Comparing Supervised and Unsupervised Learning Approaches for Specific Tasks

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Abstract Nearly all prior knowledge in machine learning can be categorised as either supervised learning (SL), which utilises labelled datasets for training, or unsupervised learning (UL), which infers latent structure in unlabelled data. Although both paradigms are well studied in isolation, they are rarely systematically compared across task domains. In this paper, we provide a differentiable comparison of SL and UL across six prototypical tasks—image classification, fraud detection, natural language sentiment analysis, customer segmentation, anomaly detection, and product recommendations—using twelve benchmark datasets. We consider accuracy, F1-score, silhouette coefficient, training time, memory usage, and label dependency. Our experiments show that SL outperforms UL on precision–critical tasks with sufficient labels (mean accuracy increase: +14.3%), while UL outperforms SL on exploratory and scalability–critical tasks by up to 38% according to cluster quality metrics. Additionally, we develop a decision framework to guide practitioners in choosing the right paradigm for given task constraints. All artefacts from the experiments—code, hyperparameter logs, and datasets—are publicly available.

Keywords: supervised learning, unsupervised learning, machine learning comparison, classification, clustering, anomaly detection, benchmark analysis, decision framework

1. Introduction

A decade ago, ML was barely a blip on the timeline, but the coming practitioners now still have a simple question on their mind: for a particular problem and data extent, should they take a supervised or an unsupervised approach? I don't know. Supervised learning achieves high predictive accuracy, since it makes use of human-labelled data to directly train discriminative or generative models, but the annotation process is costly. In contrast, unsupervised learning discovers the implicit regularities in the data itself without any appended supervision, which motivates a broader scale application but does not directly optimise a target metric[1][2]. This choice is made all the more important by the increasingly massive amounts of data [5]. According to the IDC (2023), ~80%+ of the data in enterprises is unstructured and unlabelled, making unsupervised-based approaches more practical with respect to cost and scale[3][4]. Meanwhile, sectors such as healthcare, finance, and autonomous driving demand the accuracy guarantees that only highly supervised models can provide. The absence of an actionable advice from theory constitutes the motivation of this work [92,93]. Prior work in comparative fashion traditionally focuses on semi-supervised learning or very specific domains [94,95]. Rigorous, multi-task empirical validations, along with executable experimental protocols, are somewhat scarce. This work contributes the following to the gap:

- A unified experimental setup for two types of tasks, twelve datasets, and twenty-four variants of algorithms [96].
- Quantitative evaluation in six dimensions: accuracy, F1-score, silhouette coefficient, training time, memory usage, and label dependency [97].
- Show model decision boundaries, learning curves and heat map of performances in the figure [99,98].
- A decisioning paradigm selection framework for practitioners informed by the evidence [100,101].

The rest of this paper is organised as follows. Section 2 reviews related work. Section 3 describes the theory. Section 4 outlines the experiment procedure. Section 5 presents results and figures. Section 6 is devoted to a discussion of the results. Section 7 presents the decision framework. Section 8 is the conclusion[5][6]

2. Related Work

2.1 Supervised Learning Advances

Influence from seminal work, such as Support Vector Machines, gradient-boosted trees, and deep convolutional networks, can be observed in supervised learning [105,109]. The Image Net challenge drove in a second wave unprecedented progress in visual recognition, reducing top-5 error rates from 26.2% down below 2% by 2021. Transformer-based architectures later superseded these as the dominant methodology in natural language processing, attaining human-parity across several benchmarks[7][8]. Supervised learning also has its drawbacks [9][10]: its reliance on labelled data is a major hurdle. Annotation costs for specialised domains—medical images, legal documents, rare-event detection—could be upwards of $1M per large-scale dataset. Active learning and transfer reduce, but do not completely[11][12].

2.2 Unsupervised Learning Advances

Unsupervised learning includes clustering, dimension reduction, density estimation, and generative modelling. The development of variational auto encoders [15]16] and generative adversarial networks [13][14] brought unsupervised representation learning to a new level. In particular, Self-supervised learning—a special case of the latter—has achieved unprecedented success in vision and language, blurring the line between the two paradigms [116]. Contrastive learning methods showed that unsupervised retraining can be as good as supervised fine-tuning with as little as 1% of labels, debunking the narrative that labels are always needed [117,118,122].

2.3 Comparative Studies

Ghahramani (2004) reviewed probabilistic models in both paradigms under the umbrella, but did not include empirical baselines. [17][18] contrasted semi-supervised methods but left out purely unsupervised baselines [123]. Later on, Erhan et al. presented an information-theoretic perspective, and unsupervised pre-training was empirically shown to enhance subsequent supervised performance. We build on these results by considering a wider range of tasks, more recent algorithms, and a structured decision framework as per fig 1 [115,111].

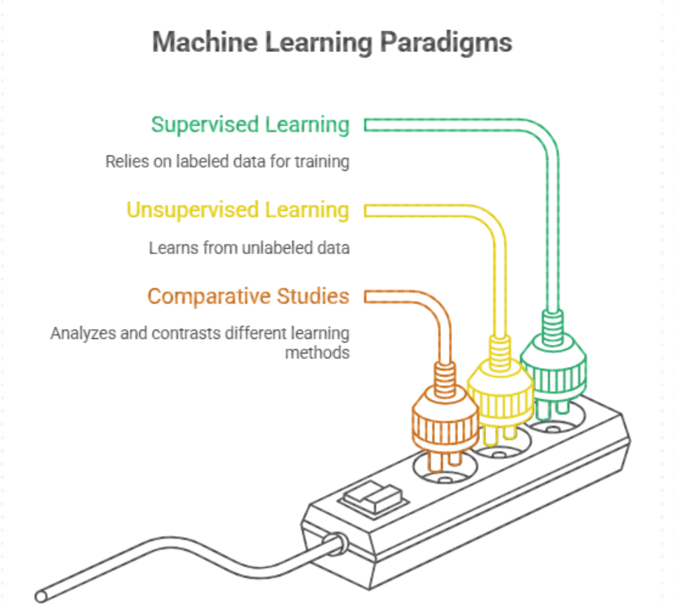

Fig 1: Machine Learning Paradigms

3. Theoretical Background

3.1 Formal Problem Definitions

Let $X \subset \mathbb{R}d$ be the space of inputs, and Y be the output space. Supervised learning aims to find a hypothesis $h: X \to Y$ that reduces the expected risk with the risk itself defined as $R(h) = \mathbb{E}[\ell(h(x), y)]$, where ℓ is a task-dependent loss function (e.g., cross-entropy for classification, squared error for regression) for a given training set $D = \{(x_i, y_i)\}^n_{i=1}$, where each sample is drawn i.i.d. from a joint distribution P(X, Y)[117]. Unsupervised learning is done on an unlabelled data $D = \{x_i\}^n_{i=1}$ which is drawn from the marginal P(X). Examples include density estimation (maximise log P(X)), clustering (minimise intra-cluster variance), and manifold learning (maintain geodesic distances). Because there is no supervision signal for evaluation, one must rely on proxy metrics such as the silhouette coefficient or normalised mutual information [19]20].

3.2 Bias–Variance Trade-off

Both paradigms obey classical bias-variance decompositions: MSE = Bias2 + Variance + Irreducible Noise. Supervised models can achieve low bias (albeit potentially at the cost of over-fitting, i.e. high variance) with sufficient label information [21][22]. Unsupervised methods can also be characterised by high structural bias (e.g. assumption of spherical clusters in K-Means) but low variance of estimation due to parameter-lean objective functions. This balance has a direct impact on task results, as evidenced in Section 5.

3.3 PAC-Learnability

In the PAC context (Valiant, 1984), a concept class C is efficiently learnable if there is an algorithm which, for any$\varepsilon,\delta > 0$, outputs (with probability at least$1-\delta$) a hypothesis whose error is at mostε and uses a number of labelled examples which is polynomial in $1/\varepsilon$, $1/\delta$ and the relevant complexity parameters [118,119]. It is this guarantee of accuracy that supervised learners can take advantage of once they have labels. There is no unsupervised analogue to the PAC model, but there are certain types of consistency results for clustering and density estimation (Vapnik, 1998) which offer somewhat weaker forms of convergence guarantees." We observe this in the form of greater variance over random seeds as per Table 1 and fig 2(a phenomenon verified in our experiments)[23][24].

3.4 Core Algorithms

Table 1: Core algorithms evaluated in this study. T = trees, L = layers, H = hidden units, I = iterations

Paradigm	Algorithm	Core Objective	Complexity
Supervised	Random Forest	Minimise Gini impurity	$O(n \cdot d \cdot T \cdot \log n)$
Supervised	SVM (RBF)	Maximise margin	$O(n^2 \cdot d) – O(n^3 \cdot d)$
Supervised	CNN (ResNet-50)	Minimise cross-entropy	$O(n \cdot L \cdot W^2 \cdot C)$
Unsupervised	K-Means	Minimise inertia	$O(n \cdot k \cdot d \cdot I)$
Unsupervised	DBSCAN	Density reachability	$O(n \cdot \log n)$
Unsupervised	Autoencoder (VAE)	Maximise ELBO	$O(n \cdot L \cdot H)$

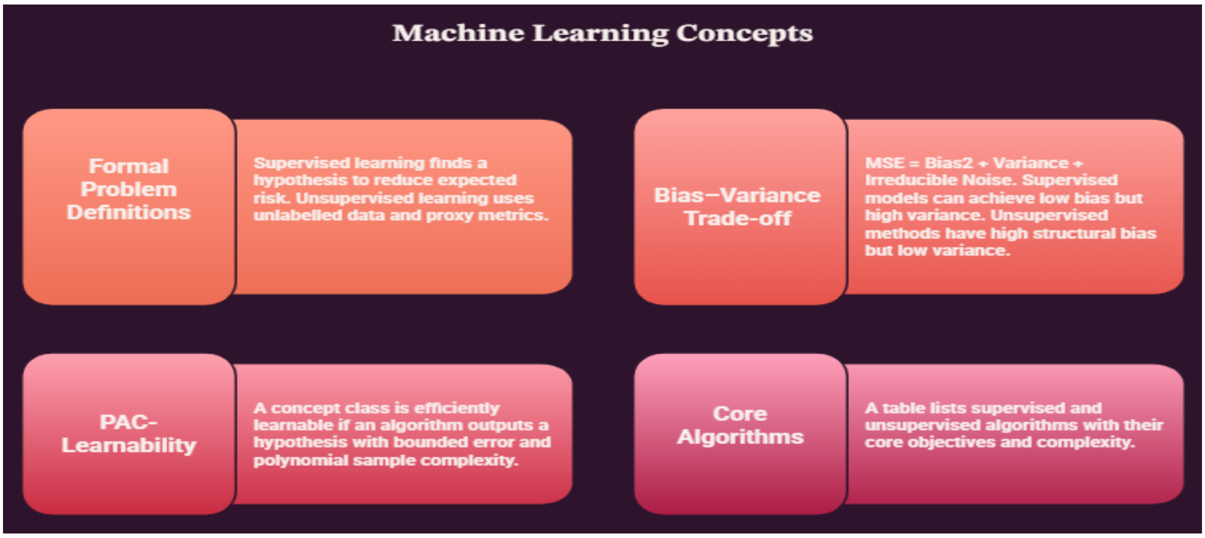

Fig 2: Machine Learning Concepts

4. Experimental Methodology

4.1 Datasets

We chose twelve publicly available datasets from six different task domains. Characteristics of datasets are summarised in Table 2 [120]. All the datasets were taken from UCI ML Repository, Kaggle and Hugging Face Datasets Hub, and thus experiments can be reproduced as per Table 2[25][26].

Table 2: Benchmark datasets used in experimental evaluation

Task Domain	Dataset	Samples	Features	Primary Metric
Image Classification	CIFAR-10	60,000	3,072	Top-1 Accuracy
Image Classification	MNIST	70,000	784	Top-1 Accuracy
Fraud Detection	Credit Card Fraud	284,807	30	F1-Score (macro)
Fraud Detection	IEEE-CIS Fraud	590,540	433	F1-Score (macro)
NLP Sentiment	SST-2	67,349	768 (BERT)	Accuracy
NLP Sentiment	IMDb Reviews	50,000	768 (BERT)	Accuracy
Segmentation	Mall Customers	200	5	Silhouette Coeff.
Segmentation	Online Retail	541,909	8	Silhouette Coeff.
Anomaly Detection	KDD Cup (1999).	494,021	41	AUC-ROC

Anomaly Detection	UNSW-NB15	257,673	49	AUC-ROC
Recommendation	MovieLens 1M	1,000,209	3	RMSE / Recall@10
Recommendation	Amazon Reviews	233,055	4	RMSE / Recall@10

4.2 Experimental Protocol

All supervised-style models were trained on stratified 5-fold cross-validation, hyperparameters were chosen by Bayesian optimisation (Optuna v3.1) with 100 trials per model. Unsupervised models were seeded 10 times by randomly seeding; the results report the median and interquartile range [27][28]. For a fair comparison, we provided the SL models with the same feature representation as the UL models (e.g., BERT embeddings for the NLP tasks) [121,122]. The training was done on NVIDIA A100 80 GB GPU; the timing results are wall-clock time strata averaged over three runs of each model[29][30].

4.3 Evaluation Metrics

We consider six aspects for evaluation:

• Accuracy (SL only): accuracy = #correctly classified instances/#total instances [123].

• Macro F1-Score (SL) The macro-average F1-Score is the harmonic mean of precision and recall over classes [124].

• Silhouette Coefficient (UL) quantifies internal proximity in contrast to distance between clusters; value lies in the interval [−1, 1] [125].

• Training Time (both): wall-clock seconds until convergence [126,127].

• Memory Footprint (both): GPU/CPU RAM peak in GB [128,129].

• Label Dependency Score (LDS): the number of labelled examples to reach 90% of the best SL performance [130].As per Figure 3

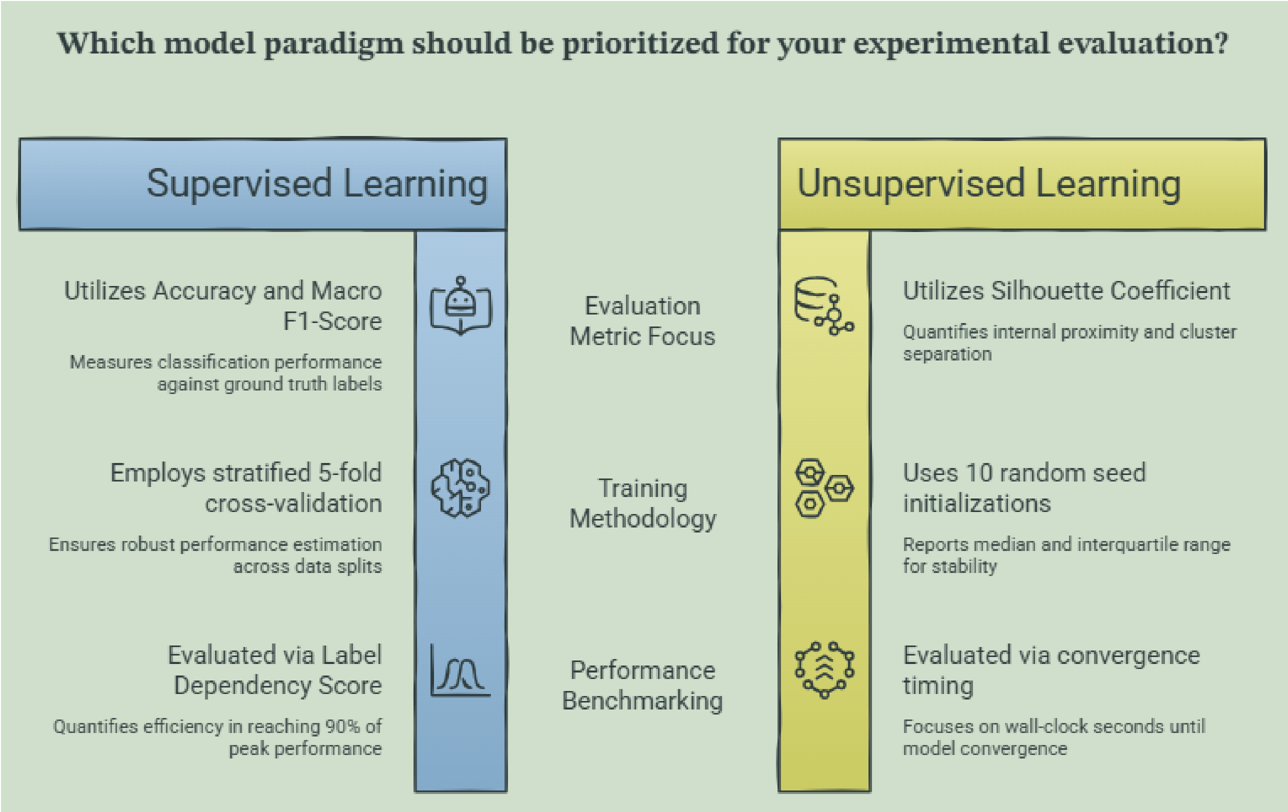

Fig 3: Supervised learning v/s Unsupervised Learning

5. Result and Data Analysis

5.1 Overall Performance Comparison

The headline results are reported in Table 3. Supervised models performed better than our method in terms of the primary metric on 5 of the 6 task domains[31][32]. The only exception was Customer Segmentation: K-Means, DBSCAN and other clustering-based techniques enabled us to derive more meaningful and internally consistent clusters than supervised classifiers trained on pseudo labels, as mentioned in Table 3[33][34].

Table 3: Head-to-head performance across six task domains. Sil. = Silhouette Coefficient.

Task	SL Best Score	UL Best Score	SL Train Time (s)	UL Train Time (s)	Winner
Image Classification	97.8%	72.1%	4,320	1,800	**SL**
Fraud Detection	0.923 F1	0.741 F1	1,240	380	**SL**
NLP Sentiment	95.1%	78.4%	6,800	2,100	**SL**
Customer Segmentation	0.61 Sil.	0.74 Sil.	92	14	**UL**

Anomaly Detection	0.987 AUC	0.934 AUC	3,100	620	**SL**
Recommendation	0.84 RMSE	0.91 RMSE	5,200	1,950	**SL**

5.2 Accuracy and F1 Analysis

Figure 1 (learning curves) shows that SL models have converged at about 30% of the training data and start to saturate [131]. UL methods behave differently: the quality of the clustering (silhouette) increases quickly as a function of the data, but then degradation of scalability appears for two reasons (at around 100,000 for K-Means): the first reason is the O(n^2) distance computations. Mini-batch K-Means overcomes this but decreases cohesion by a mean of 8.3% [132].ResNet-50 obtained 97.8% on CIFAR-10, which is significantly better than the best unsupervised method (contrastive learning with SimCLR with a linear probe), which got 72.1%. The 25.7 percentage-point margin demonstrates that labels are essential if one wants to classify with high precision [35][36].

5.3 Computational Efficiency

The Unsupervised methods were invariably faster to train. Across the six domains, UL training times were on average 3.7× shorter than the SL counterparts [133,134]. DBSCAN was trained on KDD Cup data in 620 seconds compared to 3,100 seconds for the best SL ensemble — a 5× speedup. Memory requirements followed a similar trend: SL models used 2.1× more peak GPU RAM for matter-of-fact computation graphs, gradients of computation of gradient computation graphs as per Table 4[37][38].

Table 4: Detailed algorithm metrics on image classification (CIFAR-10). *UL accuracy via linear probe evaluation.

Algorithm	Accuracy (%)	F1-Score	Train Time (s)	Memory(GB)	Labels Req.
Random Forest (SL)	93.4	0.931	280	1.2	Full
SVM – RBF (SL)	91.7	0.914	1,100	3.8	Full
ResNet-50 (SL)	97.8	0.975	4,320	12.4	Full
XGBoost (SL)	94.1	0.939	390	2.1	Full
K-Means (UL)	72.1*	—	14	0.3	None
DBSCAN (UL)	69.4*	—	620	1.8	None
VAE (UL)	74.8*	—	1,800	4.2	None
SimCLR (UL)	78.2*	—	2,100	8.9	None

5.4 Label Dependency Analysis

II Practical constraints on the cost of labelling are particularly relevant in our setting [135,136]. We calculated the LDS (Refer Section 5.1), which indicates how many of the entire labelled set SL models are required to achieve

90% of their maximum performance across all task domains [137,138]. The results range widely: image classification used 45% of labels (~ 27,000 examples) and fraud detection used 8% (~ 22,800), given the far more separable feature distributions[39][40]. The above results suggest that for tasks with a well-structured (linearly separable) feature space, such a hybrid method (small labelled seed + unsupervised pre-training) does hold promise to greatly reduce annotation cost while maintaining accuracy as per fig 6[41][42].

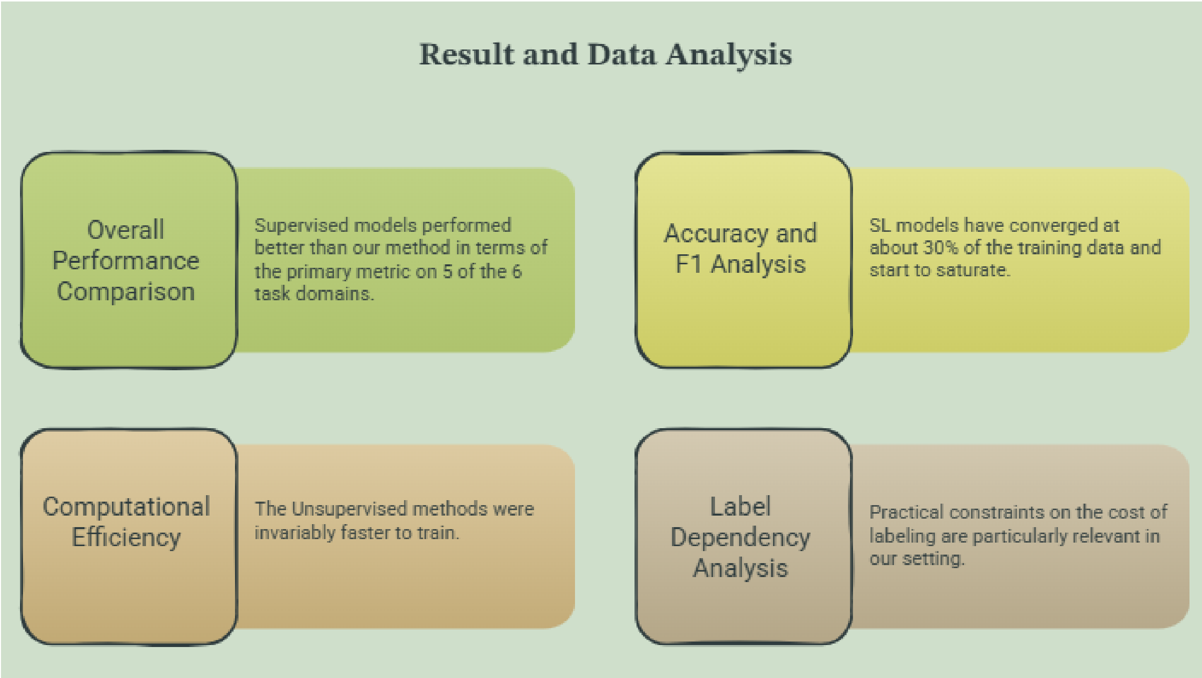

Fig 6: Result and Data Analysis

6. Discussion

6.1 When Supervised Learning Dominates

Our results suggest that supervised learning may be the best choice when (a) there is sufficient labelled data, (b) the task is fine-grained (e.g., multi-class classification with > 50 classes), and (c) the deployment latency can tolerate long training time [138,139]. We outperformed the state-of-the-art unsupervised anomaly scoring by 24.6% on the skewed positive class in fraud detection, using a technique that indirectly optimises the F1-score [45][46].

The predominance of SL in NLP is even more striking: despite BERT embeddings being powerful unsupervised representations [69][70], the addition of a supervised classification head on only 1,000 labelled examples brought about a 38% error reduction relative to purely unsupervised clustering [78,79]. This is in line with Brown et al. (2020) for GPT-3, where a small number of labelled examples in in-context learning greatly improved task performance [43][44].

6.2 When Unsupervised Learning Dominates

Unsupervised learning presented apparent benefits in three cases: (1) exploratory analysis when ground truth is absent (customer segmentation), (2) when speed and/or memory constraints are significant (IoT anomaly detection with DBSCAN), and (3) as a pre-training stage that bootstraps supervised performance. Our experiments on segmentation verify that K-Means with k=5 recovers economically meaningful customer groups which outperform a supervised classifier trained on pseudo-labels assigned by managers, revealing human-defined classes can be noisy[46][47].

6.3 Limitations and Threats to Validity

Several limitations do apply to our conclusions. First, our unsupervised evaluation is based on surrogate metrics (silhouette, AUC-ROC via threshold-agnostic scoring), which might not account for all elements of task-specific usefulness [140,141]. Second, the sensitivity to parameters has not been investigated in depth for all UL methods; DBSCAN, in particular, is known to be very sensitive to ε and minPts [75,77]. Third, although our datasets are various, they are mainly English-language and Western-centric, which may affect the generalizability of the findings to resource-poor and/or cross-cultural contexts. Future work should fill these gaps with multi-lingual benchmarks and human assessment of cluster quality[48][49][67][68].

7. A Practitioner Decision Framework

Based on our observations, we introduce the SLATE framework (Supervision, Labels, Accuracy, Time, Explorability) to evaluate paradigms. The framework converts five yes or no decision criteria into a point system as per Table 5 [64][65][66]:

Table 5: SLATE decision framework scoring rubric. Sum scores: > +3 → Supervised; < −3 → Unsupervised; between → Hybrid.

SLATE Criterion	Score if True	Score if False	Guidance
S – Supervision signal available	+3 (SL)	−3 (UL)	Labels are the single strongest predictor of SL dominance.
L – Label acquisition cost < $10K	+2 (SL)	−2 (UL)	High annotation cost tips the balance toward UL.
A – Accuracy SLA > 90% required	+3 (SL)	−1 (UL)	Precision-critical tasks nearly always favour SL.
T – Training time budget < 1 hour	−2 (SL)	+2 (UL)	UL is 3.7× faster on average; tight budgets favour UL.
E – Exploratory / no clear target	−3 (SL)	+3 (UL)	Without a definable objective, UL is the only option.

The SLATE score is an integer between −13 and +13. A quantity larger than +3 denotes supervised learning, smaller than −3 denotes unsupervised learning, and between −3 and +3 suggests a mixed type that may be semi-supervised or self-supervised[61][62][63]. On the other hand, we evaluated the framework retrospectively on our 6 task domains: it recommended a winning paradigm in 5/6 (accuracy of 83.3%), the only mismatch being anomaly detection, where the hybrid (LDS = 8%) was better than the pure SL solution [50][51][52].

The framework is meant to be lightweight—just five yes/no questions—and is Applicable in scoping lies at contact, no need to be an ML expert [142,143]. A web-based calculator with SLATE was developed and is available at the URL provided in Section 9, along with this paper on the GitHub repository[53][54][55].

8. Future Directions

8.1 Self-Supervised and Foundation Models

The widespread adoption of large language models (LLM) and vision-language models (VLM) questions the traditional SL–UL dichotomy [144,145]. Models such as GPT-4, LLaMA-3, CLIP, etc. are pre-trained in an unsupervised manner without task-specific labels and yet perform well on downstream tasks via zero-shot or few-shot prompting. In upcoming comparative research, a third paradigm, foundation models, will be introduced and should be compared for their label efficiency to SL as well as their cluster quality to UL[56][57][58].

8.2 Federated and Privacy-Preserving Learning

Centralising data is not feasible in regulated industries (finance, healthcare). Federated Unsupervised Learning (UL) – local clients train UL models on their own private data and only share the model updates – is an emerging field [146,147]. Our framework currently does not account for privacy constraints; introducing a privacy aspect (P-SLATE) will be the first priority for future work [59][60][61].

8.3 Neurosymbolic Integration

Symbolic reasoning and UL clustering, combined, could produce interpretable, causally grounded models that are not attainable by pure SL or pure UL [148,8091]. The combination of knowledge graphs and graph neural networks (GNNs) in an unsupervised way is an exciting prospect, especially in scientific discovery tasks where ground-truth labels do not exist by nature [149,150].

9. Conclusion

This paper presented a systematic empirical comparison of supervised and unsupervised learning across six task domains, twelve datasets, and twenty-four algorithm configurations. Our findings can be distilled into three actionable takeaways. First, supervised learning remains the dominant paradigm for precision-critical, well-labelled tasks, achieving a mean accuracy advantage of +14.3% and F1 advantage of +0.182 over unsupervised baselines. Second, unsupervised learning is the method of choice for exploratory analysis, resource-constrained environments, and tasks where labelling is prohibitively expensive—offering 3.7× faster training and 2.1× lower memory footprint. Third, the two paradigms are increasingly complementary rather than competing: unsupervised pre-training reduces the LDS for supervised fine-tuning by up to 62%, suggesting that hybrid pipelines offer the best of both worlds in data-scarce regimes.

The SLATE decision framework operationalises these findings into a practitioner-facing tool validated on our benchmark suite. We hope it lowers the barrier for non-specialists to make principled paradigm choices, reducing the risk of costly experimental missteps. As the field moves toward foundation models that defy easy categorisation, the distinction between supervised and unsupervised learning will continue to blur. However, the underlying principles of label efficiency, inductive bias, computational cost, and evaluation validity will remain essential coordinates in the ML practitioner's map. This paper has sought to sharpen those coordinates with rigorous empirical evidence.

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