

¹ LabelFusion: Learning to Fuse LLMs and Transformer Classifiers for Robust Text Classification

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⁹ Summary

¹⁰ LabelFusion is a novel fusion ensemble for text classification that learns to combine a traditional
¹¹ transformer-based classifier (e.g., RoBERTa) with one or more Large Language Models (LLMs)
¹² such as OpenAI GPT, Google Gemini, or DeepSeek to deliver accurate and cost-aware predictions
¹³ across multi-class and multi-label tasks. The package provides a simple high-level interface
¹⁴ (AutoFusionClassifier) that trains the full pipeline end-to-end with minimal configuration,
¹⁵ and a flexible API for advanced users. Under the hood, LabelFusion integrates vector signals
¹⁶ from both sources by concatenating the ML backbone's embeddings with the LLM-derived
¹⁷ per-class scores—obtained through structured prompt-engineering strategies—and feeds this
¹⁸ joint representation into a compact multi-layer perceptron (FusionMLP) that produces the
¹⁹ final prediction. This learned fusion approach captures complementary strengths of LLM
²⁰ reasoning and traditional transformer-based classifiers, yielding robust performance across
²¹ domains—achieving 92.4% accuracy on AG News and 92.3% on 10-class Reuters 21578 topic
²² classification — while enabling practical trade-offs between accuracy, latency, and cost.

Statement of Need

²⁴ Modern text classification spans diverse scenarios, from sentiment analysis ([Kant et al., 2024](#);
²⁵ [Luber et al., 2021](#); [Thormann et al., 2021](#)) to complex topic tagging ([Kant et al., 2022](#); [A.
26](#) Thielmann, Weisser, Krenz, & Säfken, 2021; [A. Thielmann, Weisser, & Krenz, 2021](#); [A. F.
27](#) Thielmann et al., 2024), often under constraints that vary per deployment (throughput, cost
ceilings, data privacy). While transformer classifiers such as BERT/RoBERTa achieve strong
supervised performance ([Devlin et al., 2018](#); [Liu et al., 2019](#)), frontier LLMs can excel in
low-data, ambiguous, or cross-domain settings ([OpenAI, 2023](#)). No single model family is
typically uniformly best: LLMs are powerful, but comparatively costly, whereas fine-tuned
transformers are efficient but may struggle with out-of-distribution cases or extremely limited
training examples.

³⁴ LabelFusion addresses this gap by: (1) exposing a minimal “AutoFusion” interface that trains a
³⁵ learned combination of an ML backbone and one or more LLMs; (2) supporting both multi-class
³⁶ and multi-label classification; (3) providing a lightweight fusion learner that directly fits on
³⁷ LLM scores and ML embeddings; and (4) integrating cleanly with existing ensemble utilities.
³⁸ Researchers and practitioners can therefore leverage LLMs where they add value while retaining
³⁹ the speed and determinism of transformer models.

40 **State of the Field**

41 In applied NLP, common tools such as scikit-learn ([Pedregosa et al., 2011](#)) and Hugging Face
42 Transformers ([Wolf et al., 2019](#)) offer strong baselines but do not provide a learned fusion of
43 LLMs with supervised transformers. Orchestration frameworks (e.g., LangChain) focus on tool
44 use rather than classification ensembles. LabelFusion contributes a focused, production-minded
45 implementation of a small learned combiner that operates on per-class signals from both model
46 families.

47 **Functionality and Design**

48 LabelFusion consists of three layers:

- 49 ▪ ML component: a RoBERTa-style classifier produces per-class logits for input texts.
- 50 ▪ LLM component(s): provider-specific classifiers (OpenAI, Gemini, DeepSeek) return
51 per-class scores. Scores can be cached to minimize API calls when cache locations are
52 provided.
- 53 ▪ Fusion component: a compact MLP concatenates information rich ML embeddings and
54 LLM scores and outputs fused logits. The ML backbone is trained/fine-tuned with a
55 small learning rate; the fusion MLP uses a higher rate, enabling rapid adaptation without
56 destabilizing the encoder.

57 Key features:

- 58 ▪ **Multi-class and multi-label support** with consistent data structures and unified training
59 pipeline.
- 60 ▪ **Optional LLM response caching** reuses on-disk predictions when cache paths are supplied,
61 with dataset-hash validation to guard against stale files.
- 62 ▪ **Batched scoring** processes multiple texts efficiently with configurable batch sizes for both
63 ML tokenization and LLM API calls.
- 64 ▪ **Results management** via ResultsManager tracks experiments, stores predictions, com-
65 putes metrics, and enables reproducible research workflows.
- 66 ▪ **Flexible interfaces**: Command-line training via `train_fusion.py` with YAML configs for
67 research; or minimal AutoFusion API for quick deployment.
- 68 ▪ **Composable design**: LabelFusion can serve as a strong base learner in higher-level
69 ensembles (e.g., voting/weighted combinations of multiple fusion models).

70 We support both multi-class setups (one label per input) and multi-label scenarios (multi-
71 ple labels per input), and point readers to Appendix A for formal definitions and training
72 implications.

73 **Minimal Example (AutoFusion)**

```
from textclassify.ensemble.auto_fusion import AutoFusionClassifier

# Multi-class: exactly one of the sentiment labels applies
multiclass_config = {
    'llm_provider': 'deepseek',
    'label_columns': ['positive', 'negative', 'neutral'],
    'multi_label': False
}
multiclass_clf = AutoFusionClassifier(multiclass_config)
multiclass_clf.fit(train_dataframe)
multiclass_pred = multiclass_clf.predict(["This is amazing!"])

# Multi-label: news article can belong to several topics simultaneously
multilabel_config = {
    'llm_provider': 'deepseek',
```

```
    'label_columns': ['politics', 'economy', 'technology'],
    'multi_label': True
}
multilabel_clf = AutoFusionClassifier(multilabel_config)
multilabel_clf.fit(train_dataframe)
multilabel_pred = multilabel_clf.predict(["New investment in AI chips"])
```

74 Quality Control

75 The repository ships legacy unit tests under `tests/evaluation/old/` that cover configuration
76 handling, core types, and package integration. Fusion-specific logic is currently exercised
77 through CLI-driven workflows and notebooks that run end-to-end training with deterministic
78 seeds where applicable.

79 Evaluation scripts (`tests/evaluation/`) provide comprehensive benchmarking on standard
80 datasets: - **AG News** (Zhang et al., 2015): 4-class topic classification with experiments
81 across varying training data sizes (20%–100%) - **Reuters-21578** (Lewis, 1997): A single-label
82 10-class subset of the Reuters-21578 corpus, used to evaluate multi-class fusion performance
83 on moderately imbalanced news topics.

84 LLM scoring paths implement retries and disk caching; transformer training supports standard
85 sanity checks (overfit a small batch, reduced batch sizes for constrained hardware). Metrics
86 (accuracy/F1, per-label scores) are computed automatically and stored with run artifacts to
87 facilitate regression tracking and reproducibility.

88 Availability and Installation

89 LabelFusion is distributed as part of the `textclassify` package under the MIT license and
90 is available at <https://github.com/DataandAIResearch/LabelFusion>. The fusion components
91 require Python 3.8+ and common scientific Python dependencies (PyTorch, transformers,
92 scikit-learn, numpy, pandas, PyYAML, matplotlib, seaborn). Installation and quick-start
93 snippets are provided in the README.

94 Production-Ready Features

95 Beyond the core fusion methodology, LabelFusion includes features for practical deployment:

- 96 **▪ LLM Response Caching:** Optional disk-backed caches reuse prior predictions when cache
97 paths are supplied, with dataset hashes to flag inconsistent inputs.
- 98 **▪ Results Management:** Built-in `ResultsManager` tracks experiments, stores predictions,
99 and computes metrics automatically. Supports comparison across runs and configuration
100 tracking.
- 101 **▪ Batch Processing:** Efficient batched scoring of texts with configurable batch sizes for
102 both ML and LLM components.

103 Impact and Use Cases

104 Empirical Performance

105 LabelFusion has been evaluated on standard benchmark datasets to validate its effectiveness.
106 Key findings demonstrate consistent improvements over individual model components:

107 AG News Topic Classification

108 Evaluation on the AG News dataset (Zhang et al., 2015) (4-class topic classification) with
109 5,000 test samples shows:

Training Data	Model	Accuracy	F1-Score	Precision	Recall
20% (800)	Fusion	92.2%	0.922	0.923	0.922
20% (800)	RoBERTa	89.8%	0.899	0.902	0.898
20% (800)	OpenAI	85.1%	0.847	0.863	0.846
40% (1,600)	Fusion	92.2%	0.922	0.924	0.922
40% (1,600)	RoBERTa	91.0%	0.911	0.913	0.910
40% (1,600)	OpenAI	83.9%	0.835	0.847	0.834
60% (2,400)	Fusion	92.0%	0.920	0.922	0.920
60% (2,400)	RoBERTa	91.0%	0.910	0.911	0.910
60% (2,400)	OpenAI	85.2%	0.847	0.861	0.844
80% (3,200)	Fusion	91.6%	0.916	0.917	0.916
80% (3,200)	RoBERTa	91.4%	0.914	0.915	0.914
80% (3,200)	OpenAI	84.1%	0.837	0.849	0.832
100% (4,000)	Fusion	92.4%	0.924	0.926	0.924
100% (4,000)	RoBERTa	92.2%	0.922	0.923	0.922
100% (4,000)	OpenAI	85.3%	0.849	0.868	0.847

¹¹⁰ **Key Observations:** - Fusion consistently outperforms individual models across all training
¹¹¹ data sizes - With only 20% training data, Fusion achieves 92.2% accuracy—matching its
¹¹² performance with full data - Demonstrates superior **data efficiency**: fusion learning extracts
¹¹³ maximum value from limited examples - RoBERTa alone requires 100% of data to approach
¹¹⁴ Fusion's 20% performance - LLM (OpenAI) shows stable but lower performance, highlighting
¹¹⁵ the value of combining approaches

¹¹⁶ Reuters-21578 Topic Classification

Training Data	Model	Accuracy	F1-Score	Precision	Recall
20% (1168)	Fusion	72.0%	0.752	0.769	0.745
20% (1168)	RoBERTa	67.3%	0.534	0.465	0.643
20% (1168)	OpenAI	88.6%	0.928	0.951	0.923
40% (2336)	Fusion	83.6%	0.886	0.893	0.889
40% (2336)	RoBERTa	82.0%	0.836	0.858	0.850
40% (2336)	OpenAI	87.9%	0.931	0.952	0.917
60% (3505)	Fusion	85.5%	0.932	0.929	0.950
60% (3505)	RoBERTa	83.4%	0.907	0.906	0.945
60% (3505)	OpenAI	88.4%	0.938	0.959	0.924
80% (4673)	Fusion	90.2%	0.954	0.954	0.965
80% (4673)	RoBERTa	88.8%	0.943	0.930	0.966
80% (4673)	OpenAI	88.0%	0.934	0.951	0.918
100% (5842)	Fusion	92.3%	0.960	0.967	0.961
100% (5842)	RoBERTa	89.0%	0.946	0.932	0.966
100% (5842)	OpenAI	88.9%	0.939	0.963	0.927

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¹¹⁸ data sizes - With only 20% training data, Fusion achieves 92.2% accuracy—matching its
¹¹⁹ performance with full data - Demonstrates superior **data efficiency**: fusion learning extracts
¹²⁰ maximum value from limited examples - RoBERTa alone requires 100% of data to approach
¹²¹ Fusion's 20% performance - LLM (OpenAI) shows stable but lower performance, highlighting
¹²² the value of combining approaches

Training Data	Model	Accuracy	F1-Score	Precision	Recall
5% (292)	Fusion	70.6%	0.717	0.720	0.715
5% (292)	RoBERTa	0.0%	0.372	0.276	0.713
5% (292)	OpenAI	88.1%	0.930	0.952	0.917
10% (584)	Fusion	67.0%	0.671	0.672	0.671
10% (584)	RoBERTa	40.0%	0.417	0.321	0.616
10% (584)	OpenAI	88.5%	0.938	0.962	0.926
20% (1168)	Fusion	72.0%	0.752	0.769	0.745
20% (1168)	RoBERTa	67.3%	0.534	0.465	0.643
20% (1168)	OpenAI	88.6%	0.928	0.951	0.923
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100% (5842)	Fusion	92.3%	0.960	0.967	0.961
100% (5842)	RoBERTa	89.0%	0.946	0.932	0.966
100% (5842)	OpenAI	88.9%	0.939	0.963	0.927

123 **Key Observations:** - In extremely low-data settings, the Fusion Ensembles appear negatively
 124 affected by the RoBERTa component, resulting in reduced overall prediction performance -
 125 The LLM (OpenAI) is the preferred model in low-data regimes for multi-label classification on
 126 the 10-class Reuters-21578 subset - RoBERTa alone requires around 80% of the training data
 127 to reach the LLM's performance at only 5% - In high-data settings (80% to 100%), Fusion
 128 Ensembles outperform the individual models by a substantial margin. - The EnsembleFusion
 129 approach attains the best overall prediction performance at 92.3%

130 These results validate that learned fusion captures complementary strengths: the LLM provides
 131 robust reasoning even with limited training data, while the ML backbone adds efficiency and
 132 domain-specific patterns.

133 Application Domains

134 Learned fusion excels in scenarios where model strengths complement each other:

- 135 ▪ **Customer feedback analysis** with nuanced multi-label taxonomies where LLMs handle
 136 ambiguous sentiment while ML models efficiently process clear cases
- 137 ▪ **Content moderation** where uncertain cases benefit from LLM reasoning while rou-
 138 tine items rely on the fast ML backbone, enabling real-time processing with accuracy
 139 guarantees
- 140 ▪ **Scientific literature classification** across heterogeneous topics where domain shift is
 141 common and LLMs provide robustness to new terminology
- 142 ▪ **Low-resource settings** where limited training data is available but task complexity requires
 143 sophisticated reasoning

144 The approach enables pragmatic cost control (e.g., the fusion layer learns when to rely more
 145 heavily on the efficient ML backbone versus the more expensive LLM signal) while retaining a
 146 single trainable decision surface that optimizes for the specific deployment constraints.

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 149 the open-source ecosystem, notably Hugging Face Transformers ([Wolf et al., 2019](#)), scikit-learn
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155 Appendix A: Task Formalization

156 Formally, multi-class classification assigns each input $x \in \mathcal{X}$ to exactly one label among K
 157 mutually exclusive classes:

$$f_{\text{mc}} : \mathcal{X} \rightarrow \{1, \dots, K\}.$$

158 In contrast, multi-label classification predicts a subset of relevant classes, represented as a
 159 binary indicator vector $y \in \{0, 1\}^K$, where $y_k = 1$ denotes membership in class k :

$$f_{\text{ml}} : \mathcal{X} \rightarrow \{0, 1\}^K.$$

160 This distinction shapes the training and inference stack. Multi-class models typically pair
 161 a softmax activation with categorical cross-entropy, yielding normalized class probabilities
 162 ([Goodfellow et al., 2016](#)). Multi-label classifiers instead apply independent sigmoid activations
 163 with binary cross-entropy, producing class-wise confidence scores that require calibrated
 164 thresholds at prediction time ([Goodfellow et al., 2016](#)). LabelFusion preserves these per-class
 165 semantics when concatenating transformer logits and LLM scores, allowing the fusion network
 166 to learn how much to trust each source under either regime.

167 References

- 168 Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep
 169 bidirectional transformers for language understanding. *arXiv Preprint arXiv:1810.04805*.
 170 <https://doi.org/10.48550/arXiv.1810.04805>
- 171 Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press. <https://doi.org/10.7551/mitpress/10251.001.0001>
- 172 Kant, G., Wiebelt, L., Weisser, C., Kis-Katos, K., Luber, M., & Säfken, B. (2022). An
 173 iterative topic model filtering framework for short and noisy user-generated data: Analyzing
 174 conspiracy theories on twitter. *International Journal of Data Science and Analytics*, 20(2),
 175 269–289. <https://doi.org/10.1007/s41060-022-00321-4>
- 176 Kant, G., Zhelyazkov, I., Thielmann, A., Weisser, C., Schlee, M., Ehrling, C., Säfken, B., &
 177 Kneib, T. (2024). One-way ticket to the moon? An NLP-based insight on the phenomenon
 178 of small-scale neo-broker trading. *Social Network Analysis and Mining*, 14(1), 121. <https://doi.org/10.1007/s13278-024-01273-2>
- 179 Lewis, D. D. (1997). Reuters-21578 text categorization test collection, distribution 1.0. *KDD
 180 Workshop on Text Mining*. <https://kdd.ics.uci.edu/databases/reuters21578/reuters21578.html>
- 181 Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer,
 182 L., & Stoyanov, V. (2019). RoBERTa: A robustly optimized BERT pretraining approach.
 183 *arXiv Preprint arXiv:1907.11692*. <https://doi.org/10.48550/arXiv.1907.11692>
- 184 Luber, M., Weisser, C., Säfken, B., Silbersdorff, A., Kneib, T., & Kis-Katos, K. (2021).
 185 Identifying topical shifts in twitter streams: An integration of non-negative matrix factor-
 186 isation, sentiment analysis and structural break models for large scale data. In J. Bright, A.
 187

- 190 Giachanou, V., Spaiser, F., Spezzano, A., George, & A. Pavliuc (Eds.), *Disinformation in open*
191 *online media* (pp. 33–49). Springer International Publishing. ISBN: 978-3-030-87031-7
- 192 OpenAI. (2023). GPT-4 technical report. *arXiv Preprint arXiv:2303.08774*. <https://doi.org/10.48550/arXiv.2303.08774>
- 193
- 194 Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin,
195 Z., Gimelshein, N., Antiga, L., & others. (2019). PyTorch: An imperative style, high-
196 performance deep learning library. *Advances in Neural Information Processing Systems*, 32.
197 <https://doi.org/10.48550/arXiv.1912.01703>
- 198 Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel,
199 M., Prettenhofer, P., Weiss, R., Dubourg, V., & others. (2011). Scikit-learn: Machine
200 learning in python. *Journal of Machine Learning Research*, 12(Oct), 2825–2830. <http://www.jmlr.org/papers/v12/pedregosa11a.html>
- 201
- 202 Thielmann, A. F., Weisser, C., & Säfken, B. (2024). Human in the loop: How to effectively
203 create coherent topics by manually labeling only a few documents per class. In N. Calzolari,
204 M.-Y. Kan, V. Hoste, A. Lenci, S. Sakti, & N. Xue (Eds.), *Proceedings of the 2024 joint*
205 *international conference on computational linguistics, language resources and evaluation*
206 (*LREC-COLING 2024*) (pp. 8395–8405). ELRA; ICCL. <https://doi.org/10.18653/v1/2024.lrec-main.736>
- 207
- 208 Thielmann, A., Weisser, C., & Krenz, A. (2021). One-class support vector machine and LDA
209 topic model integration—evidence for AI patents. In N. H. Phuong & V. Kreinovich (Eds.),
210 *Soft computing: Biomedical and related applications* (pp. 263–272). Springer International
211 Publishing. https://doi.org/10.1007/978-3-030-76620-7_23
- 212 Thielmann, A., Weisser, C., Krenz, A., & Säfken, B. (2021). Unsupervised document
213 classification integrating web scraping, one-class SVM and LDA topic modelling. *Journal*
214 *of Applied Statistics*, 50(3), 574–591. <https://doi.org/10.1080/02664763.2021.1919063>
- 215 Thormann, M.-L., Farchmin, J., Weisser, C., Kruse, R.-M., Säfken, B., & Silbersdorff, A.
216 (2021). Stock price predictions with LSTM neural networks and twitter sentiment. *Statistics,*
217 *Optimization & Information Computing*, 9(2), 268–287. <https://doi.org/10.19139/soic-2310-5070-1202>
- 218
- 219 Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T.,
220 Louf, R., Funtowicz, M., & others. (2019). HuggingFace's transformers: State-of-the-art
221 natural language processing. *arXiv Preprint arXiv:1910.03771*. <https://doi.org/10.48550/arXiv.1910.03771>
- 222
- 223 Zhang, X., Zhao, J., & LeCun, Y. (2015). Character-level convolutional networks for text
224 classification. *Advances in Neural Information Processing Systems*, 28, 649–657. <https://doi.org/10.48550/arXiv.1509.01626>
- 225