Rethinking and Recomputing the Value of ML Models

Burcu Sayin1, Fabio Casati1,2, Andrea Passerini1, Jie Yang3, Xinyue Chen3
1 University of Trento / Via Sommarive 9, 38123 Povo, Trento, Italy
2 Servicenow / Santa Clara, CA, USA
3 Delft University of Technology / Mekelweg 5, 2628 CD Delft, Netherlands

Abstract

In this paper, we argue that the way we have been training and evaluating ML models has largely forgotten the fact that they are applied in an organization or societal context as they provide value to people. We show that with this perspective we fundamentally change how we evaluate, select and deploy ML models - and to some extent even what it means to “learn”. Specifically, we stress that the notion of value plays a central role in learning and evaluating, and different models may require different learning practices and provide different values based on the application context they are applied. We also show that this concretely impacts how we select and embed models into human workflows based on experimental datasets. Nothing of what is presented here is hard: to a large extent it is a series of fairly trivial observations with massive practical implications.

1 Introduction

A few position papers have recently begun to challenge the assumptions that have driven the notion of quality in Machine Learning (ML) (Sayin et al., 2021; Casati et al., 2021) - namely the predominance of the notions of accuracy, precision, recall, and various measures of calibration errors. At the heart of this stance, there are two observations: (i) ML models are almost always applied with a default option where the model can abstain or the inference can be rejected (as in Figure 1), and (ii) the value (cost) of correct/incorrect inferences or rejections are the property of the use case where the model is applied. When we see this perspective, the way we evaluate or select a model and the notion of what we consider to be “learning” change.

The scenario in Figure 1 is central, not a corner case, and obviously applies to scenarios where errors are costly (i.e. self-driving cars). In such cases, we ask humans to take control rather than making an unsure inference. It is also the norm and typical path in enterprise AI applications: Siri and Alexa do not always return the most likely action if they are unsure.

When we think in these terms, and if for simplicity we discuss the problem in terms of classification (though the concepts are identical for any AI capability), what we really mean to say is that our model is applied as a selective classifier (Geifman and El-Yaniv, 2017). Once we realize that selective AI models are the rule, not the exception, our approach to model evaluation changes.

An ML model provides a utility to each, and enterprises adopting a model may come up with some overall notion of utility, or value function. In the simplest case, this value function could be accuracy or F1, but we have already seen that models are deployed as selective classifiers, and now we see that the value depends on the application use case, since for example the model being “wrong” (or right) has different consequences.

The “value” of an “ML solution workflow” depends on how often the workflow rejects the predictions, on the correctness patterns of the predictions that the workflow lets through (not rejected), and
on the “cost” of errors vs the benefits of correct predictions. Notice that the value of the solution workflow depends on the use case (e.g., on how costly errors are), so that a workflow $w_1$ may be more valuable than $w_2$ for use case $uc_1$, but the reverse may be true for $uc_2$. The value of a model therefore depends on the value of the best solution workflows we can build given that model. When we need to take a decision on which model to deploy given a set of options, the value of the resulting solution workflow is the right driving factor.

This notion of quality is not what model accuracy, F1, or AUC measure. We may argue that accuracy metrics are a “good enough” proxy for data science-led model improvements and for model selection, and that all we need is to pick the model with the best accuracy and deploy it by filtering out predictions with confidence below a threshold, but in many cases this is wrong, both in how we select the model and how we integrate into the workflow, and can even unknowingly lead to negative utilities (meaning that we are better off without AI).

To some extent, all this is so trivial that it would not make sense to waste even a second of the reader’s time. There is nothing special or difficult in having value functions, picking a model out of a set of models that performs well given a value function, or assessing if a model performs well over a class of value functions. However, in this paper, we show that if we accept the points above, then the method we use to measure, compare, and even train models change, and the implications of such changes are often neglected in the literature as well as in model leaderboards. In this paper, we specifically make the following contributions:

- We show that universal metrics used for model evaluation can lead to wrong decisions.

- We show that naïvely applying the common approach to reject predictions (filtering by threshold) leads to low or even negative model value and to significant loss of “value” with respect to what can be achieved.

- We show that the above is true even when calibration methods are applied - and discuss why measures of calibration errors fail to capture the most important property of confidence scores: the probability of confidence is high when predictions are correct.

- Finally, we show that simple, decades-old models, especially when trained in domain even with simple text encoders, behave well and often better than large, complex models and provide an intuition of why that may be.

2 Related work

Mimicking the typical use of machine learning models in many practical applications, a number of approaches rely on the combination of a machine learning model making an initial prediction and a human annotator taking over when the model’s confidence is not high enough (Callaghan et al., 2018). Selective classifiers are specifically conceived for this use, by including a rejection mechanism to decide when to abstain from making a prediction. The literature on selective classifiers is quite extensive, covering a wide range of learning algorithms ranging from nearest-neighbour classifiers (Helman, 1970) to SVM (Fumera and Roli, 2002) and neural networks (Cordella et al., 1995; De Stefano et al., 2000; Geifman and El-Yaniv, 2017). The effectiveness of this solution is, however, heavily dependent on the reliability of machine confidence, which has shown to be very poor especially for deep learning (Guo et al., 2017; Balda et al., 2020).

Hybrid Human-AI systems aim at solving classification problems by leveraging both humans and machines (Raghu et al., 2019; Wilder et al., 2021). Crowds have been extensively employed to develop this type of systems, from learning crowd vote aggregation models from features of the crowd task (Kamar et al., 2012), to leveraging crowds to learn features of ML models (Cheng and Bernstein, 2015; Rodriguez et al., 2014).

Understanding a classifier’s properties is a key step to effectively use it (Jiang et al., 2018), and crucially relies on the notion of confidence for individual predictions. Various confidence-based techniques exist in the literature to detect those examples, such as using the entropy of the softmax predictions (Teerapittayanon et al., 2017), measuring trust scores of classifiers based on the distance of samples to a calibration set (Jiang et al., 2018), finding a confidence threshold (using either Shannon entropy (Shannon, 1948), Gini coefficient (Bendel et al., 1989), or norm-based methods (Ng, 2004)) that maximizes the coverage given a target accuracy (Bukowski et al., 2021), and using semantics-preserving data transformation to estimate confidence (Bahat and Shakhnarovich, 2020). However, these confidence measures should be comple-
mented with an appropriate value metric to assess the classifier’s utility in real-world applications.

Figure 2: Typical ways of selectivity in classification.

3 Measuring model “value”

3.1 The setting

Selective classifiers can be implemented in several ways:

(a) We take a model \( m \) that outputs a prediction \( p \) and a confidence \( c \) (or a confidence vector \( c \) with a confidence for a set of possible answers). Then, we filter the predictions to take only those above a certain confidence threshold (Fig. 2a).

(b) The model \( m \) outputs predictions (and possibly a confidence), but we apply a second model \( s \) (the selector) that decides whether to accept the prediction or not, based on some features of the input item \( i \) (Fig. 2b).

(c) A hybrid of the two above cases is where the selector is actually a recalibrator \( r \) that can either take as input only the prediction and confidence measure or also the input features of \( i \) and adjust the confidence vector. We call the first as a feature-agnostic recalibrator and the latter as a feature-aware recalibrator (Fig. 2c).

(d) The model \( m \) is already trained to only output predictions that are “good enough” and includes an “I don’t know” class (Fig. 2d).

The first case is by far the most common, at least in our experience. The second case is an extension and generalization of the first case, in two ways: it can take features as input (that is, \( s \) can be trained as opposed to “just” being a formula), and it can filter based on any formula. Both the feature aware rejector and recalibrator require some form of “training” or machine teaching. An important conceptual distinction here is that a feature-aware rejector makes sense in cases where we know the use case, because that knowledge will tell us when to reject. On the other hand, a feature-aware calibrator can be considered of general usefulness. However, if we consider feature-aware calibrator, one point we make is that in that case calibration and learning really are the same thing. In the end, we have a model \( m' = r(m) \), and one could argue (we do) that calibration in this case is no different than learning or fine-tuning.

In formalizing “value”, we will progressively make a few assumptions that i) allow to simplify the presentation of the problem without altering the essence of the concepts, ii) are reasonable in many if not most use cases, and iii) make the definition of the value function easier to understand and interpret for the users who eventually have to deploy ML into their companies. This is important: people understand accuracy because it is simple, and that has value even if accuracy is “inaccurate” as a metric, and most users will not be able to express complex value functions. We also scope the conversation on classification problems as it makes it easy to ground the examples and terminology, and because it is easier to define a notion of accuracy.

3.2 Definition of value

We have a classifier \( g \) that operates on items \( x \in \mathcal{D} \) and returns either a predicted class \( y \in \mathcal{Y} \) or a special label \( y_r \), denoting "rejection" of the prediction. Given the above, we can compute the average value per prediction of applying a model \( g \) over \( \mathcal{D} \) (so note that what we are talking about here is the value of a solution workflow). Specifically,

\[
V(g, \mathcal{D}) = \rho V_r + (1 - \rho)(\alpha V_c + \sum_{ij} [\Omega \odot V_w]_{ij})
\] (1)

where \( \rho \) is the proportion of items in \( \mathcal{D} \) that are rejected by \( g \) (classified as \( y_r \)), \( \alpha \) is the accuracy for predictions above threshold, \( V_r \) and \( V_c \) are the value of rejecting an item and classifying it correctly respectively, \( \Omega \) is a matrix denoting the proportion of predictions (above threshold) in each cell of the confusion matrix, and \( V_w \) is a matrix with the cost for each type of error (set to zero on the main diagonal corresponding to correct predictions), and \( \odot \) denotes the Hadamard (element-wise) product, of which we take the summation across all elements \( ij \). Notice that \( \rho, \alpha, \Omega \) all depend on \( \mathcal{D} \) and \( g \), and we omit the indices to simplify notation. Also, if our classification problem has \( |\mathcal{Y}| \) classes,
then $\Omega$ and $V_w$ are $|\mathcal{Y}| \times |\mathcal{Y}|$ ($y_r$ is not included here). An alternative representation would be to just say that $V(g, \mathcal{D}) = \Omega V'$, where the confusion and value matrices incorporate the reject class. This would allow us to model the case where the value of rejections and of correct predictions is also class-dependent. Instead, if we only consider costs based on what we misclassify (based on the actual class) then $\Omega$ and $V_w$ become vectors, and in the most common case where all wrong predictions are considered equally bad in a first approximation, then $\Omega$ and $V_w$ are a scalar, and $\Omega = 1 - \alpha$, so in this case the formula simplifies to:

$$V(g, \mathcal{D}) = \rho V_r + (1 - \rho) (\alpha V_c + (1 - \alpha)V_w)$$  \hspace{1cm} (2)$$

At this point, while we could carry on with this math, we simplify the notation for several reasons: the first is, well, to simplify the notation. The second is to remove dimensionality (values can be measured in dollars, but here we care about relative values because we want to compare models and learning strategies), and the third is to arrive at a formulation that is digestible for process owners (the people who apply AI in their processes), for whom it may be hard to come up with the three cost parameters/vectors. None of the above simplifications change the concepts presented.

Here we depart from Sayin et al. (2021) and define as baseline the case where we do not have ML, or, equivalently, we reject any prediction. We set this baseline at 0, which means that we set $V_r = 0$. This makes it easy for us to evaluate a model in terms of whether it improves on the baseline or not - and therefore in terms of whether we should adopt AI or not for a given problem.

$$V(g, \mathcal{D}) = (1 - \rho)(\alpha V_c + (1 - \alpha)V_w)$$  \hspace{1cm} (3)$$

We also express $V_w$ in terms of $V_c$, as in $V_w = -k V_c$, where $k$ is a constant telling us how bad is an error with respect to getting the correct prediction.

This leads us to:

$$V(g, \mathcal{D}) = V_c (1 - \rho)(\alpha - k(1 - \alpha))$$  \hspace{1cm} (4)$$

$V_c$ is a scaling factor for the above value formula. When reasoning about an AI-powered solution workflow we do not really care about that factor, we can think in terms of value “per unit of $V_c$ dollars”, or equivalently assume the magnitude of $V_c$, so we can focus on value. From now on we, therefore, focus on “value per dollar unit of rejection cost” $V' = V/V_c$. We avoid introducing a new symbol and, without loss of generality with respect to the above equations, we set $V_c = 1$ and get:

$$V(g, \mathcal{D}) = (1 - \rho)(\alpha - k(1 - \alpha))$$  \hspace{1cm} (5)$$

Notice that nothing really changes in the concepts we want to stress between equations 1 and 5, but the latter simplifies the presentation.

### 3.3 Filtering by threshold

We focus now on the most common situation observed in practice, the one in which the model selectivity is applied by thresholding confidence values and rejecting predictions that have confidence $c$ less than a threshold $\tau$ (case (a) in Figure 2). In this setting, we are given a model $m$ that processes items $x \in \mathcal{D}$ and returns a vector of confidences (one per class). Typically this is the output of a softmax. Specifically, for each $x$, we consider the pair $(\hat{y}, \hat{c})$ corresponding to the top level prediction of $m(x)$ and the confidence associated with such prediction. Given a threshold $t$, we define a function $s$ as:

$$s(\hat{y}, \hat{c}, t) = \begin{cases} 
\hat{y}, & \hat{c} \geq t, \\
\hat{y}_r, & \text{otherwise.}
\end{cases}$$

where $y_r$ is a special class label denoting “rejection” of the prediction. Our classifier $g$ is therefore now expressed in terms of $m$ and $t$. This means that we can express the value as a function of $m, \mathcal{D}, t$.

In a given use case, when we are given a model $m$ and have knowledge of $\Omega$ (or of $k$ in the simplified case), we select the threshold $\tau \in [0, 1]$ that optimizes $V(g, \mathcal{D})$ (We assume here $\tau$ is unique, or that we randomly pick one if not). This means that we can express the value of our classification logic as a function of $(m, \mathcal{D}, k)$

$$V(m, \mathcal{D}, k) = (1 - \rho_r)(\alpha_r - k(1 - \alpha_r))$$  \hspace{1cm} (6)$$

Notice that $\tau$ can be set empirically on some tuning dataset $\mathcal{D}$ (it depends on $m, \mathcal{D}, k$), and $\rho_r$ and $\alpha_r$ reflect the proportions $\rho$ and $\alpha$ given $\tau$. However, if we are aware of properties of the confidence vectors, we can set $\tau$ regardless of $\mathcal{D}$. For example, if we assume perfect calibration (where the expected accuracy for a prediction of confidence $c$ is $c$), then we know that the threshold is at the point where the value of accepting a prediction is greater than zero. If calibration is perfect, then $\alpha_r = \tau$. This means that to have $V(m, \mathcal{D}, k) > 0$ we need $\tau - k + k\tau > 0$, which means $\tau > k/(k + 1)$. 


Algorithm 1 Experiment flow

1: for each (model, task) pair do
2:     Train or fine-tune the model using the training set
3:     Analyze the model's confidence distribution on the test set
4:     Analyze the model's performance on the test set based on traditional accuracy metrics
5:     Perform a value-based analysis considering different values of k:
6:         for each k do
7:             Find the theoretical threshold $t$ based on $k$ ($t = k/k + 1$)
8:             Find the empirical threshold $t_{empirical}$ (which maximizes the value) on the validation set
9:             Find the value (based on $t$) and the empirical value (based on $t_{empirical}$) on the test set
10:        end for
11:     Output the Value function (plot Value vs k)
12:     Plot confidence distributions
13: end for

This conforms to intuition: if k is large, it never makes sense to predict, better go with the default. If k=0 (no cost for errors), we might as well always predict. If k=1 (errors are the mirror image of correct predictions), then our threshold is 0.5.

4 Experiments

We can experiment with various angles based on the concepts described. In this paper, we explore:

- whether accuracy is indicative of model quality, and if a less accurate model may be preferable than a more accurate one, thereby implying that taking decisions and determining leaderboards based on accuracy could be a limiting perspective at best.

- how to set confidence threshold based on value, and the extent to which calibration or threshold tuning affect value.

- which models and in which use cases perform well for different values of $k$

Specifically, we analyze both the behavior of simple as well as state of the art models over various datasets, models, and text encoders and provide insights on what model developers and process owners should look for in a model and in how to deploy it in a selective fashion. We refer the reader to our GitHub repo for the companion code.

4.1 Experimental Setup

Tasks, Datasets and Leaderboards. We experimented on a set of text classification tasks (see Table 1 - and Table 5 in the appendix) where making errors is especially harmful. Algorithm 1 shows our experiment flow.

Hate-speech detection on Twitter. Arango et al. (2019) analyzed two widely used models (Agrawal and Awekar, 2018; Badjatiya et al., 2017) and tested on popular twitter hate-speech datasets (Waseem and Hovy, 2016; Davidson et al., 2017; Zhang et al., 2019) with different settings. We replicated the original tests in Experiment 1 and used the Arango et al. (2019) settings in Experiment 2 (more details in the appendix A.3).

Clickbait detection. The Clickbait Challenge on the Webis Clickbait Corpus 2017 was classifying Twitter posts as a clickbait or not. Both training and test sets are publicly available, while each team was free to choose a subset of the training set for validation (we followed the "blobfish" team).

Multi-Domain Sentiment Analysis - and Dataset (MDS). Sentiment analysis based on a publicly available dataset for domain adaptation. The data includes four categories of Amazon products (DVD, Books, Electronics, and Kitchen), and the task is to learn from one of these domains and analyze the sentiment on the others.

In addition to the above binary classification problems and data, we used seven publicly available multi-class datasets with different class distributions (see Table 5 in the appendix for details).

Models. We used various models for each task in our experiments (see Table 1 and appendix A.2 for the details). For the Hate Speech and Clickbait datasets we tested the leaderboard models. For MDS dataset, we used the leaderboard model “Multi-task tri-training (mttri)” by Ruder and Plank (2018), two transformer models (a T5-base model fine-tuned for sentiment analysis and SieBERT (Heitmann et al., 2020), a fine-tuned checkpoint

---

1https://tinyurl.com/rethinking-value-of-ml-models
2https://webis.de/data/webis-clickbait-17.html
3https://zenodo.org/record/5530410#.YWcFtC8RrRV
4http://nlpprogress.com/english/domain_adaptation.html
5https://tinyurl.com/5-base-finetuned-sentiment
of RoBERTa-large (Liu et al., 2019), as well as a simple Logistic Regression (LogR) model and two multi-layer perceptron models from the scikit-learn library\(^6\) with one (MLP1) and four (MLP4) hidden layers respectively. We used LogR, MLP1 and MLP4 for the multi-class datasets. We tested simple models with different text encoders: (i) TF-IDF, (ii) MPNET, and (iii) nnlm (details in A.4), but for simplicity we show the results with TF-IDF (see the appendix-Figure 16 for further results).

**Cost Settings.** Following the simplification in Section 3.2, we set \(V_f = 0\) and \(V_c = 1\), and then test the models using different values of \(k \in [0, 10]\). In binary tasks, we consider the cost of false positives \((k_{fp})\) and false negatives \((k_{fn})\) separately.

### 4.2 Results

#### 4.2.1 Accuracy vs Value

We first investigated the extent to which models are robust across varying cost factors \(k\), and consequently also whether we can use accuracy metrics to select the “best” model to deploy in an ML platform. We did so both for challenges/leaderboard models and for the set of small/simple and larger models as described. As an example, Table 2 shows results on MDS dataset that even for fairly small and very realistic cost factors, the model we would choose with a value oriented approach differ from what we would choose based on accuracy. The appendix show many other cases where this happens - as well as cases where instead the model with the best accuracy also has best value across several costs metrics. Notice that \(k = 4\) is actually a very small and realistic cost factor: it means that “being wrong is 4 times as bad” with respect to the advantage of being right. Most scenarios have values of \(k\) way more extreme. Notice also that accuracy corresponds to the case where we do not reject any predictions. This is equivalent to setting \(k = 0\). Indeed, not filtering examples (accepting even low confidence predictions) means that we do not care about being wrong. Another important observation is that in many cases, across models and datasets, we often find that even leaderboard models have negative value, and even for cost factors of \(k = 1\).

---

\(^6\)https://scikit-learn.org/
4.2.2 Calibration vs Threshold Optimization

As explained in Section 3.3, we expect that the theoretical threshold would maximize the value of a model if it is well-calibrated. If this assumption is not true, then we should either find an “optimal” threshold empirically by tuning it on a validation set, or we should first calibrate the model (e.g., via temperature scaling (Guo et al., 2017) or other methods) and then maximize expected value by filtering based on the theoretical threshold. We compared how accuracy and value are affected by either calibrating the model or tuning the threshold on a “validation” dataset. For calibration, we first calibrate models via temperature scaling and then use the theoretical threshold to compute the values. For tuning, we investigated how empirically choosing the confidence threshold for each (model, task) pair affects value. We used a validation set to find the threshold that maximizes the model’s value for every single $k$, and then used those thresholds to compute the values on test set.

Figure 3 shows the results for uncalibrated models, calibrated models (second column) and threshold tuning (third column) for the hate speech and clickbait cases (more results in the appendix and additional material). Notice that calibration helps but still leads to very low, zero, and sometimes negative values even at low-cost factors (result on the Hate speech dataset when we run Experiment 2 - see Figure 3, second column). The empirical threshold provides equal or better values than the theoretical threshold in almost all cases.

The rightmost column of Figure 3 reports the highest achievable results, obtained by optimizing the threshold on the test set, showing how threshold tuning on the validation set is close to optimal in most cases. Still, there are cases (Hate-speech, Exp. 2) in which the models are useless (Value=0, all predictions rejected) for most values of $k$. We report results on all datasets in the Appendix A.6 and show that they are consistent with these findings.

4.2.3 The effect of complexity and out-of-distribution data.

We investigated why models that rank high in terms of accuracy drop in quality when the cost ratio increases, while others are more “robust”. As an example, we show results from an experiment on the MDS dataset to see the impact on cross-over domains (on out-of-distribution samples). The leaderboard model for this task is “mttri” (Ruder and Plank, 2018) but we also tested two transformer models (a fine-tuned T5-base and SieBERT), LogR, MLP1 and MLP4 as explained in Section 4.1. We trained all the models (except T5 and SieBERT) on each domain and tested on the other 3 domains separately (so that we have 12 different cases of <source domain,target domain> pairs). We then calculated the average values of each model on each target domain (see Table 3 for the average accuracy of each model). SieBERT is the best one (even better than the leader-board mttri model) based on accuracy, but this is not the case in terms of value.

| Model  | DVD       | Books     | Electronics | KITCHEN   |
|--------|-----------|-----------|-------------|-----------|
| LOGREG | 0.762     | 0.524     | 0.319       | 0.162     | 0.055     | 0.003     |
| MLP1   | 0.749     | 0.497     | 0.327       | 0.186     | 0.081     | 0.062     |
| MLP4   | 0.735     | 0.47      | 0.24        | -0.143    | -0.78     | -1.06     |
| MTTRI  | 0.808     | 0.621     | 0.441       | 0.148     | -0.354    | -0.58     |
| T5     | 0.784     | 0.566     | 0.352       | -0.08     | -0.944    | -1.376    |
| SieBERT| 0.842     | 0.685     | 0.527       | 0.217     | -0.397    | -0.705    |

Table 3: Average accuracy of models on MDS Dataset.

Figure 4 shows the results. In most of the cases simple LogR and MLP1 models with simple text encoders (i.e. TF-IDF) have better value than the complex models for high $k$ values. We also tested a fine-tuned version of T5 – base model for sentiment analysis (which does not output the confidence values associated to each prediction), that is why we could only measure its value by accepting all the predictions (see Figure 5a). Related to this, notice how the inability to filter (reject) predictions lead to negative value, even with the fine-tuned T5 that performs very well in terms of accuracy.

We repeated the experiments on seven multi-class datasets and observed that the MLP4 model is worse than a simple MLP1 model over almost all datasets. Furthermore, MLP4 is even worse than a simple LogR model on four datasets (please see Figure 5b for an example for each case, and the rest can be found in the Appendix-Figure 14).

The pattern in results suggests that simple models (usually thought to be naturally well calibrated) perform relatively well when errors are costly and that for high-cost factors models trained on a dif-
Different domain also tend to perform poorly, which suggests that even simple models trained in domain can be preferable. This observation is crucial in enterprise AI, where each company and vertical has its own “language” skew. Interestingly and perhaps not surprisingly, large pre-trained language models that are not bottlenecked by insufficient training data perform well across the board. This can be due to two reasons (besides the models being very powerful): (i) we know that large models with very large train datasets are reasonably well calibrated (e.g. see Jiang et al., 2021), and (ii) when the training data is so large, fewer examples are out of distribution in terms of language. For example, GPT-3\(^7\) is trained on about 45TB of text data from various datasets and it performs very well on MDS dataset (see Table 4 - and the appendix A.5 and Figure 8). The reason is that the MDS dataset is quite old and probably GPT-3 model has already learned it (so the MDS dataset does not include out-of-distribution samples for GPT-3 model). However, such models may be too costly or impractical due to their scale, and the problem still remains for enterprise datasets which may be quite different from what the large pre-trained model has seen. Furthermore, as the cost grows, the difference with respect to simple models drops significantly.

7https://openai.com/api/

### Table 4: Performance of fine-tuned GPT-3 on MDS Dataset (Average values using theoretical threshold)

| TARGET    | ACCURACY | k=1 | k=2 | k=4 | k=8 | k=10 |
|-----------|----------|-----|-----|-----|-----|------|
| DVD       | 0.872    | 0.664 | 0.534 | 0.367 | 0.164 | 0.089 |
| BOOKS     | 0.806    | 0.613 | 0.46 | 0.272 | 0.077 | 0.004 |
| ELECTRONICS | 0.82    | 0.641 | 0.499 | 0.322 | 0.127 | 0.051 |
| KITCHEN   | 0.853    | 0.706 | 0.599 | 0.464 | 0.308 | 0.251 |

5 Limitations and Conclusion

The takeaway from our experiments is that using accuracy-oriented metrics (that is, metrics that assume models are applied without rejection) is as a minimum a risky proposition - and this is true even for models widely acknowledged as “leaders”. We should always assess models over a range of cost factors, and at least for reasonable cost factors we expect based on the set of application use cases we are targeting. \(k = 0\) (accuracy) is almost never a reasonable one. We also saw how applying models without thresholding can lead to negative value, and that threshold tuning seems to perform better than calibration. We also hypothesize and have obtained some support for identifying complexity and out-of-distribution as factors that may lead to rapid model quality degradation for higher cost factors.
This being said, we see this work more as providing evidence of a problem and outlining the research needs: more studies (especially with large models and in vs out of distribution datasets) are needed to validate the hypothesis and a deeper understanding of how calibration, confidence distribution, and size of validation set affect model value.

References

Sweta Agrawal and Amit Awekar. 2018. Deep learning for detecting cyberbullying across multiple social media platforms. In Advances in Information Retrieval, pages 141–153, Cham. Springer International Publishing.

Aymé Arango, Jorge Pérez, and Barbara Poblete. 2019. Hate speech detection is not as easy as you may think: A closer look at model validation. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’19, page 45–54, New York, NY, USA. Association for Computing Machinery.

Pinkesh Badjatiya, Shashank Gupta, Manish Gupta, and Vasudeva Varma. 2017. Deep learning for hate speech detection in tweets. In Proceedings of the 26th International Conference on World Wide Web Companion, WWW ’17 Companion, page 759–760, Republic and Canton of Geneva, CHE. International World Wide Web Conferences Steering Committee.

Yuval Bahat and Gregory Shakhnarovich. 2020. Classification confidence estimation with test-time data-augmentation. ArXiv, abs/2006.16705.

Emilio Balda, Arash Behboodi, and Rudolf Mathar. 2020. Adversarial examples in deep neural networks: An overview. In Deep Learning: Algorithms and Applications, pages 31–65.

Valerio Basile, Cristina Bosco, Elisabetta Fersini, Debora Nozza, Viviana Patti, Francisco Manuel Rangel Pardo, Paolo Rosso, and Manuela Sanguinetti. 2019. SemEval-2019 task 5: Multilingual detection of hate speech against immigrants and women in Twitter. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 54–63, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

R. Bendel, S. Higgins, J. Tebery, and David Pyke. 1989. Comparison of skewness coefficient, coefficient of variation, and gini coefficient as inequality measures within populations. Oecologia, 78:394–400.

Michał Bukowski, Jaroslav Kurek, Izabella Antoniuk, and Albina Jegorowa. 2021. Decision confidence assessment in multi-class classification. Sensors, 21:3834.

William Callaghan, Joslin Goh, Michael Mohareb, Andrew Lim, and Edith Law. 2018. Mechanicalheart: A human-machine framework for the classification of phonocardiograms. In CSCW’18, volume 2, pages 28:1–28:17.

Fabio Casati, Pierre Noel, and Jie Yang. 2021. On the value of ml models. In Neurips workshop on Human Decisions.

Justin Cheng and Michael S. Bernstein. 2015. Flock: Hybrid crowd-machine learning classifiers. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing.

L.P. Cordella, C. De Stefano, F. Tortorella, and M. Vento. 1995. A method for improving classification reliability of multilayer perceptrons. IEEE Transactions on Neural Networks, 6(5):1140–1147.

Thomas Davidson, Dana Warmelsey, M. Macy, and Ingmar Weber. 2017. Automated hate speech detection and the problem of offensive language. In International AAAI Conference on Web and Social Media (ICWSM).

C. De Stefano, C. Sansone, and M. Vento. 2000. To reject or not to reject: that is the question—an answer in case of neural classifiers. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 30(1):84–94.

Giorgio Fumera and Fabio Roli. 2002. Support vector machines with embedded reject option. In Proceedings of the First International Workshop on Pattern Recognition with Support Vector Machines, SVM ’02, page 68–82, Berlin, Heidelberg. Springer-Verlag.

Yonatan Geifman and Ran El-Yaniv. 2017. Selective classification for deep neural networks. In Advances in Neural Information Processing Systems, volume 30.

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger. 2017. On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning - Volume 70, ICML’17, page 1321–1330. JMLR.org.

Mark Heitmann, Christian Siebert, Jochen Hartmann, and Christina Schamp. 2020. More than a feeling: Benchmarks for sentiment analysis accuracy. Communication & Computational Methods eJournal.

Martin E. Hellman. 1970. The nearest neighbor classification rule with a reject option. IEEE Transactions on Systems Science and Cybernetics, 6(3):179–185.

Heinrich Jiang, Been Kim, Melody Y. Guan, and Maya Gupta. 2018. To trust or not to trust a classifier. In Proceedings of the 32nd International Conference on Neural Information Processing Systems, NIPS’18, page 5546–5557, Red Hook, NY, USA. Curran Associates Inc.
Zhengbao Jiang, Jun Araki, Haibo Ding, and Graham Neubig. 2021. How can we know when language models know? on the calibration of language models for question answering. Transactions of the Association for Computational Linguistics, 9:962–977.

Ece Kamar, Severin Hacker, and Eric Horvitz. 2012. Combining human and machine intelligence in large-scale crowdsourcing. In AAMAS’12 - Volume 1, pages 467–474.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. ArXiv, abs/1907.11692.

Andrew Y. Ng. 2004. Feature selection, l1 vs. l2 regularization, and rotational invariance. In Proceedings of the Twenty-First International Conference on Machine Learning, ICML ’04, page 78, New York, NY, USA. Association for Computing Machinery.

Maithra Raghu, Katy Blumer, Greg Corrado, Jon M. Kleinberg, Ziad Obermeyer, and Sendhil Mullainathan. 2019. The algorithmic automation problem: Prediction, triage, and human effort. CoRR, abs/1903.12220.

Carlos Rodriguez, Florian Daniel, and Fabio Casati. 2014. Crowd-based mining of reusable process model patterns. In Business Process Management, pages 51–66.

Sebastian Ruder and Barbara Plank. 2018. Strong baselines for neural semi-supervised learning under domain shift. In The 56th Annual Meeting of the Association for Computational Linguistics (ACL 2018), pages 1044–1054.

Burcu Sayin, Jie Yang, Andrea Passerini, and Fabio Casati. 2021. The science of rejection: A research area for human computation. In The 9th AAAI Conference on Human Computation and Crowdsourcing, HCOMP 2021. AAAI Press.

C. E. Shannon. 1948. A mathematical theory of communication. The Bell System Technical Journal, 27(3):379–423.

Surat Teerapittayanon, Bradley McDanel, and H. T. Kung. 2017. Branchynet: Fast inference via early exiting from deep neural networks. ArXiv, abs/1709.01686.

Zeerak Waseem and Dirk Hovy. 2016. Hateful symbols or hateful people? predictive features for hate speech detection on Twitter. In Proceedings of the NAACL Student Research Workshop, pages 88–93, San Diego, California. Association for Computational Linguistics.

Bryan Wilder, Eric Horvitz, and Ece Kamar. 2021. Learning to complement humans. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI’20.

Mike Zhang, Roy David, Leon Graumans, and Gerben Timmerman. 2019. Grunn2019 at SemEval-2019 task 5: Shared task on multilingual detection of hate. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 391–395, Minneapolis, Minnesota, USA. Association for Computational Linguistics.
A Supplemental material

A.1 Datasets

Table 5 shows the details of each dataset used in our experiments.

A.2 Models

For each task, we tested various models as explained below:

- For the hate-speech dataset, we test the following SOTA models: (i) Badjatiya et al. (Badjatiya et al., 2017) which uses a Recurrent Neural Network (an Embedding Layer (dimension=200) followed by an LSTM network (dimension=50) and a fully connected layer with 3 neurons plus a Softmax) to construct word embeddings and then classify them with Gradient-Boosted Decision Tree. In the original paper, test accuracy is measured as the average of the ten folds in cross validation; however, in our reproduction we separated validation and test set before cross validation, and they are used for evaluation only after training. (ii) one model from Agrawal and Awekar (Agrawal and Awekar, 2018) which is composed of an Embedding Layer (dimension=50), followed by a Bidirectional LSTM network (dimension=50), and a fully connected layer of 3 neurons with a Softmax activation. Both models use Dropout (probabilities 0.25 and 0.5, respectively) for regularization, cross-entropy as the loss function, and the Adam optimizer (10 epochs).

- For the clickbait detection dataset, we test 4 models from one leaderboard team on clickbait challenge: "fullnetconc", "weNet", "lingNet", and "fullNet" which are published on Github15. This team modified the task into binary classification - they categorized items with a score under 0.5 into "non-clickbaiting", vice versa.

- For the MDS dataset, we referred to the leaderboard for the sentiment analysis task of "Domain adaptation"16 and tested the best-performing leader-board model "Multi-task tri-training (mtri)" by Ruder et. al. (Ruder and Plank, 2018) that is an MLP model with one hidden layer of 50 dimensions, sigmoid activations, and a softmax output. There were 3 other models in the list but their source codes were not published. We further tested two transformer models: (i) Google’s T5-base model17 (12-layers, 768-hidden-state, 3072 feed-forward hidden-state, 12-heads, 220M parameters) fine-tuned on IMDB dataset18 for sentiment analysis task, and (ii) SieBERT19 (Heitmann et al., 2020): a fine-tuned version of RoBERTa-large20 model (Liu et al., 2019) (24-layer, 1024-hidden-state, 16-heads, 355M parameters) for sentiment analysis task that is fine-tuned and evaluated on 15 diverse text sources. Finally, we tested the simple Logistic Regression (LogR) and 2 different MLP models from scikit-learn library21 (all parameters we used are explained below).

- For the 7 multi-class datasets, we tested the LogR and 2 MLP models from scikit-learn with the following parameters:
  - **LogR**: We use the default parameters except the max_iter. We increased the max_iter from 100 to 1000 as it did not converge on some datasets with 100 iterations.
  - **MLP1**: We use the default parameters except one; we set early_stopping = True in our experiments.
  - **MLP4**: The only difference from MLP1 is the modification on the number of hidden layers; we set hidden_layer_sizes = (100, 100, 100, 100). This parameter is set to hidden_layer_sizes = (768, 384, 192, 192) in MDS experiments.

---

15github.com/clickbait-challenge/blobfish
16nlpprogress.com/english/domain_adaptation.html
17https://tinyurl.com/t5-base-finetuned-sentiment
18https://huggingface.co/datasets/imdb
19https://huggingface.co/SieBERT-sentiment
20https://huggingface.co/roberta-large
21https://scikit-learn.org/
A.3 Experiment details on Hate Speech Dataset

We conducted two different experiments on Hate Speech dataset:

- **Experiment 1**: We used (Waseem and Hovy, 2016) dataset for training, validation, and test set, but we could only recover 9671 of the tweets as of October 2021 (the dataset size is 14949 in the original paper).

- **Experiment 2**: We further analyzed their performance in Experiment 2 based on the observations of Arango et al. (Arango et al., 2019): we used their new dataset (5068 retrieved) as training set. For validation and test set, used the SemEval 2019 dataset from the “Multilingual detection of hate speech against immigrants and women in Twitter” task (Basile et al., 2019).

A.4 Text encoders

We used various text encoders:

- **TF-IDF**: The TfIdf vectorizer of sklearn\(^22\) with the following parameters: "min_df=0, max_features = 1024, strip_accents='unicode', analyzer='word', token_pattern=r"w{1,}|", ngram_range=(1, 1), use_idf=1, smooth_idf=1, sublinear_tf=1, stop_words='english', lowercase=False".

- **MPNET**: The transformer model from Hugging Face\(^23\) with default parameters.

- **nnlm**: Google’s universal sentence embedding model that is trained on English Google News 200B corpus, accessible via TensorFlow\(^24\).

A.5 GPT-3 Experiments

Since GPT-3 is producing human-like text given an input, we fine-tuned it using the OpenAI API\(^25\). First, we prepared the MDS dataset for GPT-3; we cleaned sentences that have more than 2049 tokens, and renamed the text column as "prompt" and the ground truth column as "completion". Then, we used OpenAI API to fine-tune GPT-3 separately on each of the 4 domains (DVD, books, electronics, and kitchen). We specified "classification_n_classes" parameter as 2 and "classification_positive_class" as 1, so that the API tunes GPT-3 for a binary sentiment analysis. Fine-tuning 4 models on MDS dataset costs a total of $7.15.

In order to test the fine-tuned models on different target domains, we specified the prompt in the format of "sentence + -> " because the API itself uses " ->" sign to teach GPT-3 that the sentiment for a prompt is (' ->') the completion. Thus, fine-tuned GPT-3 models produce either 0 or 1 for the given input. Testing each fine-tuned model on the other 3 domains (so, 12 cases in total) costs $43.89. We provide our source code on Github\(^26\) to show every step of using GPT-3 in our experiments. Figure 8 shows the average values of GPT-3 on each domain.

\(^{22}\)https://tinyurl.com/sklearn-tfidf-vectorizer

\(^{23}\)huggingface.co/docs/transformers/model_doc/mpnet

\(^{24}\)https://tinyurl.com/google-nnlm

\(^{25}\)https://openai.com/api/

\(^{26}\)https://tinyurl.com/rethinking-value-of-ml-models
A.6 Further Results

A.6.1 Binary datasets - Supplementary Results

Figure 6: Value curves of binary datasets for increasing $k$. 
Table 6: Performance of SOTA models, with theoretical threshold \((k_{fp} = 1, \text{and } k_{fn} \in \{1, 2, 4, 8, 10\})\).

| Task      | Model                  | Accuracy | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 |
|-----------|------------------------|----------|--------|--------|--------|--------|--------|--------|
| HATE-SPEECH | Badj. et al., Exp. 1    | 0.822    | 0.644  | 0.545  | 0.389  | 0.315  | 0.278  |
|           | Agr. et al., Exp. 1    | 0.732    | 0.464  | 0.405  | 0.32   | 0.157  | 0.098  |
|           | Badj. et al., Exp. 2    | 0.489    | -0.022 | -0.248 | -0.473 | -0.537 | -0.516 |
| CLICKBAIT  | FullNetConc            | 0.857    | 0.715  | 0.608  | 0.368  | 0.131  | 0.103  |
|           | LINGNet                | 0.852    | 0.703  | 0.604  | 0.381  | 0.124  | 0.094  |
|           | FULLNET                | 0.856    | 0.713  | 0.631  | 0.446  | 0.15   | 0.103  |

Table 7: Performance of SOTA models, with theoretical threshold \((k_{fp} = k_{fn} \in \{1, 2, 4, 8, 10\})\).

| Task      | Model                  | Accuracy | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 |
|-----------|------------------------|----------|--------|--------|--------|--------|--------|--------|
| HATE-SPEECH | Badj. et al., Exp. 1    | 0.822    | 0.644  | 0.51   | 0.362  | 0.272  | 0.217  |
|           | Agr. et al., Exp. 1    | 0.732    | 0.464  | 0.22   | -0.213 | -1.081 | -1.499 |
|           | Badj. et al., Exp. 2    | 0.489    | -0.022 | -0.469 | -1.077 | -1.793 | -2.06  |
| CLICKBAIT  | FullNetConc            | 0.857    | 0.715  | 0.564  | 0.266  | 0.041  | 0.013  |
|           | LINGNet                | 0.852    | 0.703  | 0.561  | 0.306  | 0.04   | 0.011  |
|           | FULLNET                | 0.856    | 0.713  | 0.588  | 0.367  | 0.061  | 0.015  |

Table 8: Performance of SOTA models after temperature scaling, with theoretical threshold \((k_{fp} = 1)\).

| Task      | Model                  | Accuracy | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 |
|-----------|------------------------|----------|--------|--------|--------|--------|--------|--------|
| HATE-SPEECH | Badj. et al., Exp. 1    | 0.822    | 0.644  | 0.545  | 0.417  | 0.309  | 0.278  |
|           | Agr. et al., Exp. 1    | 0.732    | 0.464  | 0.367  | 0.005  | 0.005  | 0.005  |
|           | Badj. et al., Exp. 2    | 0.489    | -0.022 | 0.077  | 0.077  | 0.077  | 0.077  |
| CLICKBAIT  | FullNetConc            | 0.857    | 0.715  | 0.647  | 0.562  | 0.464  | 0.424  |
|           | LINGNet                | 0.852    | 0.703  | 0.635  | 0.55   | 0.447  | 0.414  |
|           | FULLNET                | 0.856    | 0.713  | 0.64   | 0.558  | 0.458  | 0.419  |

Table 9: Performance of SOTA models after temperature scaling, with theoretical threshold \((k_{fp} = k_{fn})\).
Table 10: Performance of SOTA models, with empirical threshold (found on the validation set, $k_{fp}$ is set to 1)

| Task       | Model            | Accuracy (Value) | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 |
|------------|-----------------|------------------|--------|--------|--------|--------|--------|--------|
| HATE-SPEECH | BADI ET AL., Exp 1 | 0.822 0.646 0.539 0.38 | 0.259 0.228 |
|            | AGR. ET AL., Exp 1 | 0.732 0.503 0.452 0.363 | 0.225 0.117 |
|            | AGR. ET AL., Exp 2 | 0.489 0.077 0.077 0.077 | 0.077 0.077 |
| CLICKBAIT  | FULLNETCONC      | 0.857 0.715 0.612 0.488 | 0.375 0.332 |
|            | LINGNET          | 0.82 0.639 0.51 0.34 | 0.179 0.134 |
|            | FULLNET          | 0.856 0.712 0.637 0.554 | 0.439 0.418 |

Table 11: Performance of SOTA models with empirical threshold (found on validation set, $k_{fp} = k_{fn}$)

| Task       | Model            | Accuracy (Value) | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 |
|------------|-----------------|------------------|--------|--------|--------|--------|--------|--------|
| HATE-SPEECH | BADI ET AL., Exp 1 | 0.822 0.653 0.552 0.422 | 0.328 0.297 |
|            | AGR. ET AL., Exp 1 | 0.732 0.503 0.452 0.363 | 0.225 0.117 |
|            | AGR. ET AL., Exp 2 | 0.489 0.077 0.077 0.077 | 0.077 0.077 |
| CLICKBAIT  | FULLNETCONC      | 0.857 0.716 0.649 0.565 | 0.468 0.438 |
|            | LINGNET          | 0.82 0.643 0.536 0.394 | 0.242 0.198 |
|            | FULLNET          | 0.856 0.714 0.641 0.559 | 0.46 0.429 |

Table 12: Performance of SOTA models, with empirical threshold (found on the test set, $k_{fp}$ is set to 1)

| Task       | Model            | Accuracy (Value) | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 |
|------------|-----------------|------------------|--------|--------|--------|--------|--------|--------|
| HATE-SPEECH | BADI ET AL., Exp 1 | 0.822 0.653 0.552 0.422 | 0.328 0.297 |
|            | AGR. ET AL., Exp 1 | 0.732 0.503 0.452 0.363 | 0.225 0.117 |
|            | AGR. ET AL., Exp 2 | 0.489 0.077 0.077 0.077 | 0.077 0.077 |
| CLICKBAIT  | FULLNETCONC      | 0.857 0.716 0.649 0.565 | 0.468 0.438 |
|            | LINGNET          | 0.82 0.643 0.536 0.394 | 0.242 0.198 |
|            | FULLNET          | 0.856 0.714 0.641 0.559 | 0.46 0.429 |

Table 13: Performance of SOTA models after temperature scaling, with empirical threshold (on test set, $k_{fp} = k_{fn}$)
### A.6.2 MDS dataset - Supplementary Results

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.836    | 0.672 |

Table 14: Performance of models on Multi Domain Sentiment Dataset, TARGET = DVD, $k_f = 1$, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.836    | 0.672 |

Table 15: Performance of models on Multi Domain Sentiment Dataset, TARGET = DVD, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.826    | 0.652 |

Table 16: Performance of models on Multi Domain Sentiment Dataset, TARGET = Books, $k_f = 1$, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.826    | 0.652 |

Table 17: Performance of models on Multi Domain Sentiment Dataset, TARGET = Books, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.842    | 0.685 |

Table 18: Performance of models on Multi Domain Sentiment Dataset, TARGET = Electronics, $k_f = 1$, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.842    | 0.685 |

Table 19: Performance of models on Multi Domain Sentiment Dataset, TARGET = Electronics, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.826    | 0.672 |

Table 20: Performance of models on Multi Domain Sentiment Dataset, TARGET = Kitchen, $k_f = 1$, $k_f = k$ (Value with theoretical threshold)

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.842    | 0.685 |

Table 21: Performance of models on Multi Domain Sentiment Dataset, TARGET = Kitchen, $k_f = k$ (Value with theoretical threshold)

### Table 22: Accuracy of LogReg model on Multi Domain Sentiment Dataset.

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.826    | 0.672 |

Table 23: Accuracy of MLP1 model on Multi Domain Sentiment Dataset.

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.842    | 0.685 |

Table 24: Accuracy of MLP4 model on Multi Domain Sentiment Dataset.

| Model    | Accuracy | Value |
|----------|----------|-------|
| LogReg   | 0.74     | 0.48  |
| MLP1     | 0.72     | 0.49  |
| MLP4     | 0.72     | 0.59  |
| mtrit    | 0.75     | 0.56  |
| T5       | 0.79     | 0.57  |
| SiBERT   | 0.842    | 0.685 |

Table 25: Accuracy of mtrit model on Multi Domain Sentiment Dataset.
Figure 7: Value curves on Multi Domain Sentiment dataset for increasing $k_{fn}$. Values are averaged for simple models, the ‘mttri’ model, and GPT-3.
Figure 8: Value curves on Multi Domain Sentiment dataset for increasing $k_{fn}$. Values are averaged for simple models, the 'mttri' model, and GPT-3.
Figure 9: Value curves on Multi Domain Sentiment dataset for increasing $k_{fn}$, TARGET = ’DVD’. We use S-SOURCE_T-TARGET format in the sub-figure titles, values show the performance of each model trained on a source domain and tested on a target domain.
Figure 10: Value curves on Multi Domain Sentiment dataset for increasing $k_f, n$. TARGET = 'Books'. We use S-SOURCE_T-TARGET format in the sub-figure titles, values show the performance of each model trained on a source domain and tested on a target domain.
Figure 11: Value curves on Multi Domain Sentiment dataset for increasing $k_{fn}$, TARGET = ‘Electronics’. We use S-SOURCE_T-TARGET format in the sub-figure titles, values show the performance of each model trained on a source domain and tested on a target domain.
Figure 12: Value curves on Multi Domain Sentiment dataset for increasing $k_{fn}$. TARGET = 'Kitchen'. We use S-SOURCE_T-TARGET format in the sub-figure titles, values show the performance of each model trained on a source domain and tested on a target domain.
A.6.3 Multi-class datasets - Supplementary Results

Figure 13: Value curves of multi-class datasets for increasing $k$.

Figure 14: Value curves with theoretical threshold for increasing $k$. 
Figure 15: Value curves with theoretical and empirical threshold (on the validation set) for increasing $k$. 
Figure 16: Effect of using different text encoders. Value curves with theoretical and empirical threshold (on the validation set) for increasing $k$. 