

Generative or Discriminative? Revisiting Text Classification in the Era of Transformers

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Abstract

The comparison between discriminative and generative classifiers has intrigued researchers since Efron (1975)'s seminal analysis of logistic regression versus discriminant analysis. While early theoretical work established that generative classifiers exhibit lower sample complexity but higher asymptotic error in simple linear settings, these trade-offs remain unexplored in the transformer era. We present the first comprehensive evaluation of modern generative and discriminative architectures—Auto-regressive, Masked Language Modeling, Discrete Diffusion, and Encoders for text classification. Our study reveals that the classical “two regimes” phenomenon manifests distinctly across different architectures and training paradigms. Beyond accuracy, we analyze sample efficiency, calibration, noise robustness, and ordinality across diverse scenarios. Our findings offer practical guidance for selecting the most suitable modeling approach based on real-world constraints such as latency and data limitations.¹

1 Introduction

Text Classification (TC), a fundamental task in Natural Language Processing (NLP), encompasses various applications such as Sentiment Analysis, Topic Classification, and Emotion Detection. Since the emergence of transformer architectures, the field has been dominated by discriminative classifiers that leverage token embeddings (e.g., the [CLS] token in BERT (Devlin et al., 2019)). These models directly learn the conditional probability distribution $P_\theta(y|X)$, where X denotes the input text and y represents the ground truth label. However, as these discriminative models grow larger, they require increasingly large amounts of labeled data to achieve optimal performance, making them impractical in

many real-world scenarios where labeled data is scarce or expensive to obtain (Zheng et al., 2023). On the other hand, generative classifiers, which model the joint distribution $P_\theta(X, y)$, are known to work better in low-data settings, giving rise to the classical ‘two-regimes’ phenomenon for classification (Ng and Jordan, 2001; Yogatama et al., 2017; Zheng et al., 2023). This advantage stems from their ability to learn underlying data distributions rather than just decision boundaries, allowing them to make better use of limited training examples. The inherent data efficiency of generative approaches, combined with recent advances in generative modeling such as Discrete Diffusion (Lou et al., 2024), motivates us to revisit the classical discriminative versus generative debate in the context of TC with Transformer-based architectures.

Prior research on generative classifiers has largely focused on non-textual tabular data, utilizing linear models such as Linear Discriminant Analysis (Efron, 1975) and Naive Bayes (Ng and Jordan, 2001). While Yogatama et al. (2017) extended this analysis to neural architectures using RNNs and LSTMs (Hochreiter and Schmidhuber, 1997) for the TC task and found similar conclusions about generative advantages in low-data regimes, their study predated the transformer era. Modern NLP has seen the emergence of various successful transformer-based generative modeling paradigms, including auto-regressive (AR) models like GPT (Radford et al., 2018) that maximize likelihood directly, Discrete Diffusion models (Lou et al., 2024) that learn through iterative denoising, and masked language models (MLM) (Devlin et al., 2019) that optimize pseudo-likelihood (Wang and Cho, 2019). These approaches offer different trade-offs in terms of computational efficiency, sample complexity, and modeling flexibility. However, a systematic comparison of these paradigms for text classification remains unexplored, particularly in the context of varying model sizes and real-world deployment

¹Code available at: <https://github.com/amazon-science/Generative-vs-Discriminative-Classifiers>

considerations. Our work fills this gap by providing a practitioner-oriented study that evaluates these approaches not just on classification accuracy, but also on crucial deployment metrics including different model scales, robustness to input perturbations, reliability of output probabilities through calibration analysis, and preservation of ordinal relationships between classes. This comprehensive evaluation aims to provide concrete guidance for choosing between different generative and discriminative approaches based on specific deployment constraints and requirements. We strategically focus on widely available public benchmark datasets for reproducibility purposes. Following [Li et al. \(2025\)](#) and [Yogatama et al. \(2017\)](#), our study evaluates all models trained from scratch, rather than relying on pre-trained weights, providing crucial insights for practitioners working with domain-specific data ([Huang et al., 2019](#)) or in resource-constrained environments ([Martin et al., 2022](#)). This approach helps isolate the confounding effects of the pre-training corpus ([Razeghi et al., 2022](#)) from other factors such as the modeling approach and size, which we evaluate.

Our **main contributions** include the following: **(a)** We present the first large-scale comparative study of two major classification approaches - Discriminative (Encoder) and Generative (Text Diffusion, AR, MLM) on 9 popular classification benchmark datasets, which is a first of its kind in the transformer era. Our study reveals a more nuanced interplay between model size and sample complexity than the previously known “two regimes” phenomenon. **(b)** We provide comprehensive analyses across multiple dimensions including **model scaling behavior, sample efficiency, and performance** in low-resource settings with **models trained from scratch**. We also introduce novel evaluation perspectives by examining **ordinal relationships between classes, output calibration and robustness to input noise**, offering insights beyond traditional classification metrics. We also evaluate these paradigms **using pretrained models**. **(c)** Finally, we provide practical recommendations in Section 6 on selecting the appropriate model for deployment in various real-world scenarios, a concise summary of which is given in Table 1.

2 Related Work

Generative and Discriminative Models for Classification. The comparison between generative

Properties	ENC	AR	AR(p)	MLM	DIFF
Requires significant data	High	Low	Medium	High	Low
Requires bigger model size	Low	High	High	High	High
Sample efficiency	Low	High	Medium	Low	High
Ordinality in scores	High	Low	Medium	High	Low
Unimodality in Scores	High	Low	Medium	High	Low
Well-calibrated scores	High	Low	Medium	High	N/A
Robustness to Noise	Medium	Low	Low	Low	High
Inference Speed	High	Medium	High	High	Low

Table 1: Comparison of different classification approaches across key properties. ENC: Encoder-based classification, AR: Auto-Regressive Model, AR(p): Pseudo-AR model, MLM: Masked Language Modeling, DIFF: Discrete Text Diffusion. Values indicate relative performance/requirements (High/Medium/Low). ■ indicates preferred characteristics, □ indicates less favorable ones.

and discriminative classifiers originated with [Efron \(1975\)](#)’s analysis of logistic regression and discriminant analysis. Building on this foundation, [Ng and Jordan \(2001\)](#) examined naive Bayes and logistic regression, establishing the fundamental trade-off between generative models’ faster learning rate and discriminative models’ lower asymptotic error. Their theoretical analysis heavily depends on linearity and independence assumptions. However, subsequent work by [Xue and Titterington \(2008\)](#) challenged these findings through empirical studies and asymptotic analysis of statistical efficiency. [Yogatama et al. \(2017\)](#) provided the first empirical study of discriminative vs generative models for TC with neural architectures using LSTMs. They maximize the joint probability $P(X, y) = P(X|y)P(y)$ by concatenating the label y text at the beginning of the input text X and maximizing the class conditional likelihood i.e. $P(X | y) = \prod_{t=1}^T p(x_t | x_{<t}, y)$. The final predicted label is obtained by $\hat{y} = \operatorname{argmax}_y P(X|y)P(y)$. They found that generative LSTMs have better accuracy than their discriminative counterparts at low-sample regimes. Further, they noted that the neural generative LSTMs are generally better than baseline generative models with stronger independence assumptions (e.g. naive Bayes, Kneser–Ney Bayes ([Ney et al., 1994; Teh, 2006](#))). Next, the work by [Zheng et al. \(2023\)](#) has extended the theoretical understanding of generative classifiers to multi-class and non-linear settings. More recent studies ([Li et al., 2025; Stanley et al., 2025](#)) have found that generative classifiers tend to avoid shortcut learning and exhibit greater robustness to distribution shifts.

While prior studies provide valuable insights, the landscape of NLP has evolved dramatically with

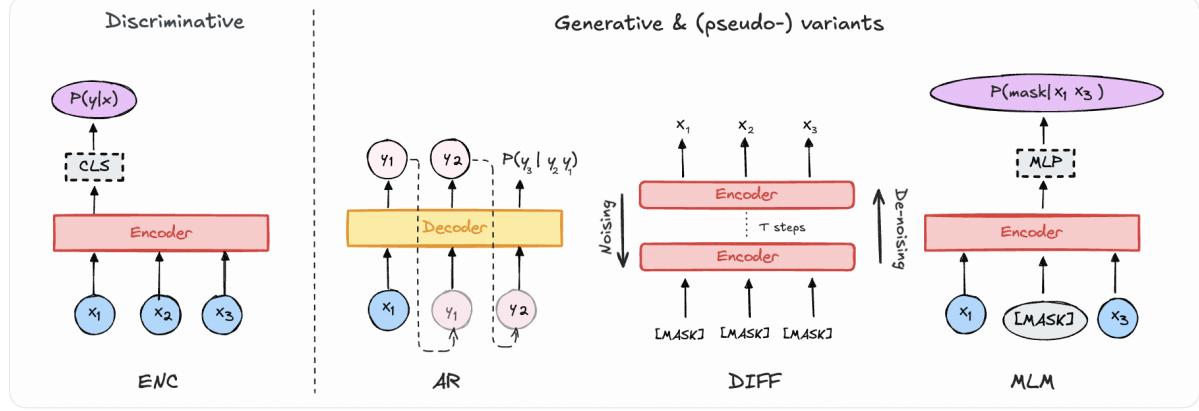


Figure 1: [Best viewed in color] Illustration of different modeling paradigms (ENC: Encoder-based classification, MLM: Masked Language Modeling, AR: Auto-Regressive Model, DIFF: Discrete Text Diffusion).

the advent of novel transformer-based generative paradigms such as Auto-Regressive (AR) models (Radford et al., 2018) and Discrete Diffusion models (Lou et al., 2024). Our work extends beyond these previous comparisons by conducting the first comprehensive evaluation of modern transformer-based generative and discriminative classifiers for TC. While previous works primarily focused on classification accuracy and sample complexity, we examine multiple dimensions that are crucial for real-world deployments. For instance, Yogatama et al. (2017) initial work with neural architectures was limited to a fixed model size, leaving open questions about how the generative-discriminative trade-off varies with model capacity and computational budget—questions that have become increasingly relevant in the era of large language models. Similarly, though Zheng et al. (2023) provided theoretical insights for multi-class settings, their analysis did not address practical considerations like calibration quality or preservation of ordinal relationships between classes.

Pseudo-Generative Models. Recent work (Sahoo et al., 2024) highlights a natural connection between Discrete Text Diffusion (Lou et al., 2024) and the Masked Language Modeling (MLM) objective in BERT (Devlin et al., 2019), showing that the diffusion objective can be expressed as a weighted sum of MLM losses. Using transformer encoder models, this approach achieves likelihood bounds comparable to or better than those in Lou et al. (2024). Motivated by this, we include vanilla MLM as a baseline for text classification by first appending *The label is* as a suffix during training and appending *The label is*[MASK] as a suffix during inference. While MLM has typically served as a

pretraining objective followed by fine-tuning (Liu et al., 2019), there has been little systematic study of its direct use for classification. Although MLM does not explicitly model $P(X|y)$, it estimates $P(x_m|x_{\setminus m})$, where x_m is a masked token and $x_{\setminus m}$ represents all other tokens. This approximates the pseudo-likelihood of $P(X, y)$ when modeled over the corpus (Wang and Cho, 2019). We therefore classify MLM as a pseudo-generative model.

Also, traditional generative classifiers aim to model $P(X|y)$ by prepending the label token. However, recent work (Li et al., 2025) shows that appending the label at the end—though not strictly modeling $P(X|y)$ —can yield better in-distribution performance. This setup also enables efficient inference, requiring only a single forward pass to predict the label, unlike traditional generative models that need $\#_{\text{label}}$ forward passes. These benefits motivate the inclusion of such pseudo-generative models in our benchmarks. Notably, these approaches involve minimal changes to standard transformer architectures—typically just altering label placement or the loss function—while preserving the core model design. This allows for fair comparisons using widely available implementations accessible to practitioners.

We also acknowledge a separate class of hybrid generative-discriminative models, where some subset of parameters are trained generatively and others discriminatively (Raina et al., 2003; McCallum et al., 2006; Hayashi, 2025). However, we exclude them from our study, as their architectural differences hinder fair comparison with fully generative or discriminative models, placing them outside the scope of this work.

Relation to Multi-task Learning. Learning

$\log P(X, y)$ jointly, when factored as $\log P(X) + \log P(y|X)$ (or $\log P(y) + \log P(X|y)$) can be viewed as a multi-task learning setup, where unsupervised learning of $\log P(X)$ ($\log P(Y)$) and supervised learning of $\log P(Y|X)$ ($\log P(X|Y)$) represent two different but related tasks. This connection is supported by empirical results showing that unsupervised pre-training helps downstream supervised tasks (Erhan et al., 2010). As demonstrated by Wu et al. (2020); Hu et al. (2023), when model capacity is sufficiently large, such multi-task learning setups tend to be more successful - the model has enough capacity to perform well on both the unsupervised and supervised objectives. However, with limited model capacity, there are inherent trade-offs between the tasks, leading to challenges in jointly optimizing for both $P(X)$ and $P(y|X)$ (or $P(y)$ and $P(X|y)$). This insight motivates us to conduct a systematic study examining the relationship between model capacity and the performance of discriminative vs generative classifiers - an analysis that has not been previously undertaken in the literature.

Refer to Appendix A for further related works review on Discrete Diffusion, Robustness to Noise, Ordinality & Calibration.

3 Methodology

We approach the problem of TC by leveraging two popular language modeling paradigms: **(a) Generative** - Discrete Diffusion models, Auto-regressive models (AR), and Masked Language Models (MLM) & **(b) Discriminative** - Encoder-based transformer models. Note that, for brevity, we use the term “*generative*” from this point onward to also include the **pseudo-generative** baselines. Let $\mathcal{D} = \{(X_i, y_i)\}_{i=1}^N$ denote the dataset where X_i is the input text and $y_i \in \mathcal{Y}$ is the corresponding label from a finite set of classes \mathcal{Y} . Generative models tend to learn the joint data distribution $P(X, y)$ first and then try to infer the label using the marginals, whereas Discriminative models directly learn the conditional distribution $P(y|X)$. Note that each $X_i = x_i^1 \dots x_i^n$, where x_i^j is a token from the associated vocabulary \mathcal{V} .

3.1 Discriminative Model for Classification

(1) Encoder-based classification (ENC): A Transformer encoder (Vaswani et al., 2017) f_θ encodes the input as $h_i = f_\theta(X_i)$ as a d -dimensional embedding, followed by a linear classifier head

$W \in \mathbb{R}^{|\mathcal{Y}| \times d}$ which is the standard discriminative learning setup:

$$\hat{y}_i = \text{softmax}(W h_i), \mathcal{L}_{\text{enc}} = - \sum_{i=1}^N \log P(y_i|X_i)$$

where \mathcal{L}_{enc} is the cross-entropy based objective for training the encoder model.

3.2 Generative Models for Classification

(2) Masked Language Modeling (MLM): During training, we first modify the input X_i to :

$$X'_i = [\text{CLS}] X_i [\text{SEP}] \text{ "The label is"}$$

We then apply the standard mask i.e., on 15% of tokens in input sequence $X'_i \oplus y_i = x_i^1 \dots x_i^{n'} y_i$ following Devlin et al. (2019) and predict them using unmasked bi-directional context. Wang and Cho (2019) show that the MLM objective stochastically captures the *pseudo-loglikelihood* which makes it similar to a denoising autoencoder (Vincent et al., 2010). Hence, we consider MLM under the generative family of models. Formally, the objective is:

$$\mathcal{L}_{\text{mlm}} = - \sum_{i=1}^N \sum_{j \in \mathcal{M}_i} \log P(x_i^j | X'_i \oplus y_i^{\setminus j}) \quad (1)$$

where \mathcal{M}_i is the set of masked positions and $X'_i \oplus y_i^{\setminus j}$ denotes the unmasked input with only token at position j masked. At inference, we use the template:

$$X'_i = [\text{CLS}] X_i [\text{SEP}] \text{ "The label is" } [\text{MASK}] .$$

and predict the masked label token. The output vocabulary is restricted to the label token set \mathcal{V}_Y . Since MLM returns token probabilities across the entire vocabulary for a [MASK] token, we extract the dimensions corresponding to the label tokens and normalize them to sum to 1, thereby obtaining the class probabilities.

(3) Auto-regressive modeling (AR): Following Radford et al. (2018), we train a causal generative model to minimize the next-token prediction loss over the entire label + input sequence:

$$\mathcal{L}_{\text{gpt}} = - \sum_{i=1}^N \sum_{j=1}^{L_i} \log P(x_i^j | y, x_i^1, \dots, x_i^{j-1}) \quad (2)$$

where L_i is the length of the i -th sequence. At inference time, we perform one forward pass per candidate label $y \in \mathcal{V}_Y$ by prepending it to the input X ,

and compute the log-likelihood. The predicted label is then obtained as $\arg \max_{y \in \mathcal{V}_Y} \log P(X \mid y)$. In AR_{pseudo} (refer pseudo-generative models in Section 2) the label is appended at the end instead of the beginning and only one forward pass is required to generate the predicted label token y . Note that label placement is only relevant for causal generative architectures (like AR) with a left-to-right attention structure. For bidirectional (pseudo-)generative models like MLM or DIFF, it has no theoretical impact.

(4) Text Diffusion (DIFF): For each input-label pair (X_i, y_i) , we first create a template:

$$X_i = X_i \text{ [SEP]} \text{ "The label is" } y_i .$$

where each template is a sequence $X_i = x_i^1 \dots x_i^{L_i}$ with tokens $x_i^j \in \mathcal{V}$.

Similar to how diffusion models gradually add noise to images, our forward process gradually corrupts text by converting tokens to pure noise (here [MASK]). Following Lou et al. (2024), we define the forward process through discrete transition matrices Q_t following a continuous markov process (see eq. 3). This process occurs at different timesteps $t \in [0, T]$, where each token position is independently corrupted, starting from the original text and progressively moving towards a completely masked sequence.

$$\frac{dp_t}{dt} = Q_t p_t, \quad \text{with} \quad p_0 = p_{\text{data}} \quad (3)$$

The reverse process learns to reconstruct the original text by predicting what token should replace each [MASK] symbol. This is done by learning score ratios $s_\theta(x, t)_z = \frac{p_t(z)}{p_t(x)}$ where x, z are tokens from \mathcal{V} and modeling the reverse process (Sun et al., 2022) as:

$$\frac{dp_{T-t}}{dt} = s_\theta(x, t)_z Q_{T-t} p_{T-t} \quad (4)$$

Denoising Score Entropy (DSE) is used for training the score model in a manner that ensures several desired properties for s_θ and ensures the computation is tractable:

$$\begin{aligned} \mathcal{L}_{\text{DSE}} = & \mathbb{E}_{\substack{x_0 \sim p_0, \\ x \sim p(\cdot | x_0)}} \left[\sum_{z \neq x} w_{xz} \left(s_\theta(x)_z \right. \right. \\ & \left. \left. - \frac{p(z \mid x_0)}{p(x \mid x_0)} \log s_\theta(x)_z \right) \right] \end{aligned} \quad (5)$$

where p is assumed to be perturbation of some base density p_0 and weights $w_{xz} > 0$.

The ELBO (Theorem 3.6 in Lou et al. (2024)) provides an upper bound on the negative log-likelihood, which is what we optimize for in generative models:

$$-\log p_0^\theta(x_0) \leq \mathcal{L}_{\text{DWDSE}}(x_0) + \text{constant} \quad (6)$$

where $\mathcal{L}_{\text{DWDSE}}$ integrates \mathcal{L}_{DSE} weighted by the forward diffusion matrix. At inference time, we mask the label token in the template X_i and use the model to predict it, restricting the possible outputs to valid labels in \mathcal{V}_Y . For further details, refer to Lou et al. (2024).

4 Experiments

Our experiments are designed towards addressing the following research questions:

- Q1.** How do different modeling approaches compare against each other when trained from scratch?
- Q2.** How much does noise perturbation via random token substitution and token dropping affect the performance of different modeling approaches ?
- Q3.** How well are the different modeling approaches calibrated ? For ordinal classification, how well the predicted distributions over ordinal categories follow a unimodal shape ?

4.1 Datasets

We evaluate our models on 9 text classification benchmark datasets to ensure a comprehensive assessment across multiple domains, text lengths, and classification types - sentiment analysis, movie reviews, news categorization, and social media analysis. These are: **AG News** (Zhang et al., 2015), **Emotion** (Saravia et al., 2018), **Stanford Sentiment Treebank (SST2 & SST5)** (Socher et al., 2013), **Multiclass Sentiment Analysis, Twitter Financial News Sentiment, IMDb** (Maas et al., 2011), and **Hate Speech Offensive** (Davidson et al., 2017). These datasets encompass varying levels of complexity, ranging from binary text classification to fine-grained multi-class categorization, with textual inputs spanning from concise single sentences to extensive paragraph-level passages. Further details are postponed to Appendix C.

4.2 Experimental Setup

We conduct an extensive benchmarking study comparing the five different modeling approaches for

text classification summarised in Section 3: AR, $\text{AR}_{\text{pseudo}}$, MLM, DIFF, and ENC. These models are evaluated on 9 popular classification benchmark datasets as mentioned in Section 4.1.

We experiment with multiple dataset sample sizes $\in \{128, 256, 512, 1024, 2048, 4096, \text{full_data}\}$. To assess the effect of model sizes, we test 3 model size configurations using the base Transformer architecture: *small* (1 layer, 1 head), *medium* (6 layers, 6 heads) and *large* (12 layers, 12 heads). Performance is measured using the weighted-F1 score. All experiments are repeated with 3 random seeds, running a total of $9 \times 7 \times 3 \times 3 \times 5 = 2835$ experiments and we report the average and shaded standard deviations in Figure 2, 3. These experiments are designed to address **Q1**.

In the second part of our evaluation, we assess each model’s robustness to input perturbations. In real-world scenarios, particularly in e-commerce platforms, often encounter various text corruptions (like OCR errors in product documentation, truncated reviews, or incomplete user queries), we focus on two systematic types of synthetic noise to evaluate model robustness: (a) **Random Token Drop** — where X% of tokens are randomly removed from the input sentence, and (b) **Random Token Substitution** — where X% of tokens are replaced with random tokens from the vocabulary (excluding special tokens like [PAD], [MASK]). We conduct these experiments to explore **Q2** about model robustness to input perturbations.

Lastly, we assess model performance on calibration and ordinal metrics—aspects often overlooked but critical for real-world deployment. While a similar study exists for pre-trained models (Kasa et al., 2024), ours focuses on models trained from scratch. For ordinal classification tasks, we verify ordinal alignment, ensuring that the predicted probability distribution reflects the natural ordering of categories (e.g., the probability of “good” should be closer to “neutral” than to “bad”).

For ordinal evaluation, we report *MSE* (Mean Squared Error), *MAE* (Mean Absolute Error), and *Unimodality* (UM). For calibration, we measure *ECE* (Expected Calibration Error) and *MCE* (Maximum Calibration Error). UM verifies that the predicted probability distribution has a single peak, thus preserving class ordering—for instance, preventing models from assigning high confidence to both extremely positive and negative sentiments simultaneously. Calibration metrics quantify the

discrepancy between predicted probabilities and empirical frequencies. For detailed descriptions, see Kasa et al. (2024) and Wang (2023). These experiments address **Q3**. Refer to Appendix B for details on hyperparameters and training setup.

5 Results

We analyze the results from all the experiments and provide valuable insights & recommendations for model selection.

Q1: For 1-layer, 1-head models (Figure 2), all approaches show near-random performance in low-data regimes. However, as training data increases, only ENC (orange line) continues to improve, ultimately outperforming others in high-data settings. This suggests that **for small models - often necessary due to real-world latency constraints - ENC is the most effective approach**. The classical ‘two regimes’ phenomenon does not manifest when the model size is small.

The pattern shifts dramatically for larger architectures. Under the **12-layer, 12-head** configuration, both generative models—AR and DIFF—outperform ENC in low-data settings, with this advantage diminishing as data increases. This aligns with previous findings (Ng and Jordan, 2001; Yogatama et al., 2017; Rezaee et al., 2021) about generative models’ advantages in data-limited scenarios. Surprisingly, for large models, the pseudo-generative MLM (blue line) consistently outperforms all methods across our 9 benchmark datasets in high-data settings, **challenging the conventional wisdom about discriminative dominance in high-sample regime**. This aligns with Erhan et al. (2010)’s finding that pseudo-generative models implicitly perform unsupervised pre-training alongside supervised learning, creating an effective multi-task setup (Section 2). Their work shows that this unsupervised phase acts as a data-dependent regularizer, guiding optimization toward better-generalizing minima. For *large* models, direct fine-tuning without this implicit pre-training often leads to suboptimal convergence, explaining ENC’s underperformance relative to MLM. Thus, **for scenarios without model size constraints, generative models emerge as the optimal choice for low-data settings** such as for low-resource languages and continual learning applications requiring frequent updates with limited samples, while **pseudo-generative MLM is superior when abundant labeled data is available**.

Another noteworthy observation is that under the

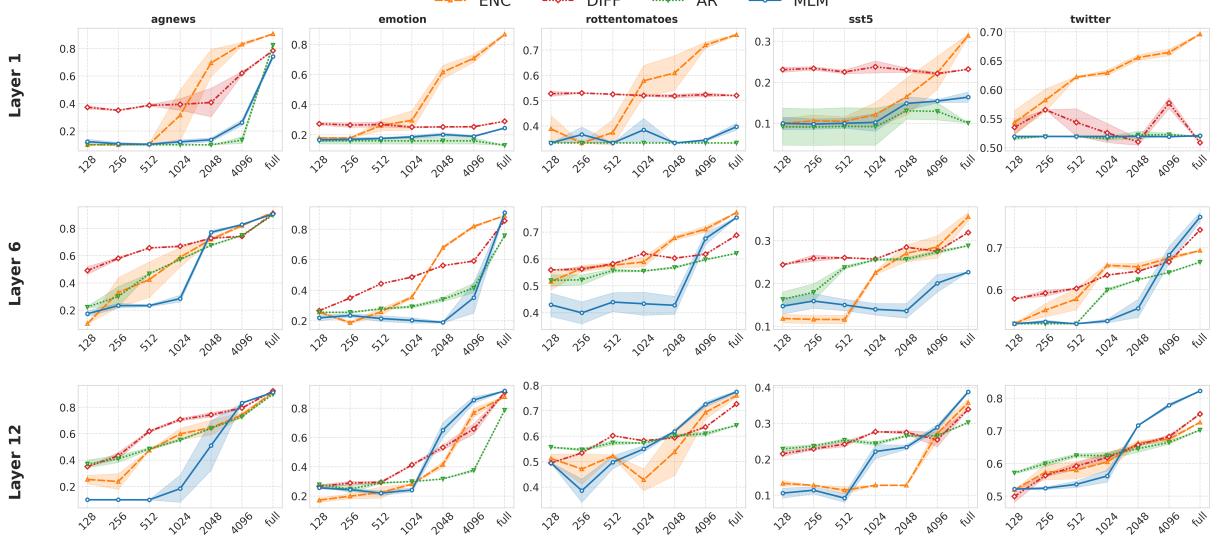


Figure 2: [Best viewed in color] Comparison of weighted-F1 scores of models across different configurations (\uparrow is better). For rest of the datasets, refer to Figure 8 in Appendix E. (X-axis: sample size, Y-axis: weighted-F1 score)

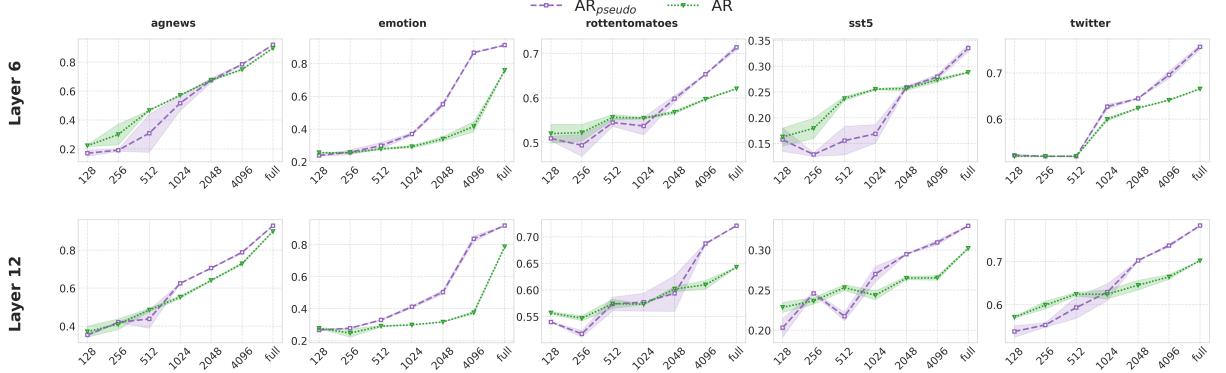


Figure 3: [Best viewed in color] Comparison of weighted-F1 scores between AR_{pseudo} and AR (\uparrow is better). 1-layer results are omitted here as they are mostly trivial in low-data settings. Results for remaining datasets are provided in Figure 9, Appendix E. (X-axis: sample size, Y-axis: weighted-F1 score)

6-layer, 6-head configuration, in low-data settings, DIFF emerges as the best performing model across all datasets, clearly outperforming even its generative counterpart AR. As the training data size increases, we see that the discriminative ENC outperforming DIFF. Thus, **in medium scale architectures, between the generative DIFF and the discriminative ENC, the classical ‘two regimes’ still holds.**

Figure 3 shows that AR_{pseudo} generally underperforms AR and also displays **higher variance** in low-data settings—the recommended use case—while the opposite holds in high-data scenarios. This reveals a new insight beyond Li et al. (2025), who only evaluated full-data settings where AR_{pseudo} performed better in-distribution. As noted in Section 3, AR requires $|label|$ -times forward passes per prediction, unlike the single pass needed for AR_{pseudo} ; however, this can be mitigated via batch-

ing or parallel processing, reducing inference time differences at the cost of higher computation. We also investigate the claim that “larger models can sometimes deteriorate performance” (Nakkiran et al., 2019) in the Appendix G. While we observe the classical bias-variance trade-off in small-data regimes, performance generally improves with model size in full-data settings especially for AR.

Q2: We evaluate the robustness of all approaches under both 6-layer and 12-layer configurations across two noise schedules in full-data settings. We exclude 1-layer models from this analysis since their performance is mostly trivial (except for ENC), making robustness comparisons uninformative. In Tables 2 and 3, we report the minimum noise level required to degrade a model’s performance by a certain threshold $X\% = \{5\%, 10\%, \dots\}$ relative to its peak, averaged across all datasets, as a mea-

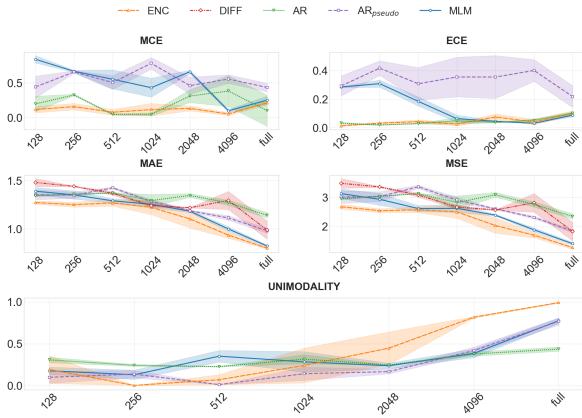


Figure 4: [Best viewed in color] Calibration and Ordinal performance of 12-layers model on SST-5. For ECE, MCE, MAE, MSE (\downarrow is better) and UM (\uparrow is better) (X-axis: sample size).

sure of **robustness boundary**. Our analysis reveals that all models exhibit lower robustness to substitution noise compared to dropping. This can be explained by the inequality: $P(\text{garbage}_t | X_{1\dots t-1}) < P(x_{t+1} | X_{1\dots t-1})$ —the model is more likely to assign lower probability to a corrupted token than to a skip token at $t+1$ -th position (assuming t -th token was dropped), which may still be contextually relevant given $X_{1\dots t-1}$.

The generative DIFF demonstrates superior robustness to both token dropping and substitution (except in 6-layers where ENC is slightly better), likely because its training paradigm involves recovering true tokens from noise/masked inputs. The discriminative ENC maintains consistent robustness under both noise types, while generative AR shows the high sensitivity to noise. Combining these findings with Q1’s results reveals that generative AR models face dual challenges compared to ENC in full data settings: they underperform in terms of both weighted-f1 and robustness. This contrasts with Li et al. (2025)’s findings that discriminative ENC models rely on shortcuts and show less robustness compared to generative AR. However, their analysis focuses on shortcut learning and distribution shifts rather than input perturbation noise across varying model sizes. Notably, while the pseudo-generative MLM and AR_{pseudo} demonstrate superior performance in larger models at full data settings, they exhibit lower robustness compared to similarly performing ENC models. Moreover the relative drop in robustness in moving from dropping to substitution noise is more severe in AR_{pseudo} compared to AR. This is likely because AR_{pseudo}

Config	Metric	5%	10%	15%	20%	30%
6L, 6H	ENC	33.3	47.8	60.0	71.1	80.0
	AR-pseudo	27.8	51.1	62.2	74.4	86.7
	AR	27.8	46.7	63.3	81.1	92.2
	MLM	32.2	46.7	63.3	72.2	86.7
	DIFF	27.8	53.3	75.6	86.7	94.4
12L, 12H	ENC	34.4	51.1	67.8	77.8	87.8
	AR-pseudo	33.3	46.7	61.1	73.3	86.7
	AR	25.6	37.8	50.0	67.8	86.7
	MLM	23.3	34.4	47.8	61.1	71.1
	DIFF	36.7	54.5	72.2	82.2	91.1

Table 2: Minimum noise% needed for X% weighted-F1 drop from the peak under Random Token **Dropping**. (\uparrow is better)

Config	Metric	5%	10%	15%	20%	30%
6L, 6H	ENC	26.7	37.8	51.1	58.9	76.7
	AR-pseudo	15.6	21.1	27.8	32.2	50.0
	AR	21.1	30.0	38.9	47.8	62.2
	MLM	20.0	32.2	44.4	51.1	63.3
	DIFF	22.2	34.4	41.1	50.0	75.6
12L, 12H	ENC	22.2	32.2	42.2	47.8	61.1
	AR-pseudo	13.3	22.2	27.8	34.4	51.1
	AR	20.0	28.9	38.9	52.2	67.8
	MLM	21.1	31.1	38.9	44.4	55.6
	DIFF	16.7	35.6	44.4	52.2	73.3

Table 3: Minimum noise% needed for X% weighted-F1 drop from the peak under Random Token **Substitution**. (\uparrow is better)

conditions on corrupted inputs, so it’s directly affected by garbage tokens polluting the predictive context. However, for AR clean label conditions the model, and the noisy input is scored globally—giving the model more flexibility to discount garbage.

Q3: Figure 4 presents ordinal and calibration results for SST-5, selected for its balanced distribution, inherent class ranking (e.g., very positive to very negative), and highest number of classes. Results for other datasets are in Appendix D. DIFF does not support calibration metrics like ECE, MCE, and UM, as its masking/absorbing noise process produces only binary outputs rather than soft probabilities. While a uniform noise schedule can yield probabilities over \mathcal{V} , it performed slightly worse, so we used the absorbing schedule in our study.

From the ECE and MCE plots, we observe that ENC outputs remain well-calibrated across all sample sizes, while MLM reaches similar calibration only in high-data regimes. We also see that MLM and ENC achieve UM in over 80% of the samples, aligning with findings from Kasa et al. (2024). Their MAE and MSE values are also low, indicating strong ordinality in high-data settings. This completes the picture for *large* models under high-data, where MLM not only outperforms others in weighted-F1 but is

also well-calibrated and ordinal, making it a strong candidate for real-world deployment. However, under low-data conditions, 12-layers AR outperforms AR_{pseudo} in 7 out of 9 datasets on calibration metrics. It also surpasses DIFF in ordinal performance, thus making it the more reliable choice among generative models in low-data scenario. Also, even though generative approaches like DIFF were recommended earlier in **Q1** based on weighted-F1 for 6-layers case (in Figure 2) deploying them in production could be risky when calibrated or ordinal probabilities are required, especially for imbalanced datasets like *twitter* and *hatespeech* (see Appendix D). These metrics are particularly important when downstream models consume output probability scores as features which is often the case in multi-stage ranking systems.

Lastly, Figure 5 in Appendix D reveals an interesting trend: as *model size* increases, calibration metrics either remain flat or worsen. This suggests that larger models or improved classification accuracy do not necessarily lead to better calibration, aligning with the findings of Guo et al. (2017) where they show similar behaviour using ResNets (He et al., 2016). However, for ordinal metrics, we observe substantial improvements when moving from 1-layer to 6-layer models, with performance plateauing at 12 layers. A similar trend was reported in Kasa et al. (2024) for pre-trained models.

5.1 Impact of Initialization with Pretrained models

To investigate the impact of pretraining, we conducted additional experiments using BERT-base (for ENC) and GPT-2 base (for AR), both featuring comparable architectures with 12 layers and 12 attention heads. These models were fine-tuned on our benchmark datasets across various sample sizes, maintaining consistency with our previous experimental protocol. Figure 10 has the detailed results.

These experiments reveal important insights that contrast with our findings from models trained from scratch. When using pretrained weights, we observe that the classical “two regimes” phenomenon no longer holds. Instead, the discriminative ENC model consistently outperforms the generative AR approach across all data regimes in most datasets. This aligns with recent findings from Zheng et al. (2023) in the vision domain, where pretraining was shown to eliminate the two-regime effect. This behavior can be theoretically explained by viewing

pretraining as providing models with “asymptotically large” amounts of data, effectively reducing the traditional advantage that generative models hold in low-data settings since both architectures begin with rich, generalized representations. However, these results should be interpreted with several caveats in mind: pretrained models often employ mixed training objectives (e.g., BERT uses both MLM and Next Sentence Prediction (NSP)), rely on different pretraining datasets with varying cutoff dates, and have distinct architectural designs. Additionally, our pretrained analysis was limited to comparing AR and ENC models due to the current unavailability of pretrained diffusion models.

6 Conclusion

Our study offers practical modeling recommendations across deployment scenarios. For latency-sensitive applications, ENC is ideal—especially in the 1-layer setting—due to its efficiency, robustness to noise, and well-calibrated, ordinal outputs. For offline settings with sufficient data, the 12-layer MLM performs best across F1, calibration, and ordinal metrics, though caution is needed with noisy inputs due to its lower robustness to token dropping. In low-resource scenarios, both AR and DIFF are strong options, with DIFF favored for its noise resilience and performance at 6-layers. However, if calibrated probability outputs are essential, such as in ranking pipelines, AR is the preferred choice.

7 Limitations

While we conducted a thorough examination of generative and discriminative classifiers under standard i.i.d. assumptions, our findings may not generalize to scenarios involving distribution shifts, such as co-variate shift (Bickel et al., 2009) or concept shift (Roychowdhury et al., 2024). Our analysis was limited to traditional fine-tuning approaches, excluding emerging paradigms such as few-shot prompt-based in-context learning (Sun et al., 2023; Gupta et al., 2023) and parameter-efficient techniques like LoRA (Hu et al., 2022), which may uncover newer insights. Furthermore, our study focused exclusively on pure text classification, leaving the exploration of multi-modal scenarios involving tabular data (Pattisapu et al., 2025), images (Lu et al., 2019), audio (Kushwaha and Fuentes, 2023), and other modalities for future work.

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A More Background and Related works

Discrete Diffusion Models for Classification. Recent advances in discrete diffusion models have shown promising results in text generation tasks, matching or surpassing autoregressive models at GPT-2 scale (Lou et al., 2024; Sahoo et al., 2024; Shi et al., 2024). While these models have demonstrated success in controlled generation tasks (Li et al., 2022a; He et al., 2023), specifically syntax controlled generation of text (Kumar et al., 2020) and text infilling, their application to classification remains relatively unexplored. Traditional diffusion models for text generation, such as Diffusion-BERT (He et al., 2023), DiffusionLM (Li et al., 2022b), and D3PM (Austin et al., 2021), operate by embedding discrete token sequences into continuous spaces and applying Gaussian noise-based diffusion. In contrast, SEDD (Lou et al., 2024) was the first to directly model diffusion in discrete space through a score entropy-driven objective. Hence, we adopt SEDD as our baseline method. Our work provides the first systematic evaluation of discrete diffusion models for classification tasks, comparing them against traditional discriminative and generative approaches.

Robustness to Noise. Previous studies have examined robustness primarily through the lens of adversarial attacks (Li et al., 2019), distribution shifts (Li et al., 2025) and domain shifts (Jaini et al., 2024). While recent work has provided certified robustness guarantees for perturbations like insertion, deletion, reordering and synonyms for specific architectures (Zeng et al., 2023; Zhang et al., 2024), our study presents comparisons across model families under two different noise conditions in the context of TC for transformer architectures.

Calibration & Ordinality. Model calibration is crucial in classification, as it reflects how well predicted probabilities align with actual frequencies. Proper Scoring Rules (PSR) (Merkle and Steyvers, 2013) offer a theoretical basis for producing calibrated predictions: a scoring rule (i.e. loss function) is proper if its expected value is minimized only when predicted probabilities match the true distribution. All our modeling approaches—Generative (AR, MLM, Discrete Diffusion) and Discriminative (Encoder)—optimize proper scoring rules, but only ENC demonstrates consistently calibrated results because it optimizes a loss directly aligned with the classification task. Although the other paradigms also optimize strictly

proper scoring rules that guarantee the lowest expected score when predictions match the target distribution, they optimize different objectives that do not perfectly align with classification. This mismatch in optimization targets explains the differences observed in calibration performance. GPT and MLM maximize likelihood, Discrete Diffusion optimizes a variational bound, and cross-entropy minimizes the KL-divergence between predicted and true distributions. Recent work (Blasiok et al., 2023) shows that models trained with PSRs are often naturally calibrated when achieving low training loss, without requiring post-hoc calibration. This motivates us to empirically assess calibration across our models, as their differing architectures and objectives may still lead to varying calibration behaviors.

Ordinality in text classification is essential for applications like sentiment analysis or medical assessments, where label order affects decisions and distant misclassifications are more harmful. Recent works (Kasa et al., 2024) systematically compare *explicit* methods—like custom losses enforcing label order—with *implicit* approaches using pretrained models’ semantics. However, no prior work focuses on exploring ordinality across diverse modeling frameworks trained from scratch.

B Implementation Details

We use the bert-base-uncased² architecture as the backbone for our **Encoder** and **MLM** experiments, without initializing the model with pre-trained weights. This architecture contains approximately 110M parameters, comprising 12 encoder layers, 12 attention heads, and a hidden size of 768. We run all experiments for 3 random seeds and report the average and standard deviation results in main paper.

For the **Encoder** experiments, we conducted a grid search over several hyperparameters, including learning rates of {1e-5, 2e-5, 3e-5, 4e-5, 5e-5}, batch sizes of {32, 64, 128, 256}, and a fixed sequence length of 512 tokens. Training was performed for 30 epochs uniformly for all datasets without early stopping. For the **MLM**-based experiments, we retained similar hyperparameter ranges but trained for 200 epochs to account for the increased complexity of masked token prediction. We observed that adding an early stopping patience

²<https://huggingface.co/google-bert/bert-base-uncased>

parameter sometimes led the model to select a sub-optimal checkpoint, as the validation loss often continued to decrease gradually after remaining flat or oscillating for several epochs.

For the **AR** and **AR_{pseudo}** experiments, we used the GPT-2 base architecture³ as the backbone with 137M parameters comparable with our other experiments. We trained a causal language model to minimize the next-token prediction loss over the concatenated input and label sequence. A grid search was conducted with the same hyperparameter range as mentioned above. The models were trained for up to 100 epochs, with early stopping based on validation loss, using a patience parameter of 10 epochs.

Our **Text Diffusion** approach follows the Diffusion Transformer architecture (Peebles and Xie, 2023) which is basically the vanilla transformer encoder with an extra time-conditioned embedding incorporated with it. The parameter count is ~ 160 M due to the addition of time-dependent embeddings required by the diffusion mechanism. To counter this, we conducted an ablation study by increasing the encoder size to 160M parameters (by adding layers) for other approaches (like ENC, MLM) to match the diffusion model size, but observed no difference in performance. Hence we retain their original settings as reported above. For diffusion-specific hyperparameters, we used a batch size of 64, learning rate 3e-4 and trained for 200K iterations. We adopted a geometric noise schedule that interpolates between 10^{-4} and 20, similar to the setup in (Lou et al., 2024), and used the following absorbing/masking matrix Q^{absorb} as part of the transition modeling. This was the best hyperparameter setting we found.

$$Q_{\text{absorb}} = \begin{bmatrix} -1 & 0 & \cdots & 0 \\ 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 0 \end{bmatrix}$$

All experiments were conducted using multi-GPU training across eight NVIDIA A100 GPUs. Training time varied depending on the methods and configurations used for each dataset. The range of training times (in hours) for various datasets is presented in Table 4. All reported training times correspond to full-data training configurations.

Our analysis of inference latency reveals significant differences across architectures - refer to

³<https://huggingface.co/openai-community/gpt2>

Config	ENC	AR _{pseudo}	AR	MLM	DIFF
(1L,1H)	1-2	2-4	2-4	1-4	1-4
(6L,6H)	1-3	3-7	3-7	3-7	2-6
(12L,12H)	2-5	5-10	5-10	5-10	5-12

Table 4: Training time (in hrs) ranges across different datasets for each configuration and approach.

Table 5. While ENC and MLM demonstrate comparable inference speeds (requiring single forward passes), AR requires $|K|$ forward passes for prediction, though this can be parallelized at the cost of increased computation. DIFF exhibits substantially higher latency, taking approximately 20-100x longer than ENC/MLM due to its iterative denoising process. Specifically, for a batch of 1024 examples (sequence length 128) on an A100 GPU, ENC and MLM take 0.03s for small models (3.3M params) to 1.3s for large models (120.4M params), while DIFF requires 16-25s across model sizes.

Model Size	Parameters	ENC	MLM	AR	DIFF
Small	3.3M	0.027	0.027	0.058	16.2
Medium	30.3M	0.292	0.292	0.510	20.52
Large	120.4M	1.260	1.260	2.070	24.8

Table 5: Model Size v/s Inference Latency (avg wall-clock time per batch in seconds)

C Dataset Details

AG News (Zhang et al., 2015): It consists of approximately 120K training samples and 7.6K test samples, divided into four categories: World, Sports, Business, and Technology. Each sample contains a short news article, typically consisting of the title and the first few sentences. **Emotion** (Saravia et al., 2018): A collection of English tweets labeled with six basic emotions: anger, fear, joy, love, sadness, and surprise. It is designed for emotion detection in text. The dataset has 20K samples divided into 16K samples for training and 2K samples each for validation and testing. **Stanford Sentiment Treebank (SST)** (Socher et al., 2013): We utilize both the SST-2 (binary sentiment) and SST-5 (fine-grained sentiment) variants of the Stanford Sentiment Treebank dataset. SST-2 consists of sentences labeled as either positive or negative, suitable for binary sentiment classification, while SST-5 includes five sentiment categories: very negative, negative, neutral, positive, and very positive,

Dataset	Split	Examples	Classes	Avg Tokens	Label Dist. (%)	Ordinal
IMDb	train	25,000	2	313.87	0: 50.0, 1: 50.0	✗
	test	25,000	2	306.77	0: 50.0, 1: 50.0	
agnews	train	120,000	4	53.17	0-3: 25.0 each	✗
	test	7,600	4	52.75	0-3: 25.0 each	
emotion	train	16,000	6	22.26	0: 29.2, 1: 33.5, 2: 8.2, 3: 13.5, 4: 12.1, 5: 3.6	✗
	test	2,000	6	21.90	0: 27.5, 1: 35.2, 2: 8.9, 3: 13.8, 4: 10.6, 5: 4.1	
hatespeech	train	22,783	3	30.04	0: 5.8, 1: 77.5, 2: 16.7	✓
	test	2,000	3	30.18	0: 5.5, 1: 76.6, 2: 17.9	
multiclasssentiment	train	31,232	3	26.59	0: 29.2, 1: 37.3, 2: 33.6	✓
	test	5,205	3	26.91	0: 29.2, 1: 37.0, 2: 33.8	
rottentomatoes	train	8,530	2	27.37	0: 50.0, 1: 50.0	✗
	test	1,066	2	27.32	0: 50.0, 1: 50.0	
sst2	train	6,920	2	25.21	0: 47.8, 1: 52.2	✗
	test	872	2	25.47	0: 49.1, 1: 50.9	
sst5	train	8,544	5	25.04	0: 12.8, 1: 26.0, 2: 19.0, 3: 27.2, 4: 15.1	✓
	test	1,101	5	25.24	0: 12.6, 1: 26.3, 2: 20.8, 3: 25.3, 4: 15.0	
twitter	train	9,543	3	27.62	0: 15.1, 1: 20.2, 2: 64.7	✓
	test	2,388	3	27.92	0: 14.5, 1: 19.9, 2: 65.6	

Table 6: Dataset statistics showing training and test split sizes, number of classes, mean and maximum token lengths, and label distribution percentages. Refer to Section C for details on datasets.

allowing for more fine-grained sentiment analysis. **Multiclass Sentiment Analysis**⁴: This dataset consists of 41.6K data points, labeled into three sentiment categories: positive, negative, and neutral. While the dataset is designed for multiclass sentiment classification, it exhibits class imbalance, with certain sentiment classes being more prevalent than others. This imbalance provides a more realistic challenge for sentiment analysis models, testing their ability to handle skewed distributions and still perform effectively across all sentiment categories. **Twitter Financial News Sentiment**⁵: A specialized English-language collection of finance-related tweets, annotated for sentiment analysis. It consists of 11,932 tweets labeled with three sentiment categories: Bearish, Bullish, and Neutral. This dataset is designed to test models’ ability to understand domain-specific language and nuanced sentiment expressions in financial contexts. **IMDb** (Maas et al., 2011): A binary sentiment analysis dataset consisting of 50K reviews from the Internet Movie Database (IMDb), labeled as positive or negative. The dataset is balanced, with an equal number of

positive and negative reviews. This dataset is characterized by longer document lengths and detailed opinions, making it a challenging benchmark. **Rotten Tomatoes** (Pang and Lee, 2005): A binary classification dataset which contains 10,662 movie review sentences, equally divided into 5,331 positive and 5,331 negative examples. The dataset is characterized by relatively short, opinion-driven sentences that reflect concise sentiments about films. **Hate Speech Offensive** (Davidson et al., 2017): A major challenge in automatic hate speech detection is distinguishing hate speech from other forms of offensive language. This dataset consists of approximately 25K tweets, labeled into three categories: hate speech, offensive language without hate speech, and neutral content.

Refer to Table 6 for details on dataset statistics.

⁴<https://huggingface.co/datasets/Sp1786/multiclass-sentiment-analysis-dataset>

⁵<https://huggingface.co/datasets/zeroshot/twitter-financial-news-sentiment>

D More Ordinal & Calibration Results

In this section, we take a closer look at ordinal and calibration results for the datasets described above. Here we report ordinal metrics on the datasets **Stanford Sentiment Treebank (SST5)** (Socher et al., 2013), **Multiclass Sentiment Analysis, Hate Speech Offensive** (Davidson et al., 2017) and **Twitter Financial News Sentiment** since these are the only multi-class ordinal datasets out of 9. Calibration metrics are reported on all 9 datasets.

In Figure 5, we compare how ordinal and calibration metrics vary with increasing model size. Figure 6 presents the ordinal metrics for all four ordinal datasets, while Figure 7 shows the calibration metrics for all nine datasets. The corresponding insights are discussed in Section 5 (see Q3).

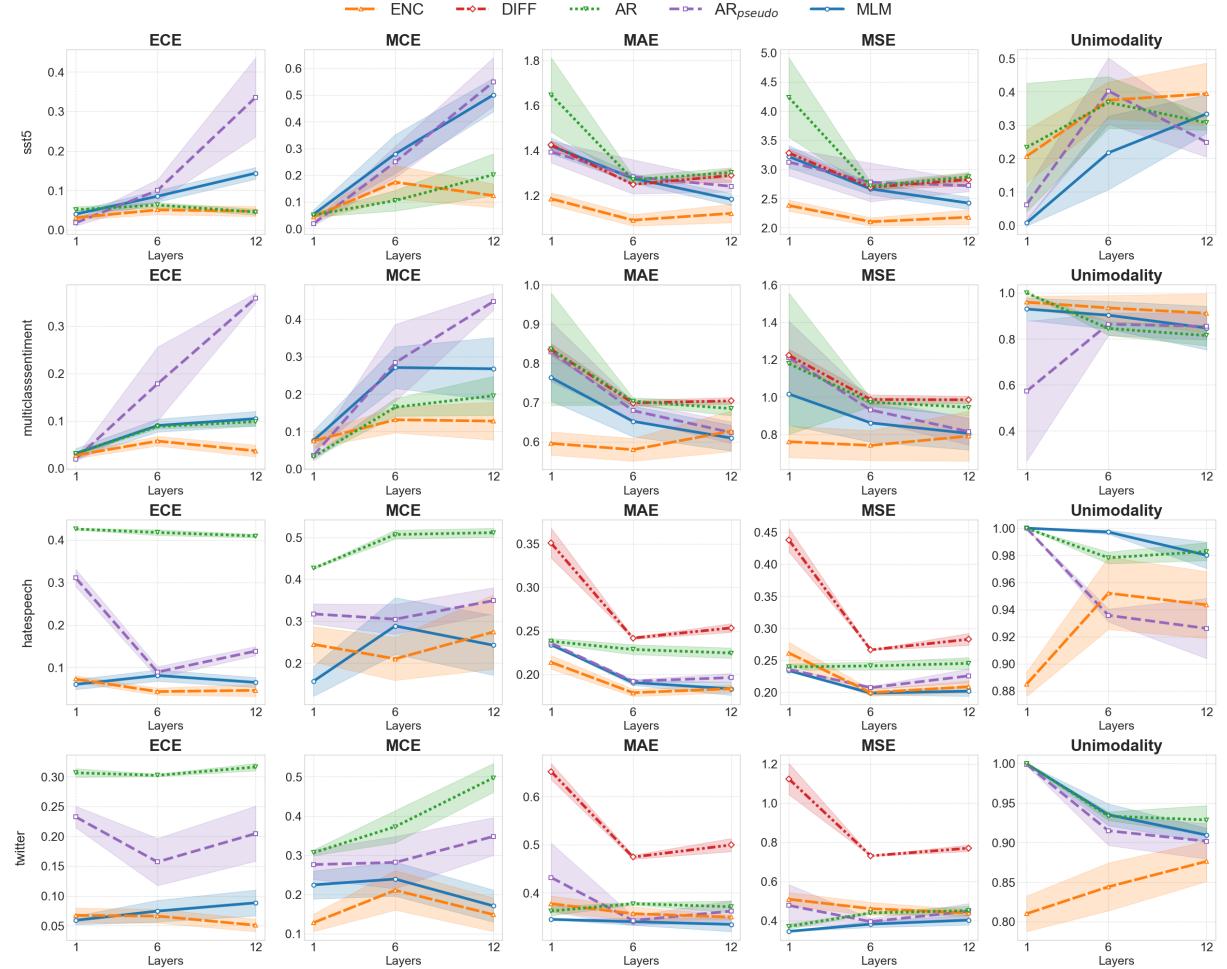


Figure 5: [Best viewed in color] Calibration and Ordinal metrics comparison across layers 1, 6 and 12. For ECE, MCE, MAE, MSE, (\downarrow is better) and UM (\uparrow is better).

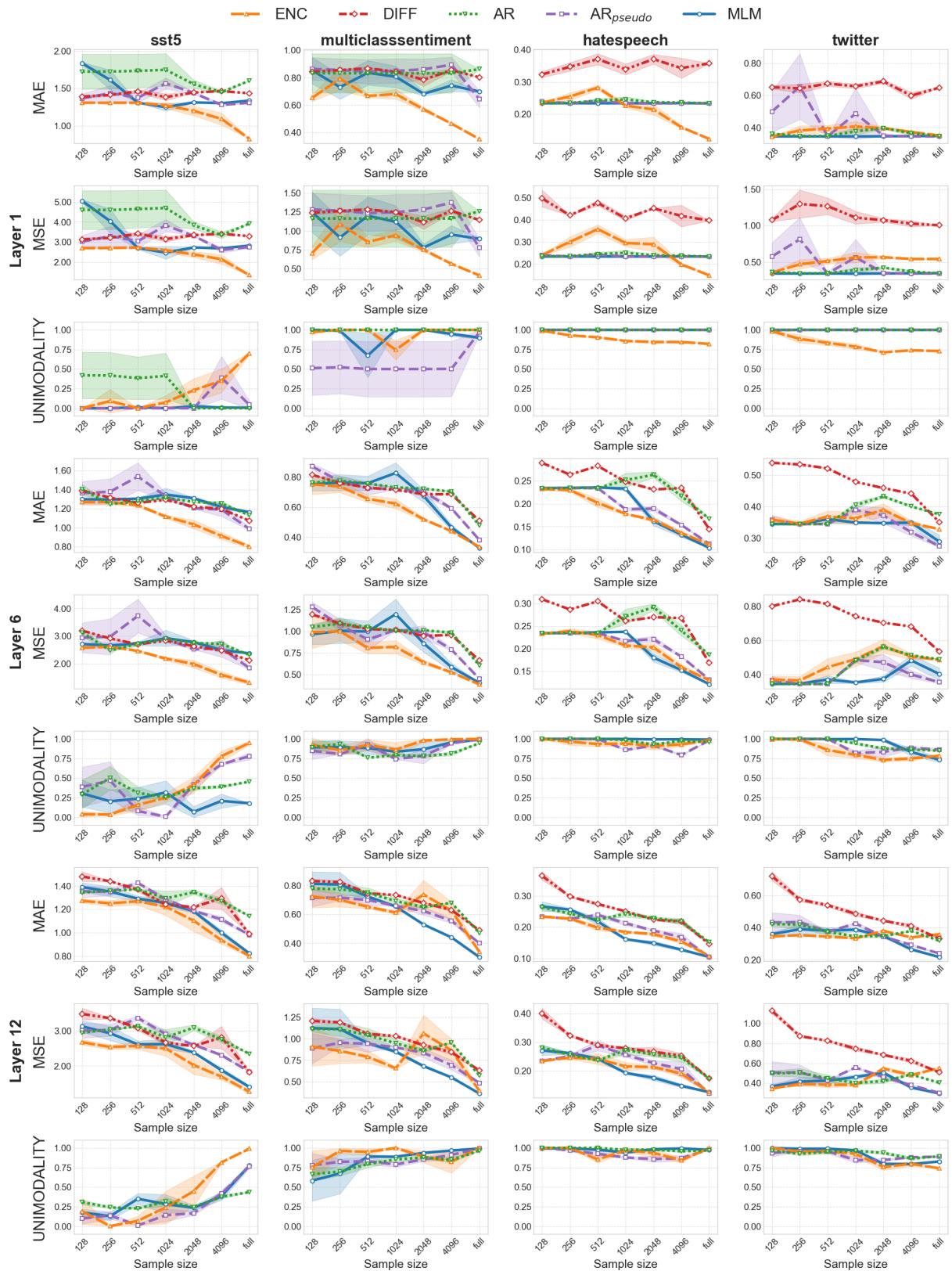


Figure 6: [Best viewed in color] Ordinal metrics. For MAE, MSE, (\downarrow is better) and UM (\uparrow is better).

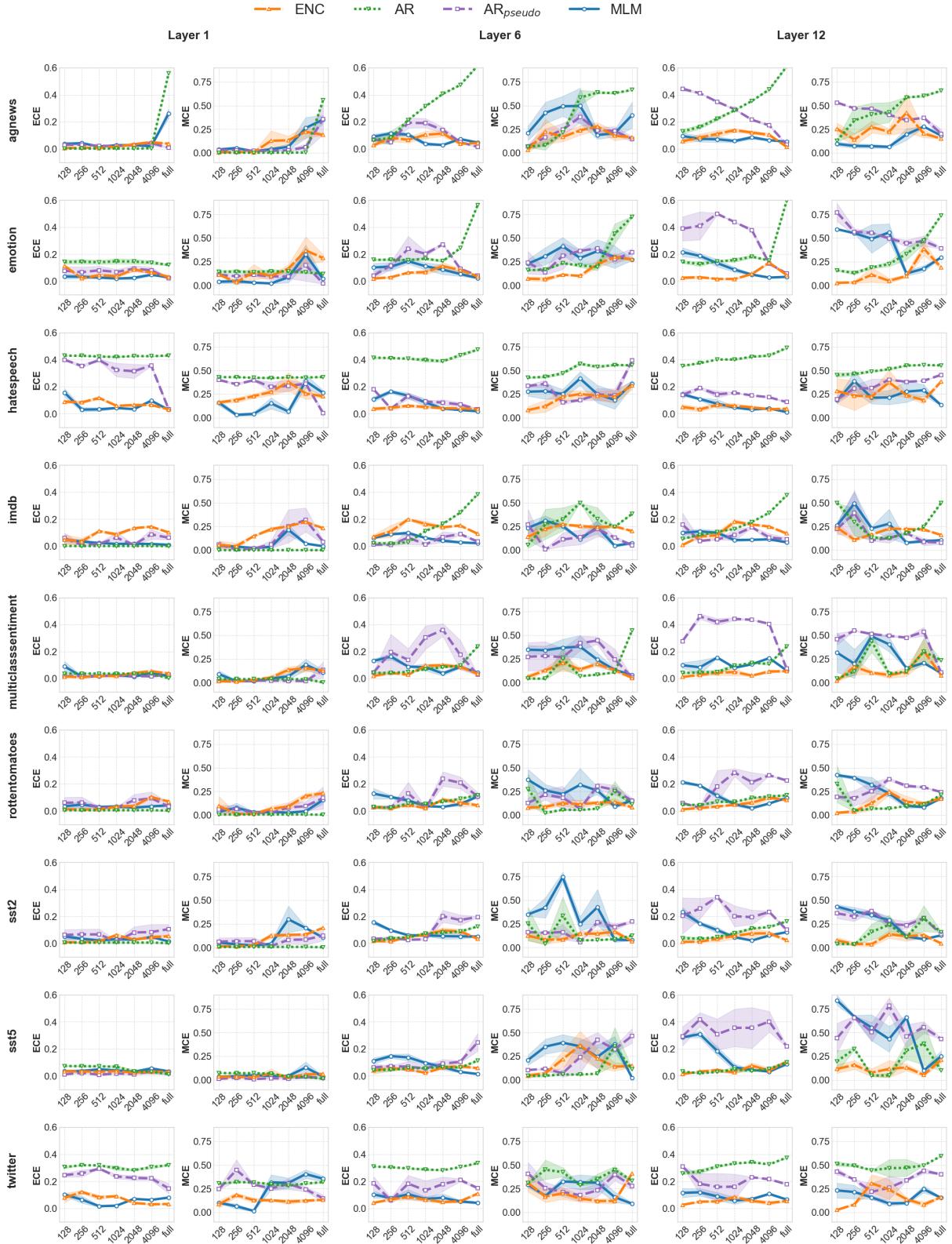


Figure 7: [Best viewed in color] Calibration metrics. For ECE, MCE (\downarrow is better)

E More Main Results

This section contains the extended results of Figure 2 (see Figure 8) and Figure 3 (see Figure 9) for all 9 datasets. We omit 1-layer plots for Figure 9 since the performance is mostly trivial for low-data settings and the same trend is observed as 6/12-layers for full-data settings.

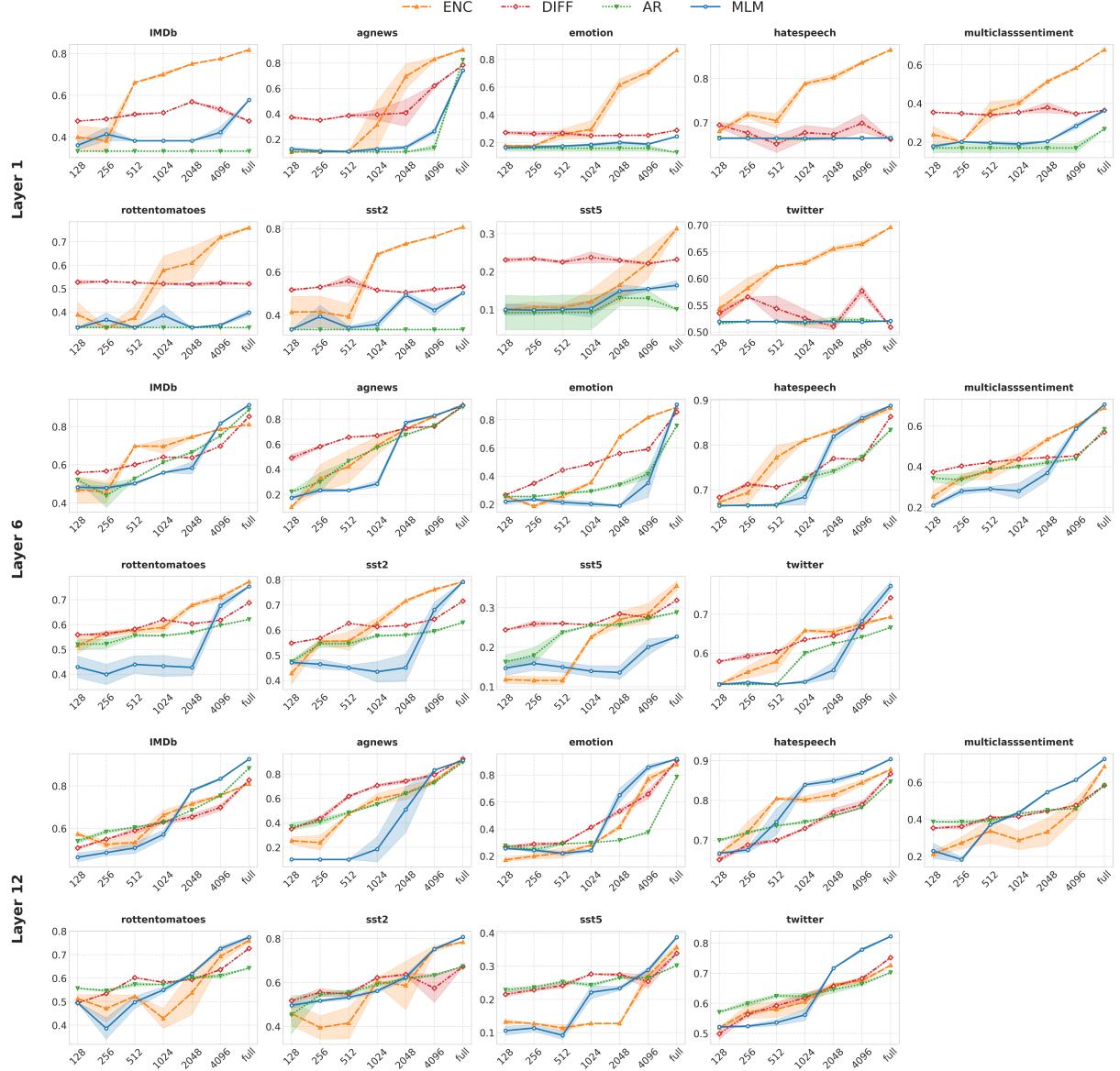


Figure 8: [Best viewed in color] Comparison of weighted-F1 scores of models across different configurations for all 9 datasets. (↑ is better) (X-axis: sample size, Y-axis: weighted-F1 score)

F Results on Pretrained models

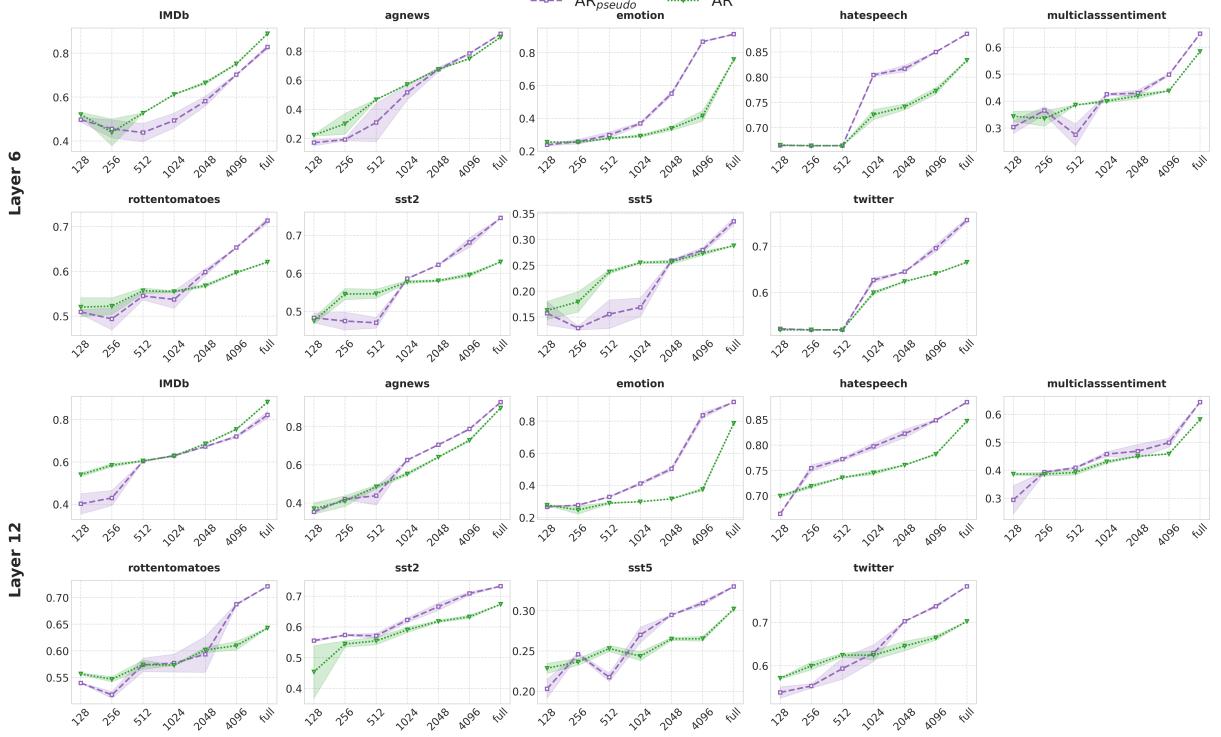


Figure 9: [Best viewed in color] Comparison of weighted-F1 scores between AR_{pseudo} and AR (\uparrow is better) for all datasets. (X-axis: sample size, Y-axis: weighted-F1 score)

G Revisiting the Bias-Variance Trade-off in Modern Text Classifiers

The classical bias-variance trade-off, which predicts a U-shaped performance curve, has long been a foundational principle in machine learning (Geman et al., 1992). However, the emergence of the “double descent” (Nakkiran et al., 2019) phenomenon has challenged this view, demonstrating that test error can decrease as model complexity increases into the highly overparameterized regime (Belkin et al., 2019; Nakkiran et al., 2019).

In this work, we also conduct a fine-grained analysis of this behavior specifically in modern text classification, exploring how different model architectures AR, MLM, DIFF, and ENC with varying data and model sizes. The results depicted in Figure 11 illustrate that the classical bias-variance trade-off is predominantly observed in small-data settings (i.e., lower sample sizes), reinforcing the foundational principle in these regimes. Our findings offer critical empirical insights that nuance the prevailing theory. While we did not scale model size sufficiently to observe the full double descent curve, our results are consistent with the overparameterization regime. Specifically, as shown in Figure 11, the classical “inverted U” phenomenon is only evident in small-data settings. In contrast, for full-data settings, model performance is consistently **non-decreasing** with increasing model size, suggesting that larger models do not necessarily perform poorly when trained on ample data. This trend is particularly pronounced for the AR architecture, which exhibits a robustly non-decreasing performance curve across our experiments.

Moreover, Figure 12 visualizes the interplay between sample size and strategy more explicitly. We further investigate the “**more data can hurt**” phenomenon (Nakkiran et al., 2019), finding that while more data generally improves performance, a performance drop is occasionally observed in specific datasets such as sst5 and multiclasssentiment. This finding, illustrated in Figure 12, suggests that although the phenomenon exists, no universal dataset-specific pattern dictates its occurrence.

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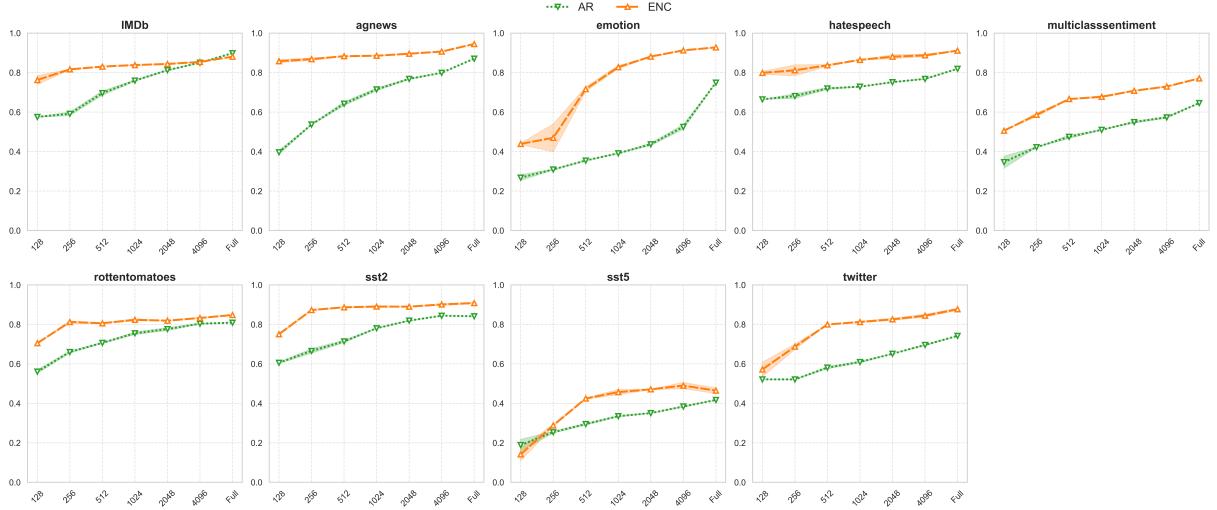


Figure 10: [Best viewed in color] Comparison of weighted-F1 scores between pretrained AR and ENC models (\uparrow is better). (X-axis: sample size, Y-axis: weighted-F1 score)

insights, and final manuscript approval. Karan Gupta managed end-to-end diffusion model experiments, owned the rebuttal and camera-ready cycles, and played a significant role in dataset details, implementation, preparing bias-variance analysis, and guiding the integration of calibration and ordinality sections. Sumegh Roychowdhury took the lead on noise robustness studies, compiled and presented the main results, generated key tables and figures, and coordinated the overall paper structure to ensure clarity and narrative cohesion across all sections. Ashutosh Kumar was instrumental in designing and implementing both the MLM and robustness experiments, contributed to pre-trained and encoder model evaluations, and co-authored substantial parts of the introduction, methodology, and related work sections, as well as leading dataset-centric analyses and diffusion studies. Yaswanth Biruduraju was responsible for all aspects of the calibration and ordinality experiments, including their conception, implementation, and analysis, ensuring these metrics were rigorously evaluated and reported. Santhosh Kumar Kasa built the core experimental infrastructure, particularly the discrete diffusion model implementation, ran experiments for both generative and discriminative paradigms, and maintained comprehensive codebase documentation to guarantee reproducibility. Nikhil Priyatam Pattisapu contributed the autoregressive and pseudo-generative methodologies, led the associated empirical studies on model and sample size scaling, authored relevant sections, and played a constructive role in team consensus around generative versus discriminative distinctions and multiple manuscript revisions. Arindam Bhattacharya anchored the theoretical framing by shaping the generative-discriminative comparison paradigm and was essential in literature review and conceptual foundations. Shailendra Agarwal and Vijay Huddar supported discussions, and provided manuscript feedbacks

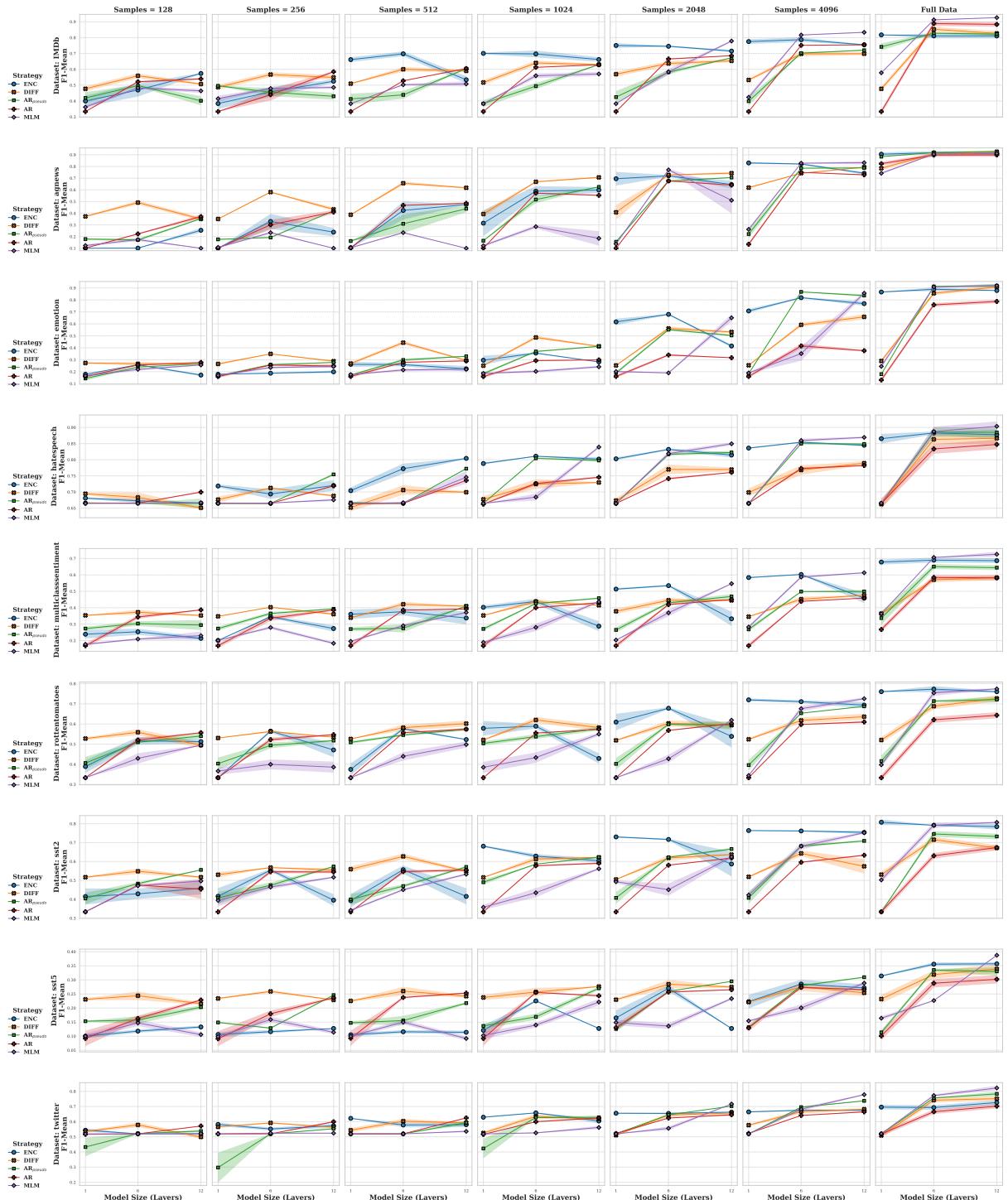


Figure 11: [Best viewed in color] Comparison of weighted F1-scores between training strategies ENC, DIFF, AR, AR_{pseudo} , and MLM across different sample sizes as model size increases. The plots highlight that the classical bias-variance trade-off phenomenon is only evident in small-data settings (i.e., lower sample sizes).

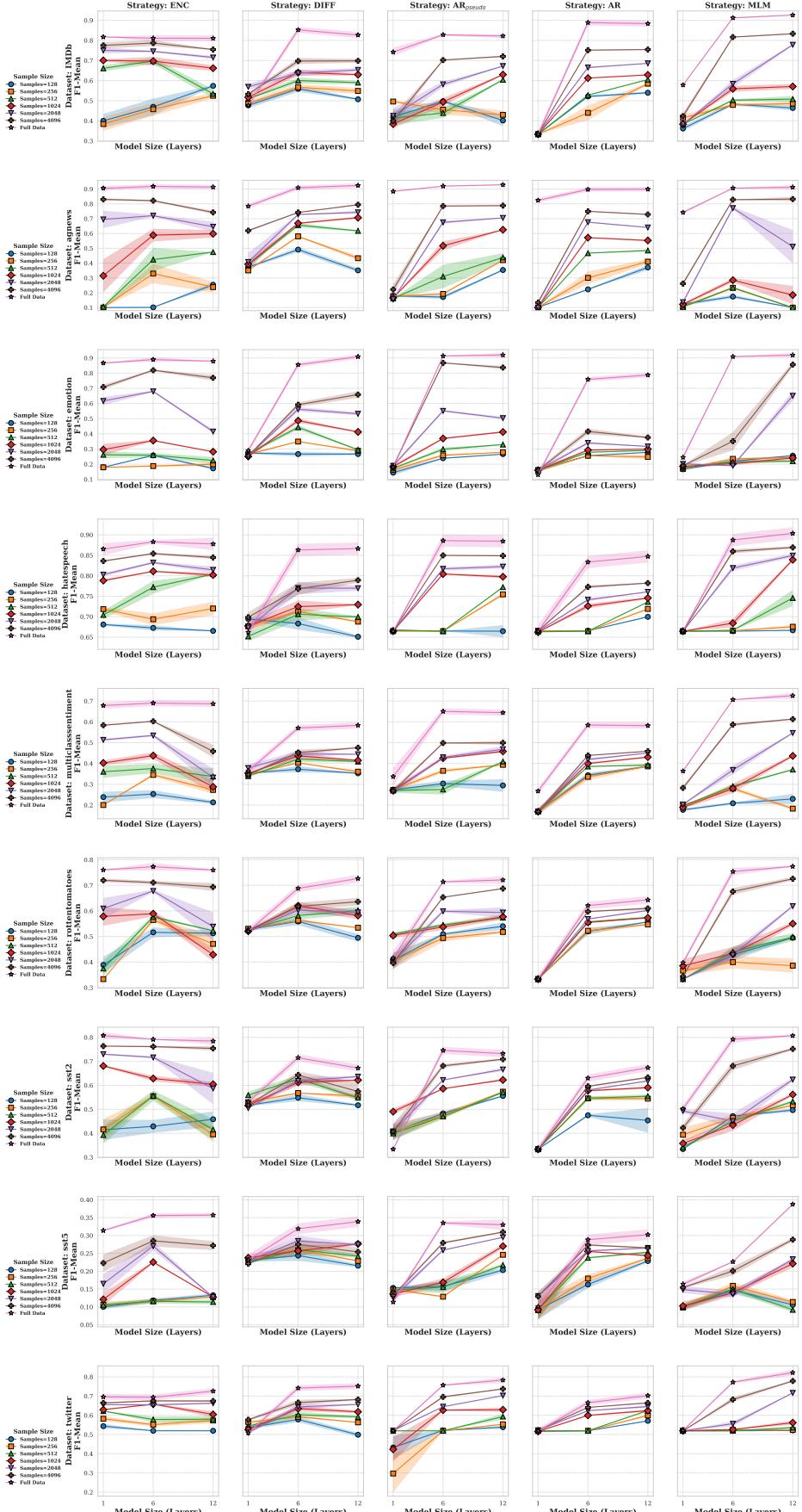


Figure 12: [Best viewed in color] Comparison of F1-Mean scores across different sample sizes and strategies as model size increases. The figure highlights that, in some cases, increasing training data can adversely affect performance.