Problem-dependent attention and effort in neural networks with an application to image resolution

Chris Rohlfs

Columbia University Department of Electrical Engineering, Mudd 1310, 500 West 120th Street, New York, 10027-6623, NY, USA

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ABSTRACT

This paper assesses a new classification approach that examines low-resolution images first, only moving to higher resolution images if the classification from the initial pass does not have a high degree of confidence. This multi-stage strategy for classification can be used with any classifier and does not require additional training. The approach is tested on five common datasets using four different classification approaches. It is found to be effective for cases in which at least some fraction of cases can be correctly classified using coarser data than are typically used. neural networks performing digit recognition, for instance, the proposed approach reduces the resource cost of classifying test cases by 60% to 85% with less than 5% reduction in accuracy.

1. Introduction

Any model of optimal research activity will generate the prediction that the effort expended increases with the importance and difficulty of the problem. Optimizing behavior of this form is ubiquitous in humans and other animals. The cost of in-depth analysis should only be incurred for problems that cannot be solved through simpler means. In biological systems, the selection of cases for learning is typically curiosity-driven, with new observations selected because they have some new features not captured by the existing framework Sinz et al. (2019). By contrast, many artificial neural networks—and machine learning systems more generally—apply a standardized and uniform process to all observations without regard to the information value of different training cases or the difficulty or confidence of classifying different test cases. Artificial neural networks are known to be more demanding of resources than their biological counterparts (Perry et al., 2017; Scheffer et al., 2020), and there is potential to generate considerable value through improving the judiciousness with which artificial systems consume data and computational resources.

This article explores the application of a relatively new approach to learning-based classification in which amount of data processing and analysis varies depending upon the difficulty of the task. The strategy described in section 4.1 is a variation on that applied by Yang et al. (2020) in which multiple classification approaches are at the researcher’s disposal that vary in some form of complexity that impacts the cost of use. When faced with a new test case, the simplest and least resource-intensive approach is used first. If it produces a classification with a high degree of confidence (above some specified threshold), then that classification is used. Otherwise, the process is repeated with the next higher level of complexity. This sequential process conserves resources by classifying the relatively straightforward test cases quickly without resorting to the use of more complex approaches. It nevertheless preserves the accuracy of the forecasts by only using the results of the simpler approaches when the confidence in those projections is high. To determine whether the simpler approach’s forecast is used, the model’s internal propensity score for the chosen classification is used as its level of confidence in its projection. In a digit classification application, for example, if the model assigns equal likelihood to a test image being a one or a seven, then the propensity score is relatively low (50% or less); thus, a closer examination with a more complex approach is warranted. But if the model projects a classification of three with 95% likelihood, then it is likely that further analysis would not be worth the cost.

In the current study, five image recognition datasets are considered that are standard in the Computer Vision literature and involve identifying digits from handwriting or house numbers, categories of Japanese characters, articles of clothing, and animals and vehicles from thumbnail-sized pictures. Model projections are generated using three different artificial neural networks as well as a logistic regression-based classifier. For each combination of dataset and model that is considered, a single classifier is trained from full-resolution images, and the parameters from this model are applied to images that are subjected to different rates of downsampling. Thus, for the purposes of the sequential threshold-based classifier, the variation in complexity across iterations is isolated to one characteristic: the resolution of the test image. This reuse of a single trained model helps both to limit resource use and to facilitate broad applicability: only one model needs to be trained, only one trained model’s parameters need to be stored, and the approach described here can be applied to any existing classifier without the need for retraining or for major reconfiguration. The classification problems considered in this study are not demanding in terms of the amount of data that they require, but the findings shed light on how this sequential threshold-based classification approach works. Considering a cascading set of classifiers that differ in one transparent and intuitive feature—the amount of downsampling applied to test images—helps to illustrate the mechanisms driving performance and data...
usage. Additionally, presenting results for multiple familiar datasets and models makes the results relatable to researchers in the field and demonstrates the ways in which these impacts vary across situations.

Two preconditions must be met for the proposed approach to be viable: first, the models’ internal propensity scores—i.e., their self-assessed levels of confidence in their selected classifications—must be informative and increase with the accuracy of the classification. Many but not all of the propensity scores generated in this study meet this requirement. In all five applications, classification accuracy rises steadily with the propensity scores from the full-resolution test images—with correlations of +0.41 to +0.56. When downsampled test images are used, these correlations decline. The propensity scores obtained from moderately downsampled images (a factor of four in each dimension, down to 7×7 or 8×8 pixel images) are generally informative, but those obtained from smaller 4×4 images are not. We do not require that the internal propensity scores reliably measure the probability of correctness; the thresholds can be adjusted to accommodate biased probabilities. In the applications considered here, the propensities obtained from the full-resolution images are roughly in line with the observed probabilities of being correct; however, the models tend to be overconfident in their projections for downsampled images.

The second requirement is that there exist low-cost alternatives to the main classifier—and that those alternatives sometimes produce accurate classifications. This second condition naturally depends upon the types of costs and classifications being considered. For standard digit recognition problems, the results from this study indicate that the full thumbnail-sized images generally contain more information than is needed. Digits have standardized formats whose meaning can often be discerned with substantially less granular data than is sent to the classifier. The story is different for the most complex object recognition problem considered in this study. In that case, two neural network classifiers reliably identify the objects from the full-sized images, but none are effective on the downsampled images.

The results from this study indicate that there is potential in some contexts for substantial savings in data and computation costs through the use of problem-dependent strategies like the one described in this study. Such approaches can be applied in a straightforward way to many types of problems, but their effectiveness is limited to cases in which there is some inefficiency in the sense of a costly resource that is being expended by the model but is not critical to the classification. For the problem of recognizing digits from thumbnail images, for example, the correct class is apparent to the human eye at much lower levels of resolution than are transmitted to classifiers. For neural networks performing this task, the threshold-based classifier proposed here reduces the resource cost of classifying test cases by 60% to 85% with less than 5% reduction in accuracy. The results also map out the rates at which classification accuracy can be sacrificed to achieve even more substantial savings in data usage. This result is consistent with the finding from Yang et al. (2020) that the canonical representation of an object (e.g., a perched owl looking straight into the camera) can be correctly labeled using a simpler model, while variations on this representation (e.g., an owl captured from a different angle or pictured together with a person) require a more resource-intensive classification approach.

The question of excessive resource use in classification is an important one, and the tools presented and demonstrated in this study provide an intuitive and easy-to-use way to achieve substantial reductions in model complexity while maintaining high standards of forecasting accuracy. As the demand for speed, scalability, and performance for classification continues to grow, so will the value of thoughtful ways to address such tradeoffs. Many researchers have found that classification exercises depend more crucially upon broad patterns in the data—such as the local averages of Convolutional Neural Networks or correlations in pixel intensities across color channels, as in Holistic Attention Networks Niu et al. (2020)—that do not necessarily require the high level of granularity of the original data. Wang et al. (2020) also find that using copies of an image with different resolutions can help neural networks to identify such patterns. Image resolution is known to have noticeable impacts on neural networks’ classification performance Koziaske and Cyganek (2018). Resolution does pose less of a constraint than it once did, however, and researchers now use neural network-based “super-resolution” approaches to identify what higher resolution images could be expected to look like based upon lower resolution data (cf. Yang et al. (2019)).

A problem-dependent approach such as the one described here has potential for use in any context in which there is a non-negligible cost of classifying test cases—for instance, if the data themselves are costly to acquire or if large numbers of cases must be classified in real time. In some practical cases of network-based classification, critical tradeoffs must be made between the costs and benefits of high resolution images, as with the chest x-ray data examined by Sabottke and Spieler (2020). A study of cognitive function by Spreng et al. (2022) involved similar considerations, with a cost of $3,000 per subject due to a large number of brain MRI scans that were conducted. While the testing performed here study focuses on image recognition problems using a single set of trained model parameters for the classifier, the sequential threshold-based classification approach outlined in this study could in principle be applied to other empirical problems or using multiple classifiers with different estimated parameters or model structures, provided that they generate reliable propensity scores that are comparable across iterations and there is some variation across approaches in resource requirements.

A secondary contribution of the current study is to highlight the value of models’ internal propensity scores as underutilized measures of classification accuracy. The analysis in section 5 of this study shows that, at least when applied to unaltered data that resemble the training cases, the
propensity scores produced by logistic and neural network classifiers estimated here provide reliable projections of model accuracy for test cases.

The remainder of this study proceeds as follows. Chapter 2 discusses recent studies in the Deep Learning literature that explore means of reducing computation cost for test cases through the use of problem-dependent attention. Chapter 3 describes the datasets and classification problems considered in this analysis. Chapter 4 outlines the estimation approach and the mechanics of the estimators used. Chapter 5 presents the empirical findings, and Chapter 6 concludes.

2. Recent Literature

While learning-based classifiers do not typically consider the difficulty of the problem being considered, some recent work explores ways in which data-driven approaches can vary the amount of effort on a case-by-case basis. One important area of such research is in the analysis of complex visual inputs. Some researchers analyze such data by first passing over downsampled coarse representations of the images to identify Regions of Interest (RoIs)—and then later extracting and analyzing full resolution versions of those segments. Gao et al. (2018) use such an RoI-based approach to detect the presence of pedestrians in images of public locations such as crosswalks, and Cordonnier et al. (2021) employ a similar strategy to detect multiple objects in images. Yuan et al. (2019) apply a sequential approach of this form to interpolate missing video frames. The authors first use coarse representations of the images to identify movement and RoIs, and they obtain refined projections based upon full-resolution segments pulled from those RoIs.

Another cost that researchers have worked to mitigate through selective analysis is the convolutional steps in classification—specifically, the calculation involved when applying an already trained network to classify a new test case. In such situations, Kaya et al. (2019) and Bolukbasi et al. (2017), for instance, introduce early exit options into traditional neural networks. Both studies consider well-known datasets for identifying different types of objects from images, and in both cases, the authors take network-based models with fixed hyperparameters from the literature, and they expand them to provide preliminary classifications at early stages of analysis. Kaya et al. (2019) obtain efficiency gains by employing a threshold-based stopping rule whereby, if one of those intermediate classifications has sufficiently high confidence, then the network exits and that preliminary classification is used.

In addition to modeling networks with early exit, Bolukbasi et al. (2017) consider a separate cascading approach in which increasingly computationally intensive network-based classifiers are used in sequence. In both cases, the authors parameterize the decision to exit or continue analyzing as a function of the projected savings in computation time and loss in precision at different potential exit points. The authors then incorporate the learning of those decision parameters into their overall optimization problem.

In an approach that is most similar to the strategy employed in this study, Yang et al. (2020) employ a series of neural network classifiers with convolution steps that, like the previous cases, are costly to perform on test cases. The authors consider a sequential approach that begins with the least computationally demanding classifier. If the confidence in the projection exceeds some threshold, then that classification is used; otherwise, the algorithm computes the projection for the next more complex classifier. While that study aims to reduce computational requirements or Floating Point Operations per Second (FLOPS), the aim of the current study is to produce classifiers that are less demanding in terms of the granularity of data and consequent bandwidth and storage capacity required when deploying on test cases. Additionally, while Yang et al. (2020) introduces a specific new neural network classifier with separate trained components for different image resolutions, the current study proposes a sequential estimation strategy that can be applied to any existing trained classifier.

In all of these cases, using problem-based effort reduces the accuracy of the classifier relative to the alternative of running the full, most complex network on each case. Nevertheless, the authors in each of these cases find that this loss in accuracy is relatively small compared to the substantial improvement in computational efficiency that is obtained by sometimes using simpler classification approaches.

While this biologically-inspired notion of problem-dependent effort has primarily been applied to complex problems—such as multi-object detection in images and videos—the strategy has potential for broader application. In many simpler classification problems, including the classification of handwritten digits, there is wide variation across cases in the amount of data required to accurately label test cases. Moreover, the approach outlined in this study does not require multiple classifiers or separate sets of trained parameters, and the concept is not restricted to neural networks and is applicable to any type of classifier. It can be used for any set of models or inputs that can be ordered in terms of the computational intensity of producing classifications on test data could be used in a sequential manner—with the simplest method used first and more costly methods only used if the prior methods are not sufficiently confident. The key requirement for such an approach to be useful is that there is some non-negligible computational cost associated with classifying test cases. This wide applicability motivates the use in this study of four different classification models to five different problems and datasets.

3. Data

The five rows of Figure 1 illustrate the original and downsampled representations of images from the first test image from each of the five image recognition datasets used in this study. Descriptions of the datasets appear in Table 1. The first image within each row shows the original image. For each of the first three rows, the image is represented as...
Problem dependent attention and effort

![Image](307x378 to 553x436)

![Image](307x529 to 553x587)

![Image](307x605 to 553x663)

![Image](307x681 to 553x738)

Table 1

Datasets used in Analysis

| Dataset | Domain | Classes | Images | Size | Training Cases | Test Cases | Models Estimated | Source |
|---------|--------|---------|--------|------|----------------|------------|-----------------|--------|
| CIFAR-10 | Pictures of animals and vehicles in varying contexts and positions | 10,000 | 784 ∗ 28 = 21,888 | 94,000 | 26,032 | LeCun et al. (1998) |
| SVHN | Pictures of cropped house numbers, sometimes with distracting adjacent information | 73,257 | 32 ∗ 32 ∗ 3 = 307,200 | 10,000 | 26,032 | Netzer et al. (2011) |
| MNIST | Handwritten digits | 60,000 | 28 ∗ 28 = 784 | 50,000 | 7,325 | Krizhevsky et al. (2014) |
| KMNIST | Handwritten Japanese characters | 60,000 | 28 ∗ 28 = 784 | 50,000 | 7,325 | Clanuwat et al. (2018) |
| Fashion MNIST | Images of clothing items | 70,000 | 32 ∗ 32 ∗ 3 = 307,200 | 10,000 | 26,032 | LeNet-5, Logisitic with 100 factors |

Notes: The table summarizes the five datasets used in this analysis. Sample images from these datasets can be seen in Figure 1.

Figure 1: First test image from each dataset at different resolution levels

4. Estimation Approach

4.1. Conceptual Framework

When performing large-scale or time-critical classification tasks, it may be desirable to sacrifice some degree of accuracy in order to reduce the amount of data required for classification. The engineering problem considered here is to perform this tradeoff between accuracy and data usage in a case-specific way, so that for easier tasks, extremely coarse representations of images can be used, but if the classifier has a low level of confidence in its projected classification, then the more granular representation of the image is pulled and analyzed. This sequential process—in which coarse data are analyzed first and granular data may or may not be used—is diagrammed in the flow chart in Figure 2, which presents the steps performed to classify a single test case. The researcher has access to an array of trained models with varying degrees of complexity and resource intensity.
Problem dependent attention and effort

Figure 2: Flow Chart Illustrating Deployment of Problem-Dependent Effort Classifier on a Single Test Case

each of which can be applied to a given test case. Step 1 initializes the iteration number at \( t = 0 \), when the coarsest representation of the image (the 2x2 representation as shown in the rightmost column of Figure 1) is extracted in step 2. A classifier is then used in step 3 to assign probabilities \( p_0, ..., p_9 \) to each of the possible classifications. For the purposes of this analysis, let these model-specific probabilities be denoted propensities. Next, step 4 determines how confident the model is in its classification, examining the distribution of these propensities across the 10 categories. If the propensities are concentrated on one classification—in the extreme case 100% for one category and 0% for the others—then the classifier is highly confident in its selection. If the propensities are relatively spread out—in the extreme case with values of 10% for each of the 10 categories—then the model and data provide little information value, and the classifier has little confidence in its selection. Step 4 compares the propensity score for the most promising candidate classification to some threshold propensity level. If the classifier is highly confident in its selection, then the classifier stops at stage 5 and chooses this category with the highest propensity score. If the classifier’s level of confidence in its choice falls below the threshold, then the iteration \( t \) increments by one, and the process repeats with a slightly larger image—in this case, the 4x4 representation as in the fourth column in Figure 1.

4.2. Classifier Specifications

For the MNIST-style datasets, including MNIST, KMNIST and Fashion MNIST, two different classifiers are used. The first, LeNet-5, is an implementation of the convolutional neural network (CNN) classifier from LeCun et al. (1998a). This classifier consists of three hidden convolutional layers and two hidden Multilayer Perceptron (MLP) layers, each with different dimensions. Softmax transformations are applied to the output from the final layer to produce propensity scores for each of the ten classes. The code-based PyTorch implementation used here is taken from Lewinson (2020), which trains model parameters over 15 epochs with a learning rate of 0.001. The classifier resizes the 28x28 grayscale images to dimensions of 32x32 before they are fed into the network. For each dataset, the model is trained once on the complete training sample of full-sized images. Test projections are generated using the parameters from these trained models. When the test cases consist of downsampling images, the images are first resized down then resized back up to the 32x32 size that is consumed by the network, and then the resulting resized inputs are fed into the model using the parameters trained from the original full-sized images.

The second classification approach used for the MNIST-style images uses logistic regression. The eigenvectors of the 784 unnormalized pixel intensities are calculated separately for each dataset based upon the training samples. The 100 top principal components are then used as predictors in ten different logistic regressions for the ten classes. The class whose forecasted propensity is highest is used. The coefficients from these logistic regressions are estimated via Maximum Likelihood Estimation from the training data. As with the LeNet-5 case, the complete training sample of full-sized images is used for training, and the same fitted parameters—both for the eigenvectors and for the logistic regression coefficients—are applied to generate projections for all downsampling images. For this logistic regression-based classifier, downsampled images are constructed by averaging pixel intensities from the full-sized images across 2x2, 4x4, 7x7, or 14x14 groups of cells.

For the RGB images from the SVHN and the CIFAR-10, the same LeNet-5 classifier is used, but the images are converted to grayscale before being passed as 32x32 inputs into the network. A similar logistic regression-based classifier is also used, but with the eigenvectors estimated from the full 3,072-variable set of RGB pixels and the first 300 principal components used as predictors.1 For downsampling, each channel of each RGB image is scaled down to sizes of 16x16, 8x8, 4x4, and 2x2.

In addition to these two classifiers, two neural network classifiers are used that are designed to consume 3,072-variable RGB images as inputs. The first of these is a simplified version of the 34-layer Deep Layer Aggregation (DLA) network developed by Yu et al. (2018), in which each successive layer makes extensive use of the aggregation of upstream layers’ outputs. The second employs the “Deep Residual Learning” approach by He et al. (2016), which expedites convergence in the learning process by incorporating outcome data and computing residuals at multiple stages in the training process; the ResNet-18 CNN, which consists of 18 layers (16 hidden convolutional layers with strides) is used here. For both networks, the code-based implementation is taken from Liu (2022), which is also the source for the simplified version of the aggregation structure used for the DLA implementation. Training proceeds in 200

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1For both the MNIST-style and RGB images, logistic regressions using more or fewer principal components yield qualitatively similar results. The values of 100 and 300 were chosen because they had strong overall performance across the respective datasets and did not exhibit substantial amounts of overfitting.
epochs with a learning rate of 0.1. The final classification in that implementation is based upon the untransformed final layer output; the softmax function is applied to produce propensities. Similar general protocols are applied for these two networks as for LeNet-5. Training is performed using the complete training dataset and the full images, and the same trained networks are also used for the downsampled images. Downsampling is performed using the Resize transform from PyTorch. Images are resized downward and then resized back up via bilinear interpolation so that the input size is the same as for the full-sized images.

5. Results

5.1. Downsampling and Accuracy

Before presenting results from the sequential threshold-based model, Table 2 shows how the classifiers used in the component steps perform on their own. No threshold or sequential approach is used; the neural network or logistic regression approach is applied to the full set of full-resolution training images, the full set of full-sized test images, or the full set of downsampled test images, where the downsampling rate varies across the columns. The values in the table illustrate the percentage of cases in which the correct class was chosen out of the ten possibilities—so that pure random chance would produce an accuracy of 10%. Results for the classification of MNIST-style images appear in panel A, and panel B shows results for the classification of RGB images. For the benchmark cases in which the full-sized images are used, the neural networks are not those that achieve peak state-of-the-art performance but are representative of the sorts of CNNs commonly seen in the literature. Additionally, some weaker classifiers—the logistic regression approach as well as the LeNet-5 applied to grayscale versions of the RGB images—are included for comparison in order to illustrate how the proposed strategy performs across a variety of situations. The different rows illustrate how the performance varies across datasets and models.

As the results from the first panel show, when the full training or test images are used, the LeNet-5 accurately classifies MNIST-style images 87.7% to 99.5% of the time. The accuracy is somewhat lower for the simpler logistic regression approach, which correctly classifies cases 67.9% to 91.5% of the time. Classifications are most accurate for the digit identification task of MNIST and less for the more complex problems of identifying classes of Japanese characters in KMNIST or types of clothing in Fashion MNIST. Performance declines as we move from left to right, and increasing amounts of downsampling are applied to the images, and at the very right, when the 2x2 images are used, only 9.5% to 24.1% of cases are correctly classified.

For the RGB images in panel B, the classifiers exhibit more varied performance on the full-sized training and test images. The LeNet-5 performs well on the grayscale SVHN images, correctly classifying 91.3% of training cases and 83.1% of test cases. The logistic regression model performs far worse, with accuracy of 28.5% and 24.7% on the same two samples. One potential explanation for the worse performance of the logistic classifier is that, due to the varying colors and distracting adjacent information in the images, the representations are more complex than can be captured effectively with the first 300 principal components. For the CIFAR-10 images, both the LeNet-5 and logistic classifiers perform poorly, correctly recognizing the objects in only 41.0% to 56.6% of the full-sized training and test cases—possibly due to the complexity of the representations and the importance of color for identification. The two deeper and more sophisticated neural networks—the DLA-Simple and ResNet-18 models—perform far better on both the SVHN and CIFAR-10 images, correctly classifying 100.0% of the full-sized training images and 94.9% to 97.3% of the full-sized test images.

As in panel A, the classifiers’ performance in panel B declines substantially as we move rightward to increasing amounts of downsampling. The drop is most severe for the CIFAR-10 images. The DLA-Simple and ResNet-18 performance drops from 94.9% and 95.4% on the full-sized test images to 26.0% and 27.7% on the 16x16 images. This sharp decline is consistent with the intuitive observation from Figure 1e that the CIFAR-10 images are difficult to classify even with at full resolution. Due to the varying positions and contexts in which the same category of animal or vehicle can be presented, accurate classification appears to require both the complexity of a deep neural network and the granular data of a full-resolution image.

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Notes: Each row presents the percent of cases correctly classified for a different dataset-model combination. In each case, the input data is a matrix of pixel intensities for an image, and the task is to assign the case to one of ten possible categories. Training is performed separately for each dataset-model combination, and the same trained model is then applied to full-resolution test images and then to downsampled variants of those same images. Additional details about the datasets and classifiers are presented in Table 2 and Section 4.2.

Table 2
Accuracy by Dataset, Model, Sample, and Downsampling Rate

| Dataset | Model | Training | Test |
|---------|-------|----------|------|
| MNIST   | LeNet-5 | 99.5% | 98.5% | 97.1% | 60.1% | 17.0% | 9.5% |
|         | Logistic | 91.2% | 91.5% | 91.0% | 78.4% | 47.8% | 14.9% |
| KMNIST  | LeNet-5 | 99.1% | 92.7% | 90.7% | 69.8% | 30.4% | 9.6% |
|         | Logistic | 81.5% | 67.6% | 64.1% | 43.9% | 19.2% | 6.0% |
| Fashion MNIST | LeNet-5 | 91.5% | 87.7% | 85.3% | 72.3% | 35.8% | 17.8% |
|         | Logistic | 85.1% | 83.8% | 80.2% | 72.7% | 46.3% | 24.1% |
| SVHN    | LeNet-5 (Grayscale) | 91.3% | 83.1% | 82.2% | 72.3% | 28.3% | 18.5% |
|         | Logistic | 28.5% | 24.7% | 24.4% | 23.1% | 19.2% | 17.5% |
|         | DLA-Simple | 100.0% | 97.3% | 96.2% | 84.9% | 28.6% | 17.7% |
|         | ResNet-18 | 100.0% | 97.2% | 96.2% | 83.7% | 27.2% | 18.1% |
| CIFAR-10| LeNet-5 (Grayscale) | 56.6% | 49.7% | 46.4% | 32.1% | 20.4% | 15.8% |
|         | Logistic | 42.1% | 41.0% | 41.0% | 40.2% | 35.6% | 26.2% |
|         | DLA-Simple | 100.0% | 94.9% | 94.9% | 13.4% | 11.9% | 11.3% |
|         | ResNet-18 | 100.0% | 95.4% | 72.7% | 20.5% | 16.2% | 14.8% |

Notes: Each row presents the percent of cases correctly classified for a different dataset-model combination. In each case, the input data is a matrix of pixel intensities for an image, and the task is to assign the case to one of ten possible categories. Training is performed separately for each dataset-model combination, and the same trained model is then applied to full-resolution test images and then to downsampled variants of those same images. Additional details about the datasets and classifiers are presented in Table 2 and Section 4.2.
5.2. Propensity Scores

The viability of the sequential threshold-based classifier introduced in this study depends crucially upon the component models’ internal propensity scores as case-specific self-assessments of the likelihood of being correct. The images in Figure 3 explore the ways in which these propensity scores vary across cases, datasets, and models, and the corresponding graphs in Figure 4 illustrate the extent to which these scores are predictive of classification accuracy.

In each of the fifteen charts in Figure 3, the test cases from each dataset are divided into nine categories based upon the models internal propensity scores for their chosen classifications for those cases. The categories are plotted along the horizontal axis in ranges of ten percentage points, from ≤ 20%, 20% – 30%, 30% – 40%, through > 90%. The 0% – 10% category does not appear because, for each test case, at least one of the classes will have propensity of 10% or greater, so a class with propensity less than 10% will never be selected for any observation. Each of the lines in the graph is a histogram, and the values plotted along the vertical axis show the percent of test cases with propensity scores falling into each of those nine ranges. The red, orange, green, blue, and violet lines show results for the MNIST, KMNIST, Fashion MNIST, SVHN, and CIFAR-10 datasets. The first row in Figure 3a shows results for LeNet-5, the second row in Figure 3b shows results for the logistic regression approach, and the third row in Figure 3c shows results for the two deeper neural networks that were estimated on the RGB images, with the DLA-Simple results shown in solid lines and the ResNet-18 results presented in dashed lines. The five columns of graphs show the five different levels of downsampling, ranging from the full-sized images on the far left to the 2x2 images on the far right.

The overall patterns in the histograms in Figure 3 are reflective of the actual differences in forecasting accuracy across the different models and dataset that were shown in Table 2. The neural networks are highly confident in their classifications of the full-sized images, as indicated by the concentration of cases with propensities > 90% in the top and bottom charts on the left-hand side. The notable exception to that pattern is the violet line corresponding to the CIFAR-10 dataset in the first row, which shows a greater dispersion of propensity score values, mainly around 30% to 50%; this finding also aligns with the low accuracy rate seen in Table 2 for the LeNet-5 model’s classifications of the CIFAR-10 images. Also in keeping with the differences observed in model performance, the results from the logistic regression classifier vary across datasets, with the propensities concentrated in the highest category for the full-sized MNIST images and in the lowest category for the full-sized RGB images. Additionally, the classifiers’ levels of confidence declines as we move to the right and the amount of downsampling increases. This decline can be seen in the histograms by the lower concentrations of cases at the top confidence levels and the higher concentrations at the middle and lower levels of confidence. These reductions in confidence are nevertheless not quite as rapid as the declines in actual test performance. While the performance of the DLA-Simple and ResNet-18 classifiers on CIFAR-10 images dropped below 30% with the move to 16x16...
images, the models continue to report levels of confidence that are concentrated in the highest category. Additionally, while none of the models perform appreciably better than random chance on the 2x2 images, the graphs on the top and bottom right show concentrations of cases with mid- and high-valued propensity scores.

Next, the fifteen graphs in Figure 4 show how the models’ internal propensity scores co-move with model accuracy. The structure of the graphs is the same as in Figure 3 above, but the variable plotted along the vertical axis is now the percentage of cases correctly classified within each propensity score bin. For the full-sized images on the left-hand side, the models’ levels of correctness generally increase steadily with their propensity scores. Some of the more unusual and jerky patterns arise because they are averages computed over small samples; for instance, the stray 100% red value in the top left chart occurs because only LeNet-5 classified only two full-sized test images with 30% – 40% confidence, and its projected classifications were correct in both cases. As we move to the right and greater amounts of downsampling are applied, the explanatory power of the propensity scores declines. For the downscaled images, the models tend to be overconfident in their classifications—i.e., they report high propensity scores for many cases in which their actual classification accuracy is low—and for the most extreme amounts of downsampling, the lines on the graph are flat, indicating that the modeled propensity would not be useful for a threshold-based classification approach. For this reason, the 4x4 and 2x2 images are ignored by the threshold-based approach that is implemented in subsection 5.3, and the sequential classifier takes the classifications of the 7x7 and 8x8 and the corresponding levels of confidence with those classifications as its starting point.

The key findings from Figures 3 and 4 are presented in a consolidated form in Figure 5, which illustrates the correlation between the modeled propensity score and accuracy as it varies by dataset, model, and amount of downsampling. Plotted along the vertical axis is the Pearson correlation coefficient between the propensity score and an indicator for the classification being correct, calculated across all images in the test sample. Plotted along the horizontal axis is the amount of downsampling applied to the test images. The results from the different models continue to be shown in different sub-figures, and the results for different datasets continue to be presented by different colored lines within each chart.

The three graphs in Figure 5 show that, for the full-sized images, the propensity scores are reasonably predictive—they are positively correlated with classification accuracy, and the correlations tend to be around 40% – 60%, with lower values for the logistic model applied to the RGB images. These correlations—and the consequent value of the propensity scores for a threshold-based model—decline substantially as the resolution of the test image declines. In the extreme case of 2x2 images, these correlations are all under 20% and in many cases negative. The decline is most immediate for the deep neural network classifications of the CIFAR-10 images in Figure 5c. In general, the propensities still tend to be informative of classification accuracy when obtained from the middle 7x7 and 8x8
pixel images (downsampling by a factor of four in each dimension), and so the threshold-based classifier takes those as a starting point.

5.3. Sequential Threshold-based Classifier

Table 3 illustrates the results from the sequential classifier outlined in Figure 2 for the different datasets and models, using a variety of different propensity thresholds for case-specific model selection. The structure of the table is similar to that of Table 2, but for each dataset and model, two rows of values are shown: the percentage of cases that were correctly classified and the number of bytes of data that were required. The column labeled “BenchmarK” shows the performance obtained by applying the trained model on the full-sized images, as in the full-sized Test results column in Table 2. In that case, the data cost is equal to the number of bytes of the full-sized image; 28 * 28 = 784 for MNIST-style images, 32 * 32 * 3 = 3,072 for the RGB images, and 32 * 32 = 1,024 for the grayscale versions of those RGB images. The columns to the right of the benchmark show the results from a sequential model in which the 7x7 or 8x8 test image is used first, the 14x14 or 16x16 image is used if the propensity for that classification falls below the threshold, and if that classification falls below the threshold, the full-sized image is used. Results are shown using thresholds of 80%, 90%, 95%, 97.5%, 99%, and 99.9%. For cases in which the 7x7 or 8x8 image is used, the number of bytes read is only 7 * 7 = 49 for the MNIST-style images, 8 * 8 * 3 = 192 for the RGB images, and 8 * 8 = 64 for the grayscale RGB. If the model’s level of confidence for that classification falls below the threshold, however, then that image is discarded and a new and larger image must be read. Thus, if the 14x14 or 16x16 image is used, the total number of bytes read is 49 + 14 * 14 = 245 for a MNIST-style image, 192 + 16 * 16 * 3 = 960 for an RGB image, and 64 + 16 * 16 = 320 for one of the RGB images converted to grayscale. If neither of the downsampled images are used for a given case, then those 245, 960, or 320 bytes have already been read, and the classifier must still incur the 784-, 3,072-, or 1,024-byte cost of reading the full-sized image. Thus, these graphs show the correlations across test cases between the models’ levels of confidence in their classifications and an indicator for whether the classifier is correct. Higher values are indicative of higher signal-to-noise ratios and greater amounts of information content coming from the propensity scores.

Figure 5: Correlations of Propensities with Correct Classification
Problem dependent attention and effort

LeNet-5 classifier only increases data usage relative to the benchmark.

For the logistic model, the results also vary across the datasets considered. For the MNIST and Fashion MNIST datasets, the sequential classifier with an 80% threshold achieves roughly the same accuracy as the benchmark but with 32.1% to 40.1% less data usage. For the KMNIST, however, the impacts are negligible, and for the SVHN and CIFAR-10, the propensities from the downsampled images consistently fall below the thresholds, so that accuracy is unaffected but data cost is increased.

With the DLA-Simple and ResNet-18 classifiers, using the threshold-based approach on the SVHN substantially reduces data usage. The DLA-Simple with a 97.5% threshold achieves 93.4% accuracy with an 84.5% reduction in data usage, and the ResNet-18 with a 90% threshold achieves 90.7% accuracy with an 85.4% reduction in data usage. For the CIFAR-10, the results continue to disappoint; the threshold-based classifier consistently reduces performance and in many cases increases the number of bytes read.

The three charts in Figure 6 illustrate the tradeoffs between performance and data requirements that are implied by the results in Table 3. For each of the classifiers whose results are shown in that table, the classification accuracy is plotted along the vertical axis of one of the three figures, and the amount of data used for the average test case is plotted along the horizontal axis. The ideal classifier is represented by the combination of values in the top left of each graph, with 100% accuracy and zero bytes read. Each colored point or line shows an achievable combination of these two objectives. The asterisks in all three charts and the diamonds in Figure 6c present the performance and resource intensity of the benchmark classifiers from Table 3. The lines illustrate the combinations obtained from the sequential classifiers with propensity thresholds ranging from 80% to 99.9% as in the table. As with Figure 5, the first chart shows results for the LeNet-5, the second for the logistic regression approach, and the third for DLA-Simple and ResNet-18.

The patterns shown in the graphs reflect the same tradeoffs as appear in the table. For the LeNet-5 classifier in Figure 6a, using the sequential classifier enables movement to the left (a reduction in data usage) with minimal downward movement (reduction in accuracy) with four out of five of the datasets. For the logistic regression classifier in Figure 6b, cost reductions are achievable for two of the five datasets, and for the DLA-Simple and ResNet-18 classifiers in 6c, substantial savings are achieved on the SVHN, but for the CIFAR-10, the threshold-based classifiers that are able to reduce data usage entail too large of a loss in performance to be viable.

6. Conclusion

This study presents and evaluates a new framework for reducing the resource intensity of AI-based classification approaches while maintaining high standards for accuracy. The strategy is inspired by biological approaches to attention and information-gathering whereby the amount of effort expended increases with the difficulty of the problem. Analysis begins with a classification model applied to a parsimonious representation of the input data that is especially undemanding in terms of bandwidth, memory, and storage. A threshold-based approach is used based upon the model’s internal level of confidence in its classification. If the simple model has a high degree of confidence in its classification, then that label is used. If, however, the coarse version of the data is not sufficiently informative to produce a classification with a high degree of confidence, then a more granular representation of the test case is analyzed.

The approach is applied to image recognition problems with five commonly used datasets, and four different classification models are considered—the neural networks and the logistic regression-based classifier. Low-resolution versions of the images are analyzed first to produce initial classifications, and higher-resolution versions are only analyzed
for cases in which the model does not have a high degree of confidence in its initial classification. For classifiers that achieve moderate to high levels of accuracy, the models’ internal self-assessments are found to be reliable measures of performance that are correlated with the correctness of the classification. The results of the sequential threshold-based classifier are found in some cases to substantially reduce the resource cost of character and object recognition with minimal sacrifice to performance. The cases in which the sequential approach is found to be most effective are for those problems and datasets for which lower resolution data are sufficient to convey the essential features of the classes being learned.

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Dr. Rohils is a Wall Street finance quant with doctorates in Economics and Electrical Engineering (expected); before joining the financial industry, he taught Economics and Syracuse University. His research examines artificial intelligence and biologically-inspired neural networks, consumer demand, particularly for intangibles, recommendation models, and applied statistics and econometrics.