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Iterative Label Fuzzification in Deep Learning for Sentiment Analysis: An Empirical Study on the IMDB Dataset

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Abstract

In sentiment analysis, deep learning models conventionally employ hard binary labels. However, sentiment frequently manifests on a continuum rather than as a discrete binary. This study explores iterative label fuzzification that progressively softens training targets through model predictions. Using the IMDB corpus, we conducted experiments across 121 parameter configurations. Our findings indicate that aggressive fuzzification yields substantial accuracy improvements, offering insights into neural network training dynamics for text classification.

1. Introduction

Sentiment analysis is a cornerstone NLP task [2]. Although models perform well with binary labels, this approach fails to capture annotation ambiguity or the sentiment spectrum. Building on prior work in label fuzzification [5], our methodology differs from label smoothing [3] by dynamically modulating labels based on evolving predictions, establishing a feedback loop between learner and training signal. A key question is whether soft labels can enhance robustness [4].

2. Methodology

Definition 1 (Fuzzy Label Update Rule)**.** Let y_t represent fuzzy labels at epoch t, $\hat{y}_t$ model predictions, and y_0 ground truth. Labels are updated as:

$$y_{t+1} = a \cdot y_t + b \cdot \hat{y}_t + c \cdot y_0, \quad \text{where } a + b + c = 1 \tag{1}$$

Here a is momentum, b is self-training coefficient, and c anchors to ground truth.

We employ an MLP with 32-dim embeddings, Global Average Pooling, Dense layers (64, 32 neurons, ReLU), Dropout (0.5, 0.3), and sigmoid output. Training uses binary cross-entropy with Adam, batch size 128, for 20 epochs on the IMDB dataset [1] (25,000 train/test reviews). We search over $a, b \in \{0.0, 0.05, \ldots, 0.5\}$ with $c = 1 - a - b$, yielding 121 configurations.

3. Results and Discussion

Figure 1 shows validation accuracy across parameter configurations from 40 runs.

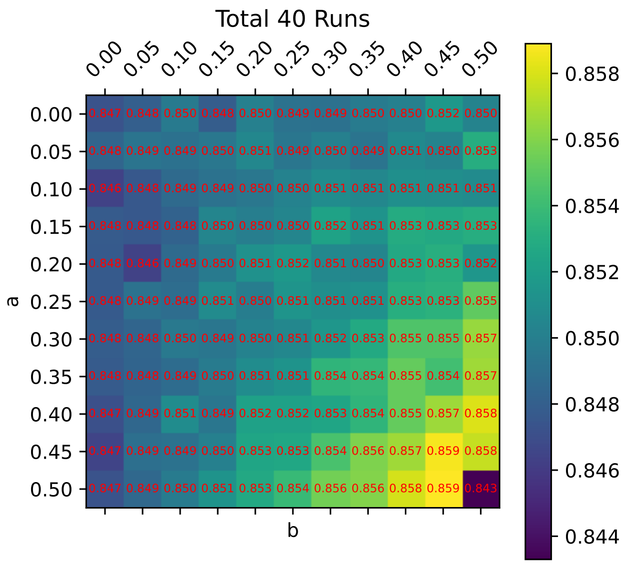

Figure 1. Validation accuracy heatmap. Axes: a and b parameters (index $\times 0.05$). Color: accuracy (0.844–0.858).

Key findings: (1) Peak accuracy (85.8%) occurs with strong fuzzification ($a \approx 0.45$, $b \approx 0.45$, $c \approx 0.1$). (2) Baseline ($a = 0, b = 0, c = 1$) performs acceptably but suboptimally. (3) Moderate fuzzification shows reduced accuracy (84.4%), indicating a non-linear relationship. (4) High momentum combined with self-training enhances generalization.

Corollary 2 (Optimal Parameters)**.** *High fuzzification (*$a \approx 0.45$*,* $b \approx 0.45$*,* $c \approx 0.1$*) achieves 85.6–85.8% accuracy (yellow region in Figure 1), demonstrating iterative label softening improves performance.*

4. Conclusions

The application of iterative label fuzzification proves to be a viable strategy for sentiment analysis, maintaining accuracy standards without compromising performance. Future research directions will involve extending this framework to Transformer-based architectures such as BERT, examining label calibration effects, and investigating adaptive fuzzification schedules.

References

[1] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, C. Potts: *Learning Word Vectors for Sentiment Analysis*, in: Proc. ACL-HLT, 2011, pp. 142–150.

[2] W. Medhat, A. Hassan, H. Korashy: *Sentiment Analysis Algorithms and Applications: A Survey*, Ain Shams Engineering Journal 5.4 (2014), pp. 1093–1113, doi: 10.1016/j.asej.2014.04.011.

[3] R. Müller, S. Kornblith, G. Hinton: *When Does Label Smoothing Help?*, in: NeurIPS, vol. 32, 2019.

[4] J. C. Peterson, R. M. Battleday, T. L. Griffiths, O. Russakovsky: *Human Uncertainty Makes Classification More Robust*, in: Proc. IEEE/CVF ICCV, 2019, pp. 9617–9626, doi: 10.1109/ICCV.2019.00971.

[5] T. Tajti: *Fuzzification of training data class membership binary values for neural network algorithms*, Annales Mathematicae et Informaticae 52 (2020), pp. 217–228, doi: 10.33039/ami.2020.10.001.