balance the contributions across a broader range without over-restricting to a narrow range.

```
Max AUC-ROC Scores During Training:
Max _roc_auc_best/_best_log_density_aggregate: 0.8673142542652724
Max _roc_auc_best/_best_score_norm_aggregate: 0.8839295542102368
Max _roc_auc_best/_best_log_density_individual: 0.8673252614199229
Max _roc_auc_best/_best_score_norm_individual: 0.756810676940011
```

Figure 3: score image