A Visualization Tool for Human-in-the-loop Machine Learning

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INTRODUCTION

As the amount of data produced by the worlds population increases year by year, the need for efficient ways to process and learn from that data arises. The field of machine learning, a marriage of statistics and computer science, is one attempt at distilling large amounts of data into a usable format. However, many machine learning models are difficult to interpret, or they learn something different from the true desire of their designers.

Our project brings a human into the learning loop (see Figure 1) so that more accurate models can be produced. The idea is that we would start with a trained machine learning model (*train* and *model* boxes). The system (or the user) would then pick a set of examples and/or summary statistics to look at (*pick* box), which are then explained to the user in some way (*explain box*). Having understood what the model's strengths and weaknesses, the user is in a position of providing some sort of feedback (*feedback box*), which could be in the form of labeling more examples, adding or removing features, changing models, etc. The loop then starts again. This formulation of the problem encompasses techniques like active learning (amongst many others), where *pick* is the most important step, and *feedback* involves labeling examples, while *explain* is ignored.

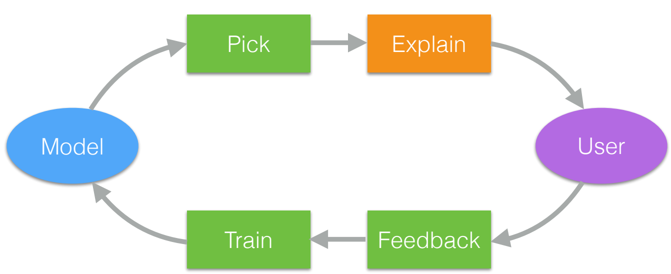


Figure 1: Machine learning loop

The critical part in the loop where visualization comes is the *explain* box. This involves giving an overview of what the models are learning, as well as explaining individual predictions. This is the primary focus of this work - along with a simple mechanism for *feedback*, which is required if we are to have a full loop. We focus primarily on text data, and on the multi-class classification task. For simplicity, we assume that the bag-of-words representation is used, although we plan on relaxing this assumption in future work, as our visualizations generally do not depend on it.

Our tool has three top "views", which share a common visualization underneath that allows the users to interact with the dataset. The first view is meant to explain individual predictions to users, in terms of feature contributions. The second view gives the users a global "summary" of the model, in the form of summary statistics and an interactive confusion matrix. Finally, the third view allows the user to give feedback to the model. The kind of feedback we allow currently concerns mainly data cleaning - which we argue is already important enough to significantly improve most text classifiers.

LITERATURE REVIEW

The statement that understanding what machine learning models are really learning leads to better models is not very controversial. Patel et al [4] conducted interviews with machine learning / HCI practitioners, and found a consensus regarding the following: (1) the machine learning process is iterative and exploratory, (2) understanding data and algorithms is really important, and (3) evaluation is hard and critical. They do a study where they observe people trying to produce a digit classifier, where they found that a lot of time people get stuck in part of the process (e.g. model selection) when the problem is somewhere else (such as lack of labeled data, or noise in the data). They also found that just looking at summary statistics in cross validation (CV) data is not enough for evaluation - all of the participants overestimated their models accuracy, when compared to a hidden test set, due to CV quirks. This led the authors to produce Gestalt [3], a system aimed at software developers that exposes the Machine Learning pipeline in steps. One can see a particular example all the way through the pipeline, implement his own visualization, click on a confusion table to see misclassified examples and click on an example and see the features or the raw data. Unfortunately, no explanation of how the model is interacting with the data is provided to the user, so it may be hard to determine what to do to improve the model.

On a similar line of research, [1] provides a visualization where examples are sorted according to the model's prediction, and colored by their true class (which was the inspiration for our databin visualization). You can click on an example to see the raw data. Any interaction (adding features, relabeling examples, etc) which makes an example move produces an arrow from the previous position to the next position. Their visualizations are helpful, but there is no support for multi-class classification, or explanation of why the model is making predictions the way it is. Also, the visualization does not scale to larger datasets, as there is not enough space in the screen for all of the points.

Some research has been done on explaining individual predictions, or giving an overall explanation for the model. In [5], the authors "distill" a matrix factorization model into rules (trying to be faithful to the original model, while being more interpretable). It is unclear as to how helpful these are, as there is still a problem of selecting which rules to show to the user. In [6], the authors focus on explaining individual classifications by highlighting individual feature contributions, taking into account the interactions between features. Contrary to the name, their method is not efficient at all, as it takes over an hour to generate an explanation for an individual prediction in a dataset with 279 features (which is very modest for today's standards), so it could not be used for interactive visualization.

More in line with our vision of machine learning as a loop, [7] did an experiment where the system explained itself to the user by showing rules, Naïve Bayes "weights" or similar examples to the one being classified. The users then provided free form feedback (on paper), which they later tried to incorporate retroactively. Both their explanations and some of their feedback are model-dependent, working only with Naïve Bayes. In fact, in follow up work [2] they develop an interactive system focused only on Naïve Bayes, where the explanation is guided by user questions, such as "why is this example classified positive". One drawback of their system is that feedback is very limited (just relabeling documents), and it's not clear how useful it is - in fact it seems that it usually harms the system's performance. It is also not very interactive, which is a feature that most participants in their study really wanted - being able to change something and seeing the results right away.

Our main contributions are combining all of the following in one system: (1) treating the process as a loop and allowing for feedback, (2) explaining individual predictions - visually and interactively, (3) allowing for multiclass classification, (4) interactivity in both the individual prediction explanations and "global" model explanations, (5) handling larger datasets (to a certain extent), and (6) being model-agnostic - i.e. working with any machine learning classification model.

THE BACKEND, FEATURE IMPORTANCE

We wrote the backend of our visualization in python, on top of scikit-learn[1]. We used different text dataset corpora, but in this report we will restrict our examples to subsets of the 20 newsgroups dataset[2]. This is a widely used dataset in the literature, and it consists of distinguishing between emails sent to different newsgroups. In this report, we either use a 2-class subset which tries to distinguish between Christianity and Atheism newsgroups, or a 3-class subset which tries to distinguish between "windows-misc", "ibm-hardware" and "windows-x". As a classification algorithm, all of our examples use L2 regularized logistic regression, although any classification algorithms that produces class prediction probabilities can be used in our tool.

In order to assess the importance of a feature (in our case, word) to a prediction, we follow a greedy procedure. We assume our classifier can return $P(Y = y|x)$ for any x, and that the classifier predicts the example as y (i.e. $pred(x) = y$). If the example being explained is x, we start with $x' = x$ and define x'_{-w} as a copy of x' without feature w. We follow the procedure outlined in Algorithm 1, which removes words from x until the class changes. The importance of a word is then defined as how much it influences the prediction if it is re-added to x afterwards.

let $x' = x$;
let $words = list()$;
while $pred(x') = y$ *and* x' *is not empty* **do**
  $w' = \mathrm{argmax}_w \quad P(Y = y|x') - P(Y = y|x'_{-w})$;
  append w' to $words$;
  if $pred(x') \neq y$ **then**
    Append to $words$ every word w' such that $pred(x'_{-w'}) \neq y$ and remove every such w' from x';
  end
  $x' = x'_{-w'}$;
end
foreach $w \in words$ **do**
  Importance(w) = $p(Y = y|x'_{-w}) - p(Y = y|x')$;
end

Algorithm 1: Explain prediction y for example x

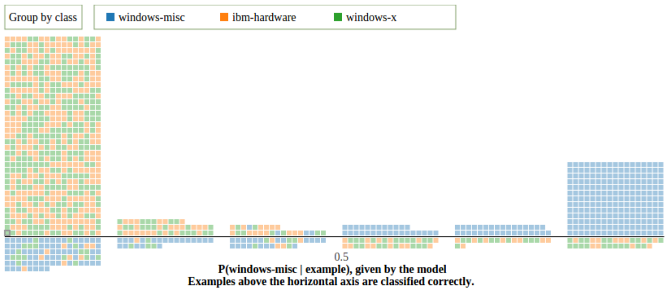
Although it is greedy and approximate, this algorithm has the following advantages: (1) it is relatively fast, assuming fast predictions are available (which is usually the case), (2) it is general, so that any classifier that outputs a prediction probability can be explained, and (3) the explanation has an easy interpretation: if all of the words that are explained as important were removed, the prediction changes.

THE DATABIN

The main tool we use for visualizing a dataset as a whole is the *databin* (see Figure 2). With this visualization, the user is given an overview of how the model classifies each document. In addition, the databin is interactive, and allows users to examine certain documents by clicking on them, or seeing more information about an example by hovering over it. With the encodings we've chosen, it is immediately evident what documents the model may be overfitting on, thereby speeding up the Explain and Feedback steps.

This visualization is similar to and inspired by [1], but with several notable changes. A major limitation of Modeltracker is that it cannot handle more than two classes, but most non-trivial machine learning classification problems consist of multiple classes. Hence, we've used different encodings and interactions in order to represent the performance on multiple classes in a two-dimensional space. In addition, in contrast to the positional encodings used by Modeltracker and our initial databin mode (*likelihood binning*), we've added an additional mode (which we call *class binning*). In this

[1]http://scikit-learn.org/
[2]http://qwone.com/ jason/20Newsgroups/



(a) Likelihood binning

(b) Class binning

Figure 2: Two databin modes

mode, examples can be binned by class instead of their model likelihood.

Likelihood binning In this mode, each example x_i is represented with a single square whose color is determined by the true class of the example y_i We encode the likelihood $p(Y = y \mid x_i)$ of an example x_i belonging to a particular class y with the horizontal bin of the square. The class y can be changed by clicking on the corresponding legend entry, and any changes are animated. We use the vertical position to encode whether or not an example was classified correctly. All examples whose true class y_i equals the model's prediction y are binned above the horizontal line, and vice versa for mistakes. This makes it very simple to see which examples the model has classified incorrectly. For instance, the model is very confident on examples at either extreme of the horizontal. If there exist some examples below the horizontal line at these extremes, then the model has made a very confident mistake, which is usually indicitive of some underlying problem that needs to be rectified by a user.

Class binning We can use an alternative horizontal encoding to see the performance on all classes in parallel. Instead of using the likelihood to encode which bin an example, we simply bin each class separately. We still use the same vertical and color encodings. In this mode, it is simple to see if a model is underperforming on one class in particular.

One criticism that could be construed against the databin is that it is limited to small datasets. In order to minimize this problem, we make the bin sizes adaptative to the number of documents that would fall in each bin - i.e. if there are enough documents in a bin to violate the vertical boundaries, we use less bins. If that is not enough, we reduce the size of the squares encoding the documents. While these measures still donot allow for huge datasets, it makes the visualization more flexible to medium-sized datasets.

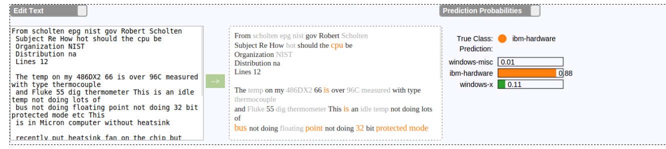


Figure 3: The "Explain prediction" window.

EXPLAINING INDIVIDUAL PREDICTIONS

It is helpful to look at specific examples to get a finer-grained idea of what the model is learning. One particularly helpful method is to select items from the databin that have very high or very low likelihood but are classified incorrectly. These documents can be selected, and they are displayed in the upper portion of our visualization. An example of this portion of our visualization is given in Figure 3.

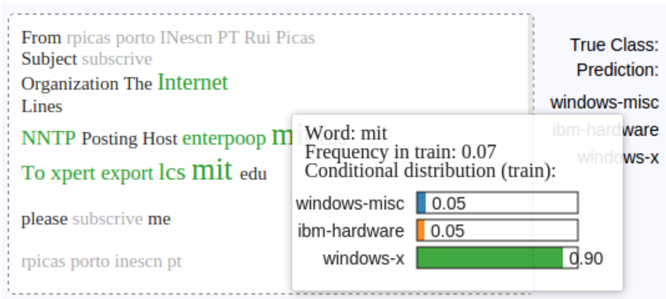
The text is interactive; that is, a user can edit the text in the left window and apply it. The document will then be (non-destructively) reclassified, and the prediction probabilities on the right are animated to show changes. This technique can be used to determine the effectiveness of specific changes, like removing certain features. In addition, the user can hover over a specific feature to see the distribution of that feature throughout the training set. This is illustrated in Figure 4. A user can "brush" certain features in this window by clicking on them. One or more features can be selected, and the examples that contain these features are "brushed" in the databin as in Figures 5 and 6.

The importance of the features are encoded with color and size so that they can quickly be discerned from the document. Intuitively, if all of the colored words were removed from the example, the example's classification would change.

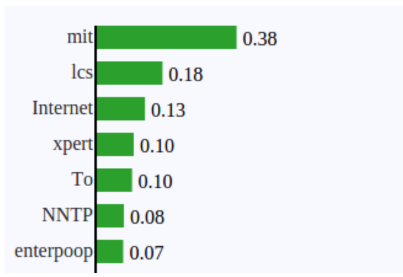
An example of the usefulness of this type of inspection is given in Figure 4. The irrelevant feature "mit" is given high weight simply because it appears mostly within the "windows-x" class. In addition, other irrelevant features like email header keywords are marked as important. The user could then use this information to apply specific feedback to the model.

GLOBAL STATISTICS

If the user wants a more quantitative view of the model performance, they can select the "Global Statistics" tab, which includes standard metrics such as accuracy and the label distributions. In addition, an interactive confusion matrix is included. We note here that we got the confusion matrix design from one of the TAs. The user can select one of the cells in the matrix, and the corresponding entries are brushed in the databin (see Figure 5). This aids the user in determining why a certain class of mistakes is made, by examining the examples in that class. For instance, a user may want to figure out if there is a common pattern in the "windows-misc"

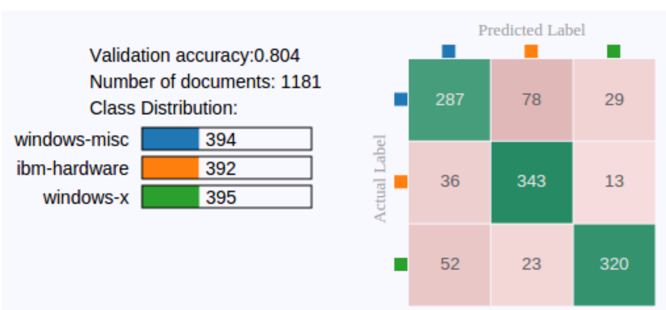


(a) Feature hover

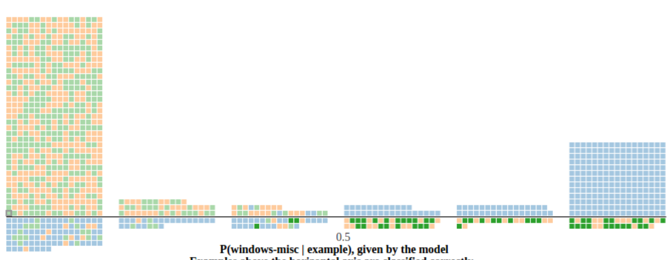


(b) Feature importance

Figure 4: The statistics that are shown when a user hovers over a feature (a) and the overall importance of features in the example (b). Note that this particular example reveals an issue with the model - the irrelevant feature "mit" appears mostly in the "windows-x" group, but it is not relevant to distinguishing between Windows and IBM hardware.



(a) Cells in the confusion matrix are interactive



(b) When a cell is clicked, the corresponding examples are brushed

Figure 5: The global statistics visualization.

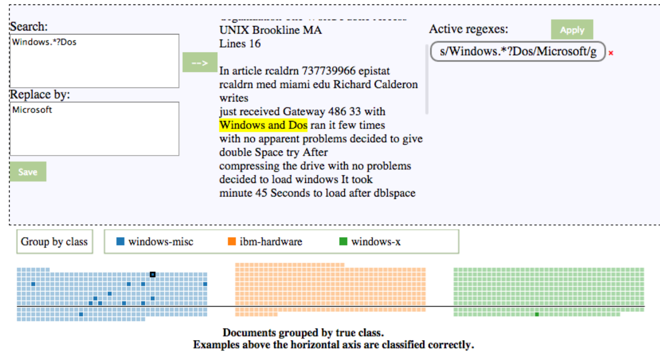


Figure 6: Data cleaning feedback.

class that the model classifies as ibm-hardware. Doing so yields the quick observation that the model is not robust to the presence of "hardware" words in other classes, such as "disk", "backup", or even "computer". We know that such words would be expected in "windows-misc", as windows runs on hardware. This king of insight allows us to determine what the next steps should be when trying to improve our classifier.

FEEDBACK

In order to close the loop, the user must be able to provide some feedback to the sytem. In this work, we let the user perform basic data cleaning, in the form of search and replace regular expressions. As shown in Figure 6, we highlight the parts of each document that match the search regular expression, in order to help the user come up with the correct expression. We also "brush" the examples in the databin that match it, so that the user can gauge the impact of the feedback before applying it. When a set of regular expressions is applied, it modifies every example it matches on the training and validation sets, and the classifier is retrained on the backend. Even this simple form of feedback already has a tremendous impact - one is able to remove very common words, remove parts of the document that may lead to overfitting (e.g. headers in the 20 newsgroups dataset), and etc.

CONCLUSIONS / FUTURE WORK

In this work, we propose and implement a tool that enables human-in-the-loop machine learning. We primarily focused on the "explain" aspect, which allows the practitioner to understand what kind of concepts the system is learning, and why. We also provide a simple form of feedback, which allows for data cleaning. Since our tool has a lot of features, we built a tutorial using Trip.js[3], which guides you through each of the features interactively. We received a lot of positive feedback when presenting the poster for this work. Some notable comments were to the effect of "this is great - I took a machine learning course last quarter and it really bothered me that I didn't know what it was learning, or how to improve it", or "are you guys thinking of turning this into a startup?".

As for future work, an obvious next step is doing a user

[3]http://eragonj.github.io/Trip.js/

study to validate the usefulness of our tool. We claim that our system allows users to come up with models that generalize better, so a study where models are evaluated on a held out dataset that was collected in a different manner than the training and validation datasets seems like the right approach. Another line of work would be overcoming the databin size limitation, by aggregating nearby points into "clusters", which could then be expanded by hovering or clicking. More work on the feedback side of the picture would greatly improve the usefulness of the tool. One can imagine the full range of feature engineering being done in the tool - and maybe even model and hyperparameter selection. Someone in the poster session suggested that we allow for explanations of classes other than the predicted one - so that one could know how to "force" the model to predict the right class, and not only to stop predicting the wrong one. Finally, one last line of work would be to expand this to other kinds of data, such as images and tabular data, which are widely used in the scientific community.

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