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Active learning in E-Commerce Merchant Classification using Website Information

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Abstract: Data and the collection and analysis of data has become an important part of everyday life. For example, navigation, e-commerce, and social media all make use of immense amounts of data to provide users with suggestions on the best routes to take, which new items they might be most interested in, and which content might fit best with their interests. A variety of algorithms and methods exist to process the data and use it to make predictions. One such algorithm is xPAL, which is a decision-theoretic approach to measure the usefulness of a labeling candidate in terms of its expected performance gain. With xPAL and other active machine learning methods an optimal strategy can be explored to classify new data points.

Keywords: probabilistic active learning xPAL machine learning multi-class classification active learning

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Introduction

One of the main challenges of creating a successful machine learning model is obtaining labeled data. With easy access to a variety of modern tools, devices, and sensors, we are able to rapidly collect unlabeled data. But, in supervised learning, prediction models are trained using labeled data. The problem is that acquiring labels for the collected data can be expensive, time-consuming, or even impossibly difficult in some cases.

However, methods have been developed to help reduce the number of labeled data required to train the classifier. Active learning is a semi-supervised machine learning framework where the model is trained with a smaller set of labeled data but which also aims to exploit trends within the unlabeled data. Active learning is a framework in which the learner has the freedom to select which data points are added to its training set (Roy and McCallum [2001]).

Active learning is different from other frameworks because it uses the unlabeled data and some evaluation criteria to determine which candidate could be the most beneficial to the model if it was given a label. In summary, the model requests the label from some oracle that provides the label then it takes this new labeled data point and rebuilds the classifier. We describe it as semi supervised active learning because of the oracle (typically a human) involved in the process that provides the label for the requested candidate data.

In our case we will provide a set of labeled data to the active learning framework (or sampling strategy). The sampling strategy will assume all the data is unlabeled and then choose a candidate from the unlabeled data pool. Then the label is revealed and the classifier is updated using the new data point. The newly labeled data point is then added to the labeled data pool and the process repeats.

We have some data (website urls) for some company or business that are given to us from our partner. From this data our partner currently utilizes human labor to browse the website and then label the url with a category (23 labels) and a sub-category (234+ tags) that branch from the main category but still have some relation. This is a repetitive and expensive task that could be supplemented using active learning.

To reduce the amount of data required to train the classifier we consider a combination of tools and frameworks, namely: Scrapy, Postgres, a translation service, and an active learning sampling strategy paired with a classifier. We also explore the use of different classifiers to determine if there is some optimal classifier.

A website is required as input, then we use the Scrapy framework to navigate to the webpage, and collect then store the scraped data into the database. Next we access the data, translate the text, and add the translated data back into the database. During this process we also remove some html tags and other unnecessary data.

Once the the data is close to just pure text we use TF-IDF to transform it into a vectorized representation. This data is used by the active learning sampling strategy and the model is trained iteratively. We also explore different classifiers to determine if there is some optimal classifier other than the one implemented within the sampling strategy framework.

In the first section we introduce active learning and the different components of active learning. In the second section we look more into the details of xPAL and how it works. In the third section we discuss the data and the steps we took to collect and process the data. In the fourth section we conduct a variety of experiments to explore the performance of the sampling strategies and alternative classifiers.

Our goal is to understand the entire process including the web scraping, translation, storing, and performance of the selection strategies and classifiers. This analysis will allow our partner to learn from our tests and experiments. It will also allow them to make an informed decision on which models and selection strategies may be best suited for their needs moving forward.

Notable Definitions

In this section we define some terms and ideas that will be helpful in understanding the upcoming sections.

Definition 1 (Beta Prior)**.** *A beta prior is a conjugate prior for the binomial distribution. It is a continuous probability distribution defined on the interval [0, 1] and is parameterized by two positive shape parameters, α and β. The beta distribution is defined as:*

$$Beta(\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$

where Γ is the gamma function and x is a random variable. The gamma function is defined as:

$$\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt$$

The gamma function is used as a normalizing constant to ensure that the probability density function integrates to 1 over the simplex, which is the space of all probability vectors that sum to 1.

Definition 2 (Conjugate Prior)**.** *A conjugate prior is a prior distribution that is in the same family of distributions as the likelihood function. In other words, the posterior distribution will have a similar functional form to the prior distribution.*

Definition 3 (Decision-Theoretic)**.** *Decision-theoretic active learning is a framework that uses the expected performance gain of a candidate to determine which candidate to label. The expected performance gain is the expected performance of the classifier after labeling the candidate minus the expected performance of the classifier before labeling the candidate. The expected performance of the classifier is the expected value of the performance measure given the posterior distribution of the classifier.*

Definition 4 (Dirichlet Distribution)**.** *The Dirichlet distribution is a multivariate generalization of the beta distribution. It is a continuous probability distribution defined on the K-simplex, $\Delta_K = \{x \in \mathbb{R}^K : x_i \geq 0, \sum_{i=1}^{K} x_i = 1\}$. The*

Dirichlet distribution is parameterized by a vector of positive shape parameters, $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_K)$. The Dirichlet distribution is defined as:

$$Dir(\alpha) = \frac{\Gamma(\sum_{i=1}^{K} \alpha_i)}{\prod_{i=1}^{K} \Gamma(\alpha_i)} \prod_{i=1}^{K} x_i^{\alpha_i - 1}$$

where Γ is the gamma function as defined in Definition 1 and where x is a random vector.

Definition 5 (Ground Truth)**.** *Ground truth is the true label of a data point.*

Definition 6 (Posterior Probabilities)**.** *Posterior probability is a type of conditional probability that results from updating the prior probability with information summarized by the likelihood via an application of Bayes' rule. The posterior probability is the probability of an event occurring given that another event has occurred.*

Definition 7 (Omniscient Oracles)**.** *Omniscient oracle is a hypothetical entity that has complete knowledge of the true labels of all data points in a given dataset. An omniscient oracle knows the ground truth labels of all data points.*

Definition 8 (TF-IDF)**.** *TF-IDF is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in information retrieval and text mining. The TF-IDF value increases proportionally to the number of times a word appears in the document and is offset by the frequency of the word in the corpus (large structured set or collection of speech or text data).*

1. Active Learning

1.1 Introduction

Russel and Norvig succinctly define an agent and different types of learning in their book "Artificial Intelligence: A Modern Approach" (Russell and Norvig [2009]), their definition is paraphrased here. They define an agent as something that acts and a rational agent as one that acts so as to achieve the best outcome. If there is uncertainty, then the agent tries to achieve the best expected outcome. Any component of an agent can be improved by learning from data. The improvements and techniques used to make them depend on four major factors:

- Which component is to be improved.
- What prior knowledge the agent already has.
- What representation is used for the data and the component.
- What feedback is available to learn from.

Here we will mostly be focused on the final point, "What feedback is available to learn from". However, we will also discuss the importance of the second and third points because of our use of Bayesian learning and how the form and quality of the data affects the experiments. There are three main types of feedback that determine the three main types of learning, which are: unsupervised, reinforcement, and supervised.

In unsupervised learning an agents goal is to discover patterns in the data even though no feedback or labels are provided. In reinforcement learning, the agent learns from a series of rewards or punishments that are dealt out based on its decisions. In supervised learning, an agent learns from input-output pairs, which can be discrete or continuous, to find a function that maps the pairs as best as possible.

The goal of supervised learning is given a training set of N example input-output pairs:

$$(x_1, y_1), (x_2, y_2), ...(x_N, y_N),$$

where each y_j was generated by some unknown function $y = f(x)$, find a function h that approximates the true function f.

In reality, the lines separating the types of learning aren't so clear. Semi-supervised learning is also an important and widely used approach. In semi-supervised learning we are given a few labeled examples that were labeled by some oracle (labeler, data annotator, etc.) and we must then make the most of a large collection of unlabeled examples. But what can we do with the unlabeled data?

Supervised learning models almost always get more accurate with more labeled data. Active learning is the process of deciding which data to select for annotation (Munro [2021]). In other words, the central component of an active learning algorithm is the selection strategy, or deciding which of the unlabeled data could be the most useful to the model if it was labeled. Active learning uses a selection strategy that augments the existing classifier, it is not itself a classifier but rather an evaluation methodology working with a classifier.

Many different sampling strategies exist. First we will discuss query functions then we will briefly define three basic sampling approaches: uncertainty, diversity, and random sampling to get an idea of sampling. We will then discuss some other more advanced sampling approaches that are used in our experiments. When sampling the unlabeled data an ordered list is returned and the top candidate is the candidate that is expected to be most valuable for the model, but we are not strictly limited to taking just one candidate.

1.2 Query Function Construction

There are various techniques used to construct the querying functions we have discussed. We will focus on pool-based active learning, but a number of interesting and relevant ideas appear within other active-learning frameworks that are worth mentioning.

1.2.1 Pool-Based

The learner calculates the potential gain of all the unlabeled points in the pool, then requests the label for the point that maximizes the expected information gain for the classifier (Huang and Lin [2016]). For pool-based multiclass active learning, a labeled pool and an unlabeled pool are presented to the algorithm. In each iteration, the algorithm selects one instance from the unlabeled pool to query its label.

1.2.2 Stream-Based

The learner is provided with a stream of unlabeled points. On each trial, a new unlabeled point is drawn and introduced to the learner who must decide whether or not to request its label (Baram et al. [2004]). Note that the stream-based model can be viewed as an online version of the pool-based model.

1.2.3 Membership Queries

On each trial the learner constructs a point in input space and requests its label (Baram et al. [2004]). This model can be viewed as a pool-based game where the pool consists of all possible points in the domain.

1.3 Sampling Strategies

Sampling strategies, also referred to as selection strategies, are the core of the active learning process. The goal of sampling is to select the most useful data points from the unlabeled pool to label. The most useful data points are those that are expected to improve the classifier the most.

1.3.1 Random Sampling

Random sampling is self explanatory as it randomly selects an unlabeled data point from the pool and requests to have it labeled then it uses this newly selected data point to update the model. Random sampling is good to use as a baseline to compare other sampling strategies with.

1.3.2 Diversity Sampling

Diversity sampling is the set of strategies for identifying unlabeled items that are underrepresented or unknown to the machine learning model in its current state (Munro [2021]). The items may have features that are unique or obscure in the training data, or they might represent data that are currently under-represented in the model.

Either way this can result in poor or uneven performance when the model is applied or the data is changing over time. The goal of diversity sampling is to target new, unusual, or underrepresented items for annotation to give the algorithm a more complete picture of the problem space.

1.3.3 Uncertainty Sampling

Uncertainty sampling is the set of strategies for identifying unlabeled items that are near a decision boundary in the current machine learning model (Munro [2021]). Uncertainty sampling is simple given a classifier that estimates $P(C|w)$ (Lewis and Gale [1994]). On each iteration, the current version of classifier can be applied to each data point, and the data with estimated $P(C|w)$ values closest to 0.5 are selected, since 0.5 corresponds to the classifier being most uncertain of the class label.

These items are most likely to be wrongly classified, so they are the most likely to result in a label that differs from the predicted label, moving the decision boundary after they have been added to the training data and the model has been retrained.

1.3.4 PAL

Probabilistic Active Learning (PAL) follows a smoothness assumption and models for a candidate instance both the true posterior in its neighborhood and its label as random variables (Krempl et al. [2014]). By computing for each candidate its expected gain in classification performance over both variables, PAL selects the candidate for labeling that is optimal in expectation. PAL shows comparable or better classification performance than error reduction and uncertainty sampling, has the same asymptotic linear time complexity as uncertainty sampling, and is faster than error reduction.

1.3.5 xPAL

Extended probabilistic gain for active learning (xPAL) is a decision-theoretic selection strategy that directly optimizes the gain and misclassification error, and uses a Bayesian approach by introducing a conjugate prior distribution to determine the class posterior to deal with uncertainties (Kottke et al. [2021]). Although the data distribution can be estimated, there is still uncertainty about the true class posterior probabilities.

These class posterior probabilities can be modeled as a random variable based on the current observations in the dataset. For this model, a Bayesian approach is used by incorporating a conjugate prior to the observations. This produces more robust usefulness estimates for the candidates.

1.3.6 ALCE

Active Learning with Cost Embedding (ALCE) is a non-probabilistic uncertainty sampling algorithm for cost-sensitive multiclass active learning (Huang and Lin [2016]). They first designed a cost-sensitive multiclass classification algorithm called cost embedding (CE), which embeds the cost information in the distance measure in a special hidden space by non-metric multidimensional scaling. They then use a mirroring trick to let CE embed the possibly asymmetric cost information in the symmetric distance measure.

1.3.7 QBC

Query by committee uses an ensemble of classifiers that are trained on bootstrapped replicates of the labeled set (Seung et al. [1992]). The idea is to train a committee of classifiers on the available labeled data and then use the committee to select the most informative unlabeled data for labeling (Freund et al. [1997]). The committee consists of several classifiers, each trained on a slightly different subset of the available labeled data.

The QBC algorithm measures the disagreement of the committee's predictions on each unlabeled data point. The intuition is that if the committee members disagree then it is likely to be a difficult data point for the current classifier and thus informative for labeling.

The algorithm selects a fixed number of the most informative examples and asks the user or oracle to label them. The labeled examples are then added to the labeled dataset, and the committee is retrained on the expanded labeled dataset. This process is repeated until the algorithm achieves a desired level of accuracy or the available labeling budget is exhausted.

1.3.8 EER

Monte Carlo estimation of error reduction (EER) estimates future error rate by log-loss, using the entropy of the posterior class distribution on a sample of the unlabeled examples, or by 0-1 loss, using the posterior probabilities of the most probable class for the sampled unlabeled examples (Roy and McCallum [2001]).

1.4 Classifiers

The main classifier used with the active learning sampling strategies is the Parzen Window Classifier (PWC). It is a non-parametric method used for classification and density estimation in machine learning. It works by estimating the probability density function of a given class using a kernel density estimator, and then using Bayes' theorem to classify new instances based on their estimated probability densities.

We will also explore using other classifiers from Scikit-Learn and TensorFlow and compare their performance on the data without using active learning to see if there is any improvement beyond the PWC classifier.

1.5 Summary

It should now be more clear how the sampling strategy is the major component of active learning. The query function construction is also important but it is just a means of routing the data to be sampled. In the next chapter we will look into the specifics of xPAL.

2. Understanding xPAL

We have introduced many different active learning sampling strategies in the previous section, and we will use them to test which strategy performs best with our data. However, we will mainly focus on using the xPAL sampling strategy and a pool based query function. The xPAL sampling strategy is a decision-theoretic approach to measure the usefulness of a labeling candidate in terms of its expected performance gain (Kottke et al. [2021]). We can estimate the data distribution but we are uncertain about the true class posterior probabilities. The class posterior probabilities are modeled as a random variable based on the current observations. Therefore a Bayesian approach is used by incorporating a conjugate prior to the observations. In general, the idea is to estimate the expected performance gain for the classifier, using the unlabeled data, and then select the best data point and request or reveal its label. Descriptions of the variables used throughout the paper are listed in Table 2.1.

	Descriptions
C	Number of classes
x	Input $x \in \mathbb{R}^D$ (D-dimensional vector space)
y	Class label $y \in \mathcal{Y}$
$\mathcal{Y}$	Set of all labels $\mathcal{Y} = \{1, ..., C\}$
$f^{\mathcal{L}}$	Classifier that maps input x to label y
L	Loss
R	Risk $R(f^{\mathcal{L}}) \in \mathbb{R}_0^x$
$R_{\mathcal{E}}$	Empirical risk
$\mathcal{L}$	Set of labeled data $\{(x_1, y_1), ..., (x_n, y_n)\}$
$\mathcal{U}$	Set of unlabeled data $\{x_1, ..., x_n\}$
$\mathcal{E}$	Set of available labeled and unlabeled data $\{x : (x, y) \in \mathcal{L}\} \cup \mathcal{U}$

Table 2.1: Variable names and descriptions.

2.1 Kernel

A kernel based classifier is used in xPAL which determines the similarity of two data points. The kernel function $\boldsymbol{K}(x, x')$ is a function that maps two data points to a real number, which is then used to estimate the probability density of the data. The kernel frequency estimate $\boldsymbol{k}_x^{\mathcal{L}}$ of an instance x is calculated using the labeled instances $\mathcal{L}$. The y-th element of that C-dimensional vector describes the similarity-weighted number of labels of class y.

$$\boldsymbol{k}_x^{\mathcal{L}}, y = \sum_{(x', y') \in \mathcal{L}} \mathbb{1}_{y=y'} \boldsymbol{K}(x, x') \tag{2.1}$$

The Parzen Window Classifier uses the labeled data for training and predicts the most frequent class and was selected by Kottke et al. to use because of its speed and ability to implement different kernels depending on the data (Kottke et al. [2021]). It was used for all the selection strategies in their experiments.

$$f^{\mathcal{L}}(x) = \arg\max_{y \in \mathcal{Y}} \left(\boldsymbol{k}^{\mathcal{L}}_{x,y} \right) \tag{2.2}$$

We will use the PWC classifier for our experiments because that is what is implemented with the active learning strategies, but we will also evaluate other classifiers and compare their performance less active learning.

2.2 Risk

For xPAL, Kottke et al. use the classifications error as the performance measure and minimize the zero-one loss. The risk describes the expected value of the loss relative to the joint distribution given some classifier. The zero-one loss returns 0 if the prediction from the classifier is equal to the true class else it returns 1. The risk is a theoretical concept that cannot be computed directly since it requires knowledge of the entire population distribution. Instead, we typically try to approximate the risk using the empirical risk.

$$\begin{aligned} R(f^{\mathcal{L}}) &= \mathop{\mathbb{E}}_{p(x,y)}[\boldsymbol{L}(y, f^{\mathcal{L}}(x))] && (2.3)\\ &= \mathop{\mathbb{E}}_{p(x)}\left[\mathop{\mathbb{E}}_{p(y|x)}[\boldsymbol{L}(y, f^{\mathcal{L}}(x))]\right] && (2.4)\\ \boldsymbol{L}(y, f^{\mathcal{L}}(x)) &= \mathbb{1}_{f^{\mathcal{L}}(x) \neq y} && (2.5) \end{aligned}$$

Because it is not known how the data is generated Kottke et al. use a Monte-Carlo integration with all available data $\mathcal{E}$ to represent the generator. The empirical risk $R_{\mathcal{E}}$ is the average of the loss over all the data points in the dataset. It refers to the average value of a given loss function over a finite set of observed data points.

$$\begin{aligned} R_{\mathcal{E}}(f^{\mathcal{L}}) &= \frac{1}{|\mathcal{E}|} \sum_{x \in \mathcal{E}} \mathop{\mathbb{E}}_{p(y|x)} \left[\boldsymbol{L}(y, f^{\mathcal{L}}(x))\right] && (2.6)\\ &= \frac{1}{|\mathcal{E}|} \sum_{x \in \mathcal{E}} \sum_{y \in \mathcal{Y}} p(y|x) \boldsymbol{L}(y, f^{\mathcal{L}}(x)) && (2.7) \end{aligned}$$

The empirical risk is a computable quantity that can be used as an estimate of the risk. However, it is only an approximation and is subject to sampling error.

2.3 Conjugate Prior

The conditional class probability $p(y|x)$ depends on the ground truth which is unknown. As a result the conditional class probability is exactly the y-th element of the unknown ground truth vector $\boldsymbol{p}$. The nearby labels from $\mathcal{L}$ can be used to estimate the ground truth $\boldsymbol{p}$ because the oracle provides the labels according to

$\boldsymbol{p}$. If we assume a smooth distribution then the estimate is relatively close to the ground truth if we have enough labeled instances.

$$p(y|x) = p(y|t(x)) = p(y|\boldsymbol{p}) = \text{Cat}(y|\boldsymbol{p}) = p_y \tag{2.8}$$

A Bayesian approach is used for estimation by calculating the posterior predictive distribution (calculating the expected value over all possible ground truth values). The probability of y given some x is approximately equal to the kernel frequency estimate of x.

$$p(y|x) \approx p(y|\boldsymbol{k}_x^{\mathcal{L}}) = \mathop{\mathbb{E}}_{p(\boldsymbol{p}|\boldsymbol{k}_x^{\mathcal{L}})}[p_y] = \int p(\boldsymbol{p}|\boldsymbol{k}_x^{\mathcal{L}}) p_y d\boldsymbol{p} \tag{2.9}$$

Bayes theorem is then used to determine the posterior probability of the ground truth at instance x in Equation 2.10. The likelihood $p(\boldsymbol{k}_x^{\mathcal{L}}|p)$ is a multinomial distribution because each label has been drawn from $\text{Cat}(y|\boldsymbol{p})$. A prior is introduced and selected as a Dirichlet distribution with $\alpha \in \mathbb{R}^C$ as this is the conjugate prior of the multinomial distribution. An indifferent prior is chosen and each element of alpha is set to the same value. The Dirichlet distribution is an analytical solution for the posterior when the conjugate prior of the multinomial likelihood are used.

$$\begin{aligned} p(\boldsymbol{p}|\boldsymbol{k}_x^{\mathcal{L}}) &= \frac{p(\boldsymbol{k}_x^{\mathcal{L}}|\boldsymbol{p})p(\boldsymbol{p})}{p(\boldsymbol{k}_x^{\mathcal{L}})} && (2.10) \\ &= \frac{\text{Mult}(\boldsymbol{k}_x^{\mathcal{L}}|\boldsymbol{p}) \cdot \text{Dir}(\boldsymbol{p}|\alpha)}{\int \text{Mult}(\boldsymbol{k}_x^{\mathcal{L}}|\boldsymbol{p}) \cdot \text{Dir}(\boldsymbol{p}|\alpha) d\boldsymbol{p}} && (2.11) \\ &= \text{Dir}(\boldsymbol{p}|\boldsymbol{k}_x^{\mathcal{L}} + \alpha) && (2.12) \end{aligned}$$

The conditional class probability is determined next from Equation 2.9. It is calculated with the expected value of the Dirichlet distribution.

$$\begin{aligned} p(y|\boldsymbol{k}_x^{\mathcal{L}}) &= \mathop{\mathbb{E}}_{\text{Dir}(\boldsymbol{p}|\boldsymbol{k}_x^{\mathcal{L}}+\alpha)}[p_y] && (2.13) \\ &= \int \text{Dir}(\boldsymbol{p}|\boldsymbol{k}_x^{\mathcal{L}} + \alpha) p_y d\boldsymbol{p} && (2.14) \\ &= \frac{(\boldsymbol{k}_x^{\mathcal{L}} + \alpha)_y}{||\boldsymbol{k}_x^{\mathcal{L}} + \alpha||_1} && (2.15) \end{aligned}$$

The last term is the y-th element of the normalized vector. The 1-norm is used to normalize the vector.

2.4 Risk Difference Using the Conjugate Prior

Next, we insert equation 2.15 into the empirical risk equation 2.7. We are approximating $p(y|x)$ with $p(y|\boldsymbol{k}_x^{\mathcal{L}})$ which is the empirical risk based on the labeled data $\mathcal{L}$.

$$\hat{R}_{\mathcal{E}}(f^{\mathcal{L}}, \mathcal{L}) = \frac{1}{|\mathcal{E}|} \sum_{x \in \mathcal{E}} \sum_{y \in \mathcal{Y}} \frac{(\boldsymbol{k}_x^{\mathcal{L}} + \alpha)_y}{||\boldsymbol{k}_x^{\mathcal{L}} + \alpha||_1} \cdot L(y, f^{\mathcal{L}}(x)) \tag{2.16}$$

Now lets assume we add a new labeled candidate (x_c, y_c) to the labeled data set $\mathcal{L}$. We will now denote the set with the newly labeled data point $\mathcal{L}^+ = \mathcal{L} \cup \{(x_c, y_c)\}$. Next we need to determine how much this new data point improved our classifier. We then make an estimate of the gain in terms of risk difference using the probability to estimate the ground truth.

$$\Delta \hat{R}_{\mathcal{E}}(f^{\mathcal{L}^+}, f^{\mathcal{L}}, \mathcal{L}^+) = \hat{R}_{\mathcal{E}}(f^{\mathcal{L}^+}, \mathcal{L}^+) - \hat{R}_{\mathcal{E}}(f^{\mathcal{L}}, \mathcal{L}^+) \tag{2.17}$$

$$= \frac{1}{|\mathcal{E}|} \sum_{x \in \mathcal{E}} \sum_{y \in \mathcal{Y}} \frac{(\boldsymbol{k}_x^{\mathcal{L}^+} + \alpha)_y}{||\boldsymbol{k}_x^{\mathcal{L}^+} + \alpha||_1} \cdot \Big(L(y, f^{\mathcal{L}^+}(x)) - L(y, f^{\mathcal{L}}(x)) \Big) \tag{2.18}$$

The observations used to estimate the risk are the same for both the old and new classifiers. We do this because we assume that adding labeled data will make the classifier better, so this allows us to more accurately compare the current classifier and the new one.

2.5 Expected Probabilistic Gain

If we are able to reduce the error with the new $\mathcal{L}^+$ model then equation 2.18 will be negative. As a result, we negate this term and maximize the expected probabilistic gain. To simplify we set $\alpha = \beta$.

$$\text{xgain}(x_c, \mathcal{L}, \mathcal{E}) = \mathop{\mathbb{E}}_{p(y_c|\boldsymbol{k}_{x_c}^{\mathcal{L}})} \Big[-\Delta \hat{R}_{\mathcal{E}}(f^{\mathcal{L}^+}, f^{\mathcal{L}}, \mathcal{L}^+) \Big] \tag{2.19}$$

$$= - \sum_{y \in \mathcal{Y}} \frac{(\boldsymbol{k}_x^{\mathcal{L}} + \beta)_y}{||\boldsymbol{k}_x^{\mathcal{L}} + \beta||_1} \cdot \frac{1}{|\mathcal{E}|} \sum_{x \in \mathcal{E}} \sum_{y \in \mathcal{Y}} \frac{(\boldsymbol{k}_x^{\mathcal{L}^+} + \alpha)_y}{||\boldsymbol{k}_x^{\mathcal{L}^+} + \alpha||_1} \cdot \Big(\boldsymbol{L}(y, f^{\mathcal{L}^+}(x)) - \boldsymbol{L}(y, f^{\mathcal{L}}(x)) \Big) \tag{2.20}$$

Finally, for the xPAL selection strategy, we simply choose this candidate $x_c^* \in \mathcal{U}$ where the gain is maximized:

$$x_c^* = \arg\max_{x_c \in \mathcal{U}} \left(\text{xgain}(x_c, \mathcal{L}, \mathcal{E}) \right). \tag{2.21}$$

3. Data Review

In this chapter we take a deeper look into the data and the process of collecting, translating, and encoding the data. Our partner has provided a small sample of 1000 labeled data points. This data was manually labeled by an human annotator.

3.1 Overview

The data consists of a merchant name, merchant website (url), merchant category, and merchant tag as shown in Table 3.1.

merchant name	merchant url	merchant category	merchant tags
State Hospital	http://hospital.com/	Health	'{"Clinic"}'

Table 3.1: This is an example of a single data point from the original data set.

The current process consists of giving the merchant url to an annotator. The annotator then views the website and either can instantly (after viewing the homepage) provide a label and tags for the website. However, in some cases the annotator may need to browse further (by viewing sibling pages such as the 'About Us' section or individual product pages) to get an idea of how the website should be classified.

The annotator simply needs to view then mentally process the text and images from the website and make some reasonable decisions on how the site should be classified. However, the annotator does not record what the content on the site said or what drove them to make their decision.As a result we are missing a key portion of data for the classification process.

Tags are also when labeling the data to provide further granularity. The merchant tags are ordered by specificity, with the first tag in the list being the most general and the final being the most specific. An example of the tag hierarchy is show in Table. 3.2 where we can see that this sample consists of data from various categories all contained within the 'Eco' side tag grouping.

Category	Level 1 Tag	Level 2 Tag	Level 3 Tag	Side Tag
Travel	Local Transport	Micro-mobility	Bike Sharing	Eco
		Public Transport		Eco
Fashion	Clothing - Other	Second Hand		Eco
Car	Charging Station			Eco
	Car Sharing			Eco

Table 3.2: This is an example of how the tags use different levels.

The tags are important because they allow us to separate the data even further and group or sort the data differently. However, in our work we didn't opt to include the tags in the classification or selection strategy process at this time.

3.2 Collection

Similarly to the annotator our goal is to automate the navigation, collection/ storing process, and classification of the website. This speeds up the browsing process by navigating to websites that have already been labeled and scraping the text data and storing it into a database. We also make the obvious checks to see if the website has already been scraped and stored in the database to ensure we are not wasting time and resources.

The initial 1000 data points we received were labels with a pointer (a url) to where the text data is located (the website). The labels needed to be augmented with the text from the websites. For the human annotator, this text data is stored is simply stored in their short term memory while they view the website. Once they have a category for the website they can mostly forget about the text data and move on to assigning a category to the next website.

To gather the text data from the websites we used the Scrapy framework to extract text data from a single top level page of a website. We chose only to scrape the top level (main or home) page text because of the results published in another study where it was observed that adding more pages to the data set does not necessarily mean obtaining better results (Sahid et al. [2019]).

Out of these initial data points 184 contained links that could not be accessed or links that provided no text data that could be scraped. Two websites were particularly problematic. Facebook and Instagram both are used by businesses as main information webpages. However, neither site allows for simple text scraping and a more advanced approach was needed to extract data from business with information on these platforms. In an effort to reduce the complexity of our scraper we decided to not create an additional scraper or integrate an API to handle these websites. Out of the remaining 816 data points 275 of them were in English. Out of the remaining 275 English data points the data was distributed into the categories as shown in Figure 3.1.

Our goal was to see how well the classifier and active learning sampling strategies would perform with limited data, but 275 samples with 23 categories was a bit to small and we still had a significant amount of data that wasn't being used (i.e. the untranslated data) so we decided we needed to find a way to translate the existing data. We tried various libraries available on GitHub but weren't getting good consistent results and we were hitting API request limits. After some time, we found that Azure had a service available and a free option of up to 2 million characters translated per month. This was a viable option and we were able to use this API to translate the remaining data. We limited the number of characters to 1000 per non English data point from the scraped text to avoid maxing out the API.

3.3 Processing

It is important for us to have the data in English as it allows us to exploit stop words when using the Scikit-Learn TF-IDF vectorizer to construct our data set. Stop words are words like "and", "the", "him", which are presumed to be uninformative in representing the content of a text, and which may be removed to avoid them being construed as signal for prediction (Pedregosa et al. [2011]).

This holds true for our data set as well because we are not analyzing the text for sentiment or other linguistic features. We are simply looking for the most common words in each category.

At this stage, it was clear that our data set wasn't representing all categories equally. The 'Food and Drink' category has many more data points then the 'Culture' and 'Investments' categories which each had a single data point, see Figure 3.1. The 'Children' and 'Financial Services' categories weren't represented at all. Obviously this was problematic because we would like to have, minimum, three data points in each category to build train and test sets.

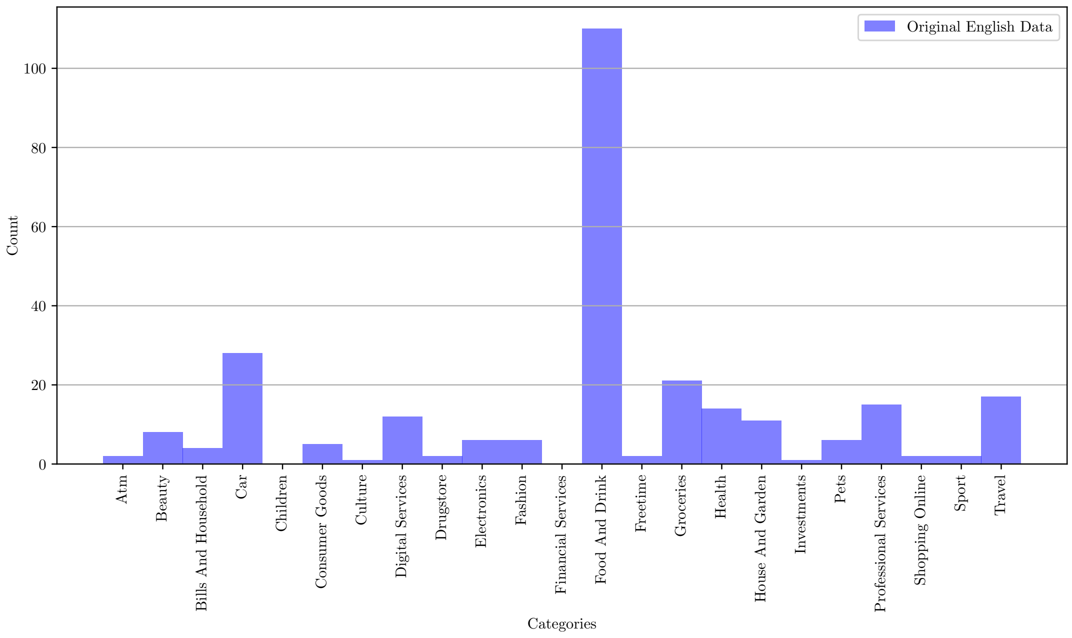


Figure 3.1: The histograms for the original usable english data.

An example of the first 100 characters of raw scraped text data from a website is shown in Table 3.3. The scraped text data is a single string of text that is a concatenation of all the text data pulled from the website url.

Table 3.3: Raw text collected by scraper and the translated text.

Raw	DentalVision - Profesionální soukromá zubní klinika v centru Hradce Králové ÚvodSlužby a ceníkOrdina
Translated	DentalVision Professional private dental clinic in the center of Hradec Králové IntroductionServices

We can see that html and other symbols are removed and the majority of the words were translated. There are still some issues with words being concatenated such as 'IntroductionServices' however we do try to separate these words after translation using a regex pattern, but we attempt to break these words apart before passing the text to the TF-IDF vectorizer.

To complement the original data we manually collected and labeled 141 additional data points for the categories that had low representation. This consisted of searching the internet for lists of websites similar to the ones in each category.

Next we would browse the site to see if it was relevant and then add it to our list of additional websites and provide it a label. This was necessary because some categories only had 2 or 3 samples, however it was quite time consuming. The additional data are almost all from English language websites, this made it easier for us to explore and provide accurate labels for the sites. These data group splits will be referenced in the following experiments and a table of the exact counts for each group can be found in Appendix Table A.1. In Figure 3.2. we show a bar chart of the counts of the original data and the additional data for each category and for each language, with the two letter language codes used to represent the languages.

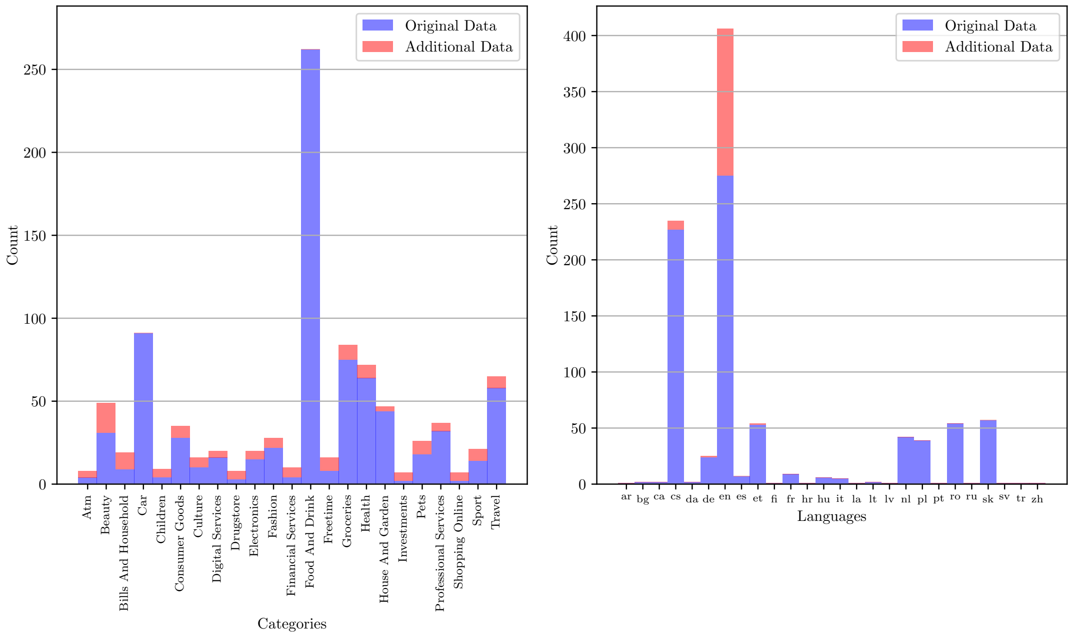


Figure 3.2: The histograms for the original and additional data for all languages.

After translating the data we used the TF-IDF vectorizer from Scikit-Learn. TF-IDF is an important tool commonly used in natural language processing and data science. The first part, TF, stands for term frequency and is a measure of how often a term appears in a document, while IDF (inverse document frequency) is a measure of how important a term is in a set of documents. The idea behind IDF is that a term that appears in many documents is less important than a term that appears in only a few documents, as the former is likely to be more common and less discriminative. The formula for calculating TF-IDF is as follows:

$$\text{TF-IDF} = TF \times IDF \tag{3.1}$$

where:

$$\text{TF} = \frac{\text{number of occurrences of term } t \text{ in document}}{\text{total number of terms in document}}$$
$$\text{IDF} = \log_e\left(\frac{\text{total number of documents}}{\text{number of documents with term } t \text{ in it}}\right)$$

To calculate the TF-IDF score for a given term in a document, we would first calculate the term frequency (TF) by counting the number of times the term appears in the document and dividing it by the total number of terms in the document. Then, we would calculate the inverse document frequency (IDF) by taking the logarithm of the total number of documents in the set divided by the number of documents that contain the term. Finally, we would multiply TF by IDF to get the TF-IDF score for the term in the document as shown in Equation 3.1.

This process is repeated for each term in each document in the corpus, resulting in a TF-IDF matrix that can be used for various natural language processing tasks such as text classification, information retrieval, and clustering. It is important to understand TF-IDF because it is the basis for the feature selection we use throughout our experiments.

We were also able to find highly correlated words for each category using chi-squared analysis with all useable data, shown below in Table 3.4. Chi-squared analysis is a statistical method used to determine the association between two categorical variables. It is used to test whether two categorical variables are independent of each other or not. In other words, it helps to determine if there is a significant relationship between two variables.

The chi-squared test involves comparing the observed frequencies of each category in a contingency table to the expected frequencies. A contingency table is a two-dimensional table that shows the frequency distribution of two categorical variables. The expected frequencies are the frequencies that would be expected if the two variables were independent. The difference between the observed and expected frequencies is then squared, divided by the expected frequency, and summed over all categories to give the chi-squared statistic. The formula for calculating the chi-squared statistic is as follows:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{3.2}$$

where:

$$\begin{aligned} \chi^2 &= \text{the chi-squared statistic} \\ O_i &= \text{the observed frequency of category i} \\ E_i &= \text{the expected frequency of category i} \end{aligned}$$

The degrees of freedom for the chi-squared test are calculated as (number of rows - 1) x (number of columns - 1). The chi-squared statistic is then compared to a critical value from a chi-squared distribution table with the degrees of freedom and a specified level of significance. If the calculated chi-squared statistic is greater than the critical value, then we reject the null hypothesis that the two variables are independent.

Some categories such as 'Culture', 'Digital Services', 'Shopping Online' that have few data points have words such as 'kihnu', 'synnex', 'joom', respectively, which have no relative meaning to the category in English but also show the limitations of our website scraping and translation capabilities. We also have the problem where some words are actually important but weren't translated correctly such as 'maso' in the 'Groceries' category, which means 'meat' in Czech but wasn't translated properly.

From what we discussed in the previous section, we can see that the 'Culture' category has only one data point and the 'Digital Services' category has only two data points. This is problematic because if the single data point we have doesn't represent the category well then we will continue to have difficulty classifying until we have more robust data.

Table 3.4: Keywords from TF-IDF with chi-squared using the original data.

	Keyword 1	Keyword 2	Keyword 3
Atm	banking	individuals	caixa
Beauty	hairdressing	hairdresser	hair
Bills And Household	liberty	internet	fullness
Car	cars	auto	car
Children	toy	sold	toysrus
Consumer Goods	kiosk	flowers	flower
Culture	theater	museum	kihnu
Digital Services	synnex	bitly	servers
Drugstore	esodrogeria	detergent	drimble
Electronics	laptops	onoff	computers
Fashion	rings	jewellery	women
Financial Services	pre	nissan	insurance
Food And Drink	cafe	bar	restaurant
Freetime	representation	casino	likely
Groceries	liquor	maso	bakery
Health	drug	dental	pharmacy
House And Garden	skylights	paints	hardware
Investments	mistakes	investment	patria
Pets	mat	pet	veterinary
Professional Services	toilet	faculty	parcel
Shopping Online	owner	default	joom
Sport	adidas	singltrek	functional
Travel	rooms	accommodation	hotel

We also calculated the variable importance using the RandomForestRegressor from Scikit-Learn and provided a list of the top 20 most important words from the TF-IDF vectorizer. This helps orient ourselves within the data and check if there may be any major anomalies. This list can be found in Appendix Table A.2.

4. Testing with Original Data

Here we will explore the results of different classifiers and active learning strategies on the original data. The original data consisted of data shown previously in Figure 3.1 and discretely in Table A.1 in Appendix A. The original data was comprised of the original and translated data but not the additionally collected data.

4.1 Active Learning with PWC and RBF Kernel

In Figure 4.1 we have the train and test errors for four different active learning sampling strategies. XPAL appears to perform slightly better than PAL but not significantly better. With our data we found that PAL runs slower than xPAL, which was unexpected based on the mean computation time results published by Kottke et al. [2021]. We expect this drop in calculation time is a result of the high dimensional data.

We weren't satisfied with the testing error which leveled out to about 70% for each sampling strategy. PAL and xPAL were able to rapidly reduce the testing error early on in the training process while random selection and QBC weren't able to determine the data with the highest information gain.

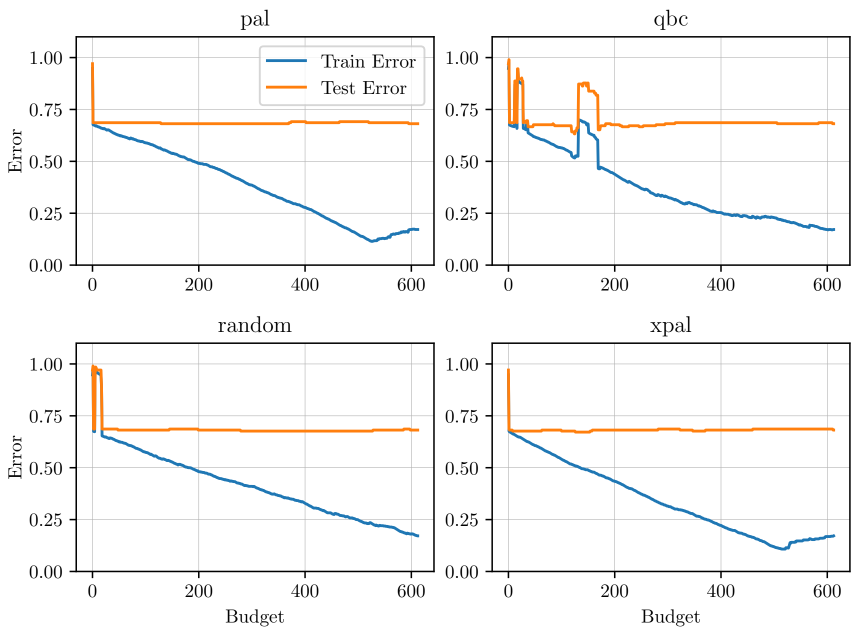


Figure 4.1: Train and test error using different query strategies and RBF kernel for the PWC classifier.

The radial bias function (RBF) kernel is a popular kernel function. It is defined as:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{4.1}$$

where σ is a parameter that controls the smoothness of the kernel and x_i and x_j are the two points in the feature space to compare. As seen in the Figure 4.1 when the PWC classifier uses the RBF kernel it doesn't perform well with this data.

Starting with the data in Figure 4.1 we made an error while constructing the x dataset. While preparing the data, the TF-IDF vectorizer was fitted using all the data instead of just the training data. This resulted in the TF-IDF matrix having more information about the test data than it should have so our testing error results are likely lower than they should be. This error persists throughout the rest of the experiments in this chapter up until the experiments in Section 5.

4.2 Active Learning with PWC and Cosine Kernel

In Figure 4.2 we have the train and test errors for the same four different active learning sampling strategies tested on the same data. The only change was that we used Cosine kernel instead of the RBF kernel.The Cosine kernel is another important kernel function that is used in many machine learning algorithms. It is defined as:

$$K(x_i, x_j) = \frac{x_i \cdot x_j}{\|x_i\| \, \|x_j\|} \tag{4.2}$$

where x_i and x_j are the two points in the feature space to compare. We found that using the Cosine kernel reduced the test error across the board by ~15%.

In Figure 4.2 PAL and xPAL were able to reduce the training error, by about 20% and 25% respectively, early in the training process compared to random selection and QBC. We also tested the other sampling strategies with the Cosine kernel and found that the results were similar. The other sampling strategies and their test data results are shown in Table 4.3 along with the test data from Figure 4.2.

We can see that the sampling strategies test performance converges over time (as we are using the same data and classifier) but xPAL appears to have an absolute minimum near the 600 budget mark in comparison to all sampling strategies. XPAL also appears to be performing well early on in the training process, in the 100-200 budget range. However, this test is only showing the results of one data split. We can get a better idea if we run more tests with different train-test splits and see how the results average out.

Figure 4.3 shows that xPAL seems to be performing the best with our data but we wanted to see if we ran more tests with different train-test splits how the results would average out and which sampling strategy would perform the best on average. We ran 10 different data splits with each of the 7 sampling strategies and then took the average to get a smoother curve compared to the single run results shown in Figure 4.3. The results for this experiment are shown in Figure 4.4.

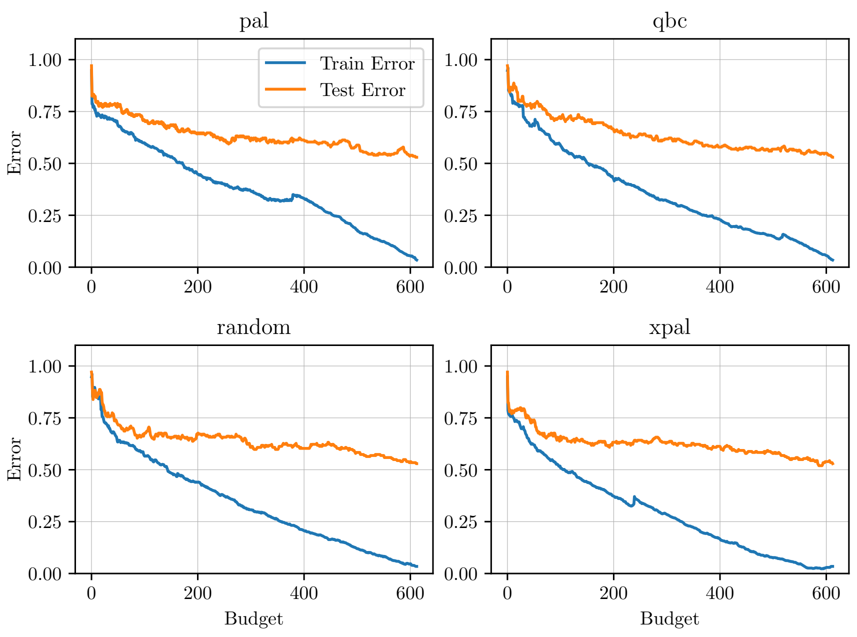


Figure 4.2: Train and test error using different query strategies and Cosine kernel for the PWC classifier.

It is clear in Figure 4.4 that xPAL is performing the best early on (budget from 0-100) in the sample selection process. XPAL selects the data that minimizes the test error and builds the strongest classifier quickly while it takes the other sampling strategies more data points to get to the same level of performance. Around the 100 budget mark we can see that the other selection strategies catch up to xPAL performance wise. We want to note that for each plot where we averaged query strategies (10 runs/ splits per query strategy) that it took 24 hours on average to run the experiment on a CPU cluster with PAL taking the longest of any of the sampling strategies.

4.3 Classifier Evaluation

We also decided to test out some classifiers from the Scikit-Learn library to compare performances. Again we used the original data with the same TF-IDF vectorizer as used with the previous active learning models to stay consistent. It should be noted that cross validation was used here for evaluation but it was not used in the previous sections.

The goal of this exploratory phase was to try and decide which classifier to conduct more thorough testing with. As a result, we didn't use GridSearchCV for each classifier at this stage and we mostly used the default parameters and their cross validation scores with all of the original data (i.e. additional data not included). In some cases where using weights was an option for the classifier we included the precomputed Cosine decay weights. A table of the parameters used for each classifier is shown in Appendix Table A.4.

Initially we made a minor error while evaluating the classifiers that used the precomputed weights in the following experiments. While computing the accu-

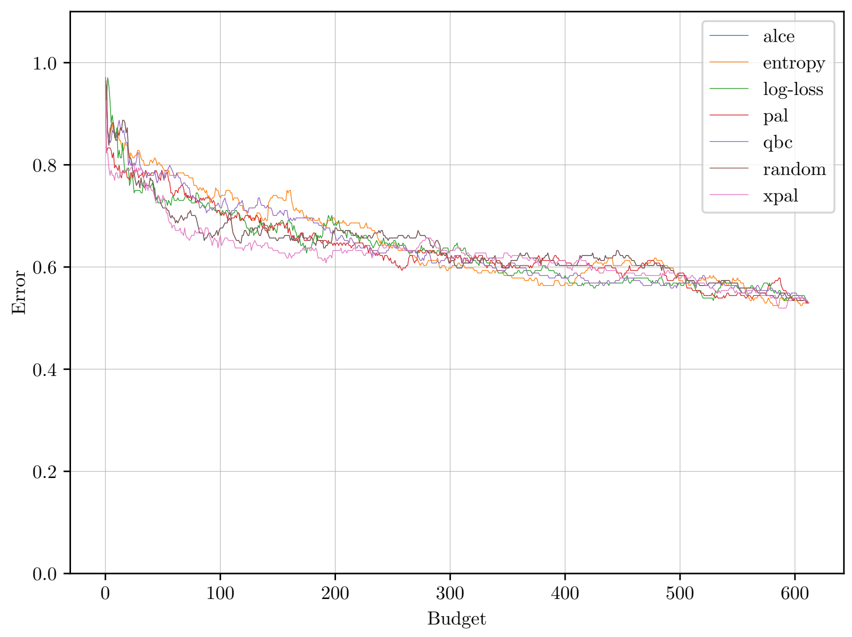


Figure 4.3: Comparing test error with one data split using different query strategies and Cosine kernel for the PWC classifier.

racy scores for the classifiers, we failed to incorporate the class weights that were used in training the classifier. This resulted in the accuracy scores being incorrectly calculated. This error persists throughout the rest of the experiments in this chapter up until the experiments in Section 5.

The results for the different classifiers are shown in Figure 4.5. In the boxplot, the whiskers extend from the box to the furthest data points that are within 1.5 times the inter-quartile range (IQR) of the box. Any data points that are beyond the whiskers are considered outliers and are plotted as individual points or symbols (diamonds) as seen in the figure.

The base LinearSVC classifier model performed best compared to other classifiers and it is a fast running algorithm even with data that has many features. We decided to look further into LinearSVC because it performed so well.

The LinearSVC is a type of machine learning algorithm that can be used for binary or multiclass classification problems. It's designed to predict one of two possible outcomes based on a set of input features.

The basic idea behind the LinearSVC is to find the best line (or hyperplane) that can separate the two classes in the feature space. To do this, the algorithm looks for the line that maximizes the margin between the two classes. The margin is the distance between the decision boundary (i.e., the separating line) and the closest data points from each class. By maximizing the margin, the LinearSVC can achieve good generalization performance on new data.

In the case of multiclass classification, the LinearSVC works by dividing the data into multiple binary classification problems, one for each possible combination of classes. It then trains a separate binary classifier for each of these problems, which can then be used to classify new data points.

For example, if we have three classes A, B, C, then we have three classifiers, one for A versus B and C, one for B versus A and C, and another for C versus A

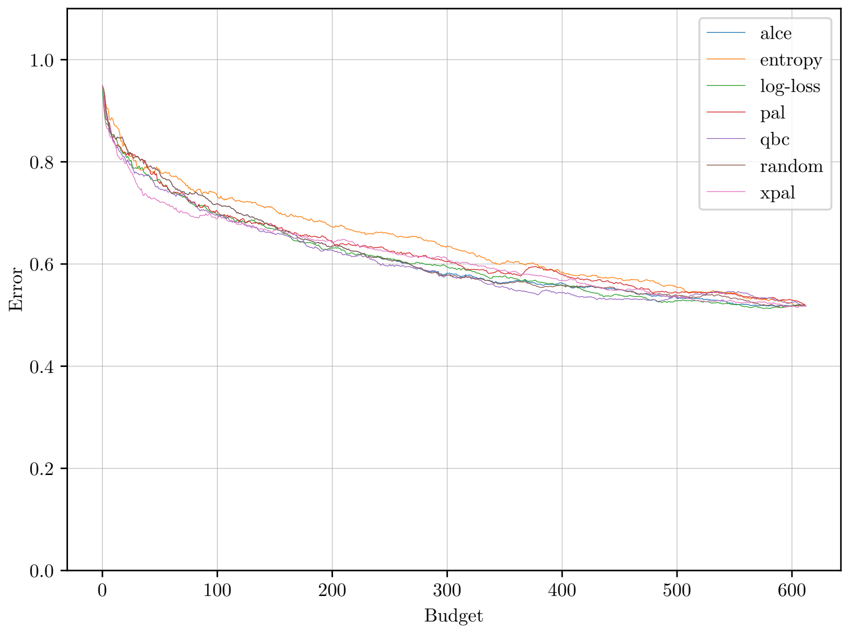


Figure 4.4: Comparing test error using different query strategies and Cosine kernel for the PWC classifier with results averaged over ten different data splits.

and B. Once we have trained a separate LinearSVC for each binary classification problem, we can use them to classify new data points. To classify a new data point, we simply apply each binary classifier to the data point and see which classes it is predicted to belong to. If a data point is predicted to belong to more than one class, we can use a tie-breaking rule or simply choose the class with the highest predicted probability.

The LinearSVC algorithm seeks to find the hyperplane that maximally separates the classes in feature space, and weights are sometimes used that correspond to the coefficients of the hyperplane equation.

Consider a binary classification problem where we have two classes labeled as -1 and +1. Given a set of training examples, the goal of the LinearSVC algorithm is to learn a hyperplane that separates the examples of the two classes in feature space. The hyperplane is defined by the equation:

$$w^T x + b = 0 \tag{4.3}$$

where w is a weight vector of the same dimension as the feature vectors x, and b is a bias term that shifts the hyperplane in the direction of the negative class.

During training, the LinearSVC algorithm tries to find the values of w and b that minimize the classification error while also maximizing the margin between the hyperplane and the closest examples of each class. This is achieved by solving a constrained optimization problem that involves minimizing the norm of the weight vector subject to the constraint that all training examples are correctly classified with a margin of at least 1.

Once the weights are learned, they can be used to make predictions on new examples by evaluating the sign of the decision function:

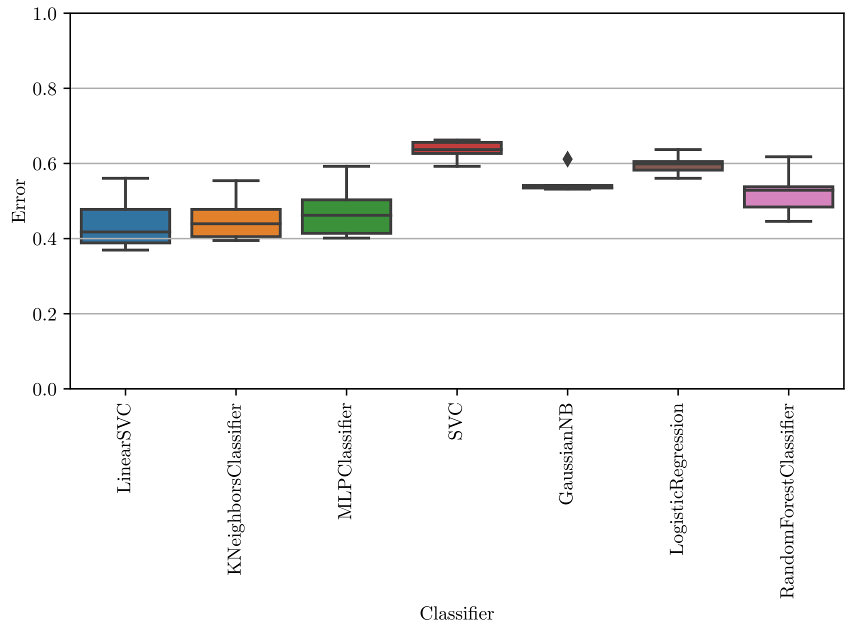


Figure 4.5: Performance of base classifiers.

$$f(x) = w^T x + b \tag{4.4}$$

If $f(x)$ is positive, the example is classified as the positive class, and if it is negative, the example is classified as the negative class. We also wanted to conduct more testing with KNeighborsClassifier and Neural Networks.

We created three models for LinearSVC, the first was a boilerplate LinearSVC with no argument modifications, the second model used the class weights parameter set to 'balanced'. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as $n\_samples/(n\_classes * np.bincount(y))$.

For the third test we created a dictionary of weights for each class using the Cosine decay function. The weights for each category ranged from 0.1 to 1.0 where the most frequent classes had smaller weights. The Cosine decay function is defined as:

$$w_i = \frac{1}{2}\left(1 + \cos\left(\frac{\pi t}{T}\right)\right) \tag{4.5}$$

where w_i is the weight for the i^{th} class, t is the current iteration, and T is the total number of iterations. The Cosine decay function is a common function used for weights in machine learning algorithms. The calculated cosine weights are shown in the appendix in Table A.6.

The results for the LinearSVC classifier experiments are shown in Table 4.1 where the LinearSVC with the Cosine decay weights didn't perform better than the other LinearSVC models.

Using K-Neighbors Classifier (KNN) and a Neural Network from TensorFlow we conducted additional experiments. For the KNN we found that using 8 neighbors and the cosine distance metric yielded the lowest error.

Table 4.1: Error for three differing LinearSVC models.

Model	Error
Boilerplate One-vs-rest	0.426
Crammer Singer	0.447
Cosine Decay Weights One-vs-rest	0.486

For the Neural Network we used a dense hidden-layer with 1000 neurons with Sigmoid activation and 23 output neurons with Softmax activation. For the NN optimizer we used Adamax with Cosine decay with an initial learning rate of 0.1, alpha value of 0.1 and 915 decay steps ($X\_data\_size//batch\_size * num_epochs$). The results are shown in Table 4.2. We can see that the K-Nearest Neighbors classifier and the Neural Network classifier performed slightly worse compared to LinearSVC.

The LinearSVC outperformed the other classifiers and we decided to experiment with it further. We attempted to boost performance of the LinearSVC classifier using multiple cross validation grid searches with the bagging. Bagging (bootstrap aggregating) is a type of ensemble learning, where multiple models are trained on different subsets of the training data and their predictions are combined to make the final prediction. In Scikit-Learn we used the BaggingClassifier to implement bagging. An example of our setup and parameters are shown in the code snippet.

```
intercepts = np.linspace(0.1, 1, 20)
c_vals = np.linspace(0.1, 1000, 20)
base_classifier = LinearSVC(
    random_state=args.seed,
    max_iter=10000)
bagging_classifier = BaggingClassifier(
    base_estimator=base_classifier,
    n_estimators=10,
    random_state=args.seed)
params = {
    'base_estimator__random_state': [args.seed],
    'base_estimator__intercept_scaling':
        np.concatenate((intercepts, [1])),
    'base_estimator__loss': ['hinge', 'squared_hinge'],
    'base_estimator__penalty': ['l2'],
    'base_estimator__C':
        np.concatenate((c_vals, [1])),
    'base_estimator__multi_class':
        ['ovr', 'crammer_singer']
    }
grid_search = GridSearchCV(
    estimator=bagging_classifier,
    param_grid=params,
    cv=5,
    scoring='accuracy',
        n_jobs=6)
```

Performance was not improved from what we had already seen. Using bagging may not be the best approach at this stage because there are some categories that have very few samples so bagging may be unable to create a good model. We will revisit bagging in future chapters when we have more data at our disposal. We also didn't use the balanced class weights parameter because we had already seen that it was the worst performing class weight parameter in previous tests. The BaggingClassifier and GridSearchCV combination didn't improve the performance of the LinearSVC classifier beyond what we had already achieved.

Table 4.2: Testing errors for best performing classifiers using original data.

Model	Error
LinearSVC	0.382
Tensor Flow Neural Network	0.417
K Neighbors Classifier	0.451

The precision-recall curve for the best performing classifier (LinearSVC) is shown in Figure 4.6 and the confusion matrix is shown in Figure 4.7 for the best performing LinearSVC classifier.The precision-recall curve gives us an idea at how well our classifier can correctly categorize the data. It also gives us a visualization of how unbalanced our categories are. We can see this imbalance clearly in Figure 4.6 where we have straight lines and large steps for some categories. This is a result of having a small number of data in a class. However, we can also see that for some classes the precision is relatively high even though we have few data points. Here we are namely concerned with the 'Culture' and 'Beauty' categories which have 10 and 31 data points respectively. It may be that the keywords in the 'Culture' and 'Beauty' categories are drastically different from the other categories so the performance is better.

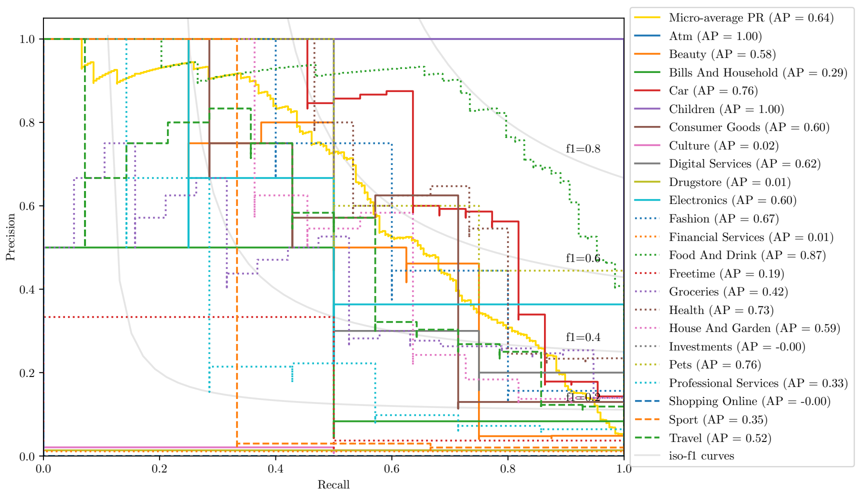


Figure 4.6: Precision-recall curve for the best performing LinearSVC classifier.

The confusion matrix shown in Figure 4.7 may be a better metric for visualizing this data. In addition, the classification report for the LinearSVC classifier is shown in Appendix Table A.3 with F1, accuracy, precision, recall, and support scores.

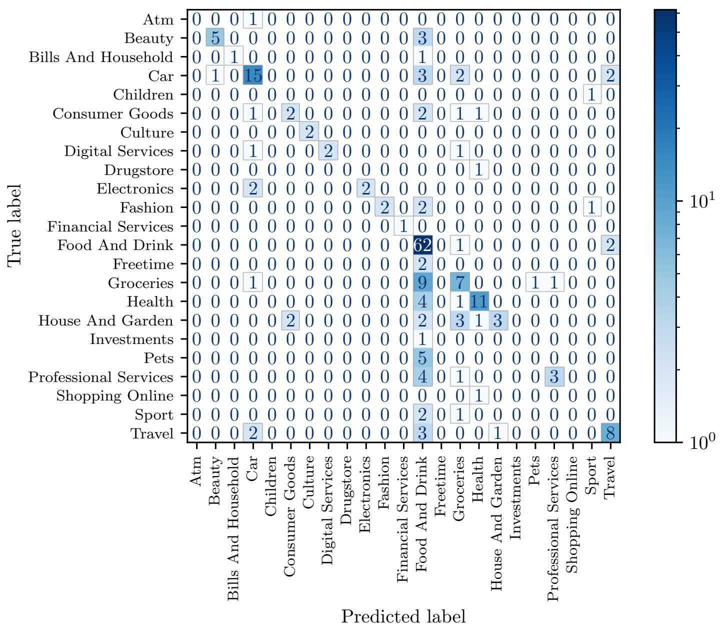


Figure 4.7: Confusion matrix for the best performing LinearSVC classifier using the original data.

5. Testing with All Data

In this section we will take what we have learned from the experiments in the previous sections and apply that knowledge to the original data set augmented with the additional data that we collected. The total category count tallies can be located in the Appendix in Table A.1. These experiments will provide us with a better understanding of how the data is interacting with the active learning sampling strategies and the PWC classifier. We will also try removing some data from the set if the text length is below some threshold, evaluate the performance with a reduced number of categories, and explore the performance of xPAL using all available data.

5.1 Classifier Evaluation Revisited

We wanted to re-run the classifier experiment that we ran with the original data with the new data to get an idea of how the new data effected influenced the classifiers from Scikit-Learn. The results are shown in Table 5.1.

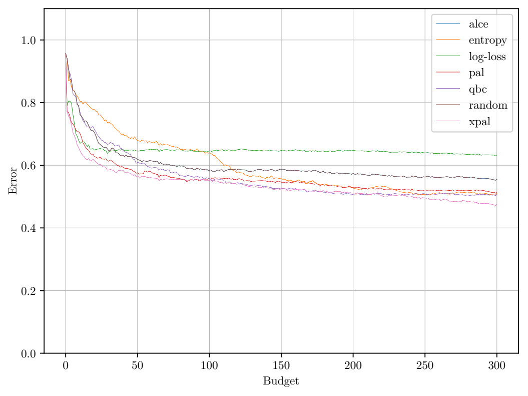
Table 5.1: Testing errors for best performing classifiers using all data.

Model	Error
LinearSVC	0.429
Tensor Flow Neural Network	0.433
K Neighbors Classifier	0.471

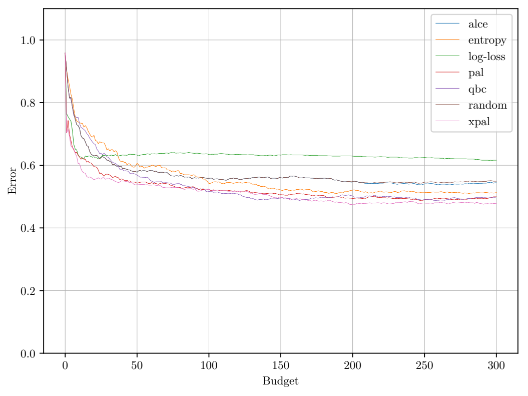
Its interesting to see that the errors increased across the board but our previous results could have been skewed possibly because we had so few data samples in some categories. We ran the Bagging Classifier GridSearchCV from the previous chapter and again could not tune the model to perform better than the base untuned LinearSVC.

5.2 Active Learning using All Data

In these experiments we tested all the active learning methods with the corrected TF-IDF vectorizer transformation. Instead of incorrectly vectorizing the data then importing the matrix to be used with Kottke et al. [2021] probablistic active learning code, we exported the raw text data and then split the text data, fit and transformed the vectorizer to the train data, then transformed the test data and conducted our experiments with the modified code. In Figure 5.1a we re-ran a previous experiment using just the original data so we could have a more accurate comparison with the results for all the data shown in Figure 5.2a. In Figures 5.1b and 5.2b we used an arbitrary text length filter of 50 characters to see how the performance of the selection strategies changed when we removed some of the data. The categorical data splits for the 50 character filter can be found in the Appendix in Table A.5.



(a) No text length filter and proper vectorization.



(b) Text length data > 50 and proper vectorization.

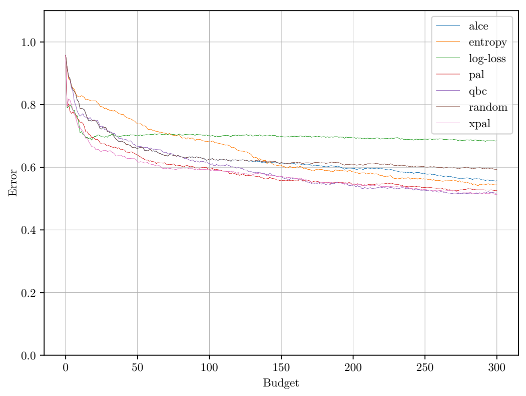
Figure 5.1: Active learning results using the original data.

We again used the different active learning methods and PWC with the Cosine kernel to run our experiments. We ran 10 test runs for each method and then averaged the test error of all the runs resulting in a single curve for each sampling strategy, exactly as we did previously. We only used the first 300 data points instead of using the entire budget because we have seen that the error plateaus and we want to reduce the amount of time it takes to run our experiments. As a result, the test error doesn't converge in these plots because we are only using a portion of the budget. With the original data we can see that the xPAL sampling strategy finds the best data early (20-30 budget range) in the sampling process and exploits this to improve the classifier the most. Eventually we see that PAL and QBC have similar performance to xPAL but, ultimately, after 300 samples xPAL is the best performing sampling strategy.

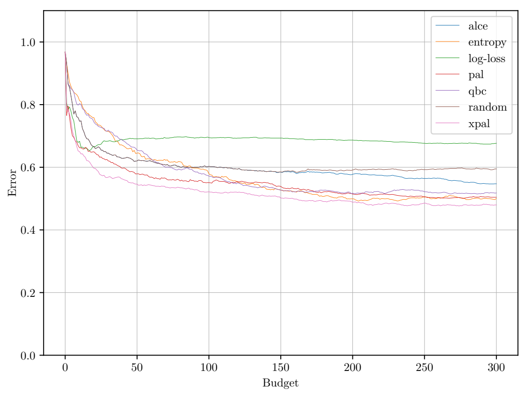
Using all the data, we repeated this same experiment and found that the selection strategies testing error results seemed to have a bit more separation. The results are shown in Figure 5.2a. In both experiments in this section it appeared that the test error for xPAL was converging to around roughly 50%. But for the second experiment using all the data xPAL was finding and exploiting the best data points earlier and for longer in the sampling process. We can see the dominance of xPAL throughout the plot except around the 200 budget range where entropy sampling starts to momentarily perform well.

In both the re-run original data and all data experiments, xPAL appears to perform well an average over 10 different runs in comparison to the other selection strategies, it even seemed to perform markedly well with more data available and then having some filtering applied as shown in Figure 5.2b where its dominance over the other selection was even more apparent. This led us to believe that the more data that is available and the more text that is available per data sample the better xPAL will perform. This will not always be true but it seems that if we have a large enough amount of text, 50 characters being an arbitrary example, xPAL will have an easier time selecting the best data points to label.

We were curious what xPAL was doing when more data was available, so while running the experiments we recorded when a data point was selected (its index in the selection budget) and for which category it was selected from. This data



(a) No text length filter and proper vectorization.



(b) Text length data > 50 and proper vectorization.

Figure 5.2: Active learning results using all data.

is shown here in Figure 5.3.

This distribution data is not averaged and is from a sample run for each of the data sets without any filtering. In this data split the 'Shopping Online' category for the original data went without asking for a label in the given budget window. It is interesting that it chose not to select its sole sample but intuitively it may make sense because there is only one other 'Online Shopping' sample point and it is in the test set. Its possible that because there is only one sample xPAL may not yet find it necessary to know its label this early in the budget and other data points labels are more valuable to know. It is clear from Figure 5.3 that when new data is available the xPAL selection strategy reevaluates what is important and selects data points that are more likely to be helpful. This is a good sign that xPAL is able to adapt to the data and find the most helpful data points.

5.3 LinearSVC with Text Length Filtering

We have some data that may not have enough text to classify correctly and others that have more than 1000 characters of text that may be noisy. We also know that sometimes while scraping the text data from a website we collected a non empty string that actually provided no words that were related to the label, such as a simple error or warning message.

However, using all available data, we now have the luxury of having more than the minimum of 2 data points in some categories and can afford to remove data from the set that may have unhelpful or confusing words in the text. We decided to explore if filtering the data based on text length could improve the performance of the classifier and use LinearSVC as it has performed well with this data previously and it is relatively fast to train.

Before conducting the filtering data experiments we can view how the text length is distributed throughout our preprocessed and scrubbed text data as shown in Figure 5.4a. This can help us visualize how much data we may be removing if we filter the data based on text length.

The distribution of the text show a steady decrease in length and frequency until around the 850 length mark where we have an increase of data with large

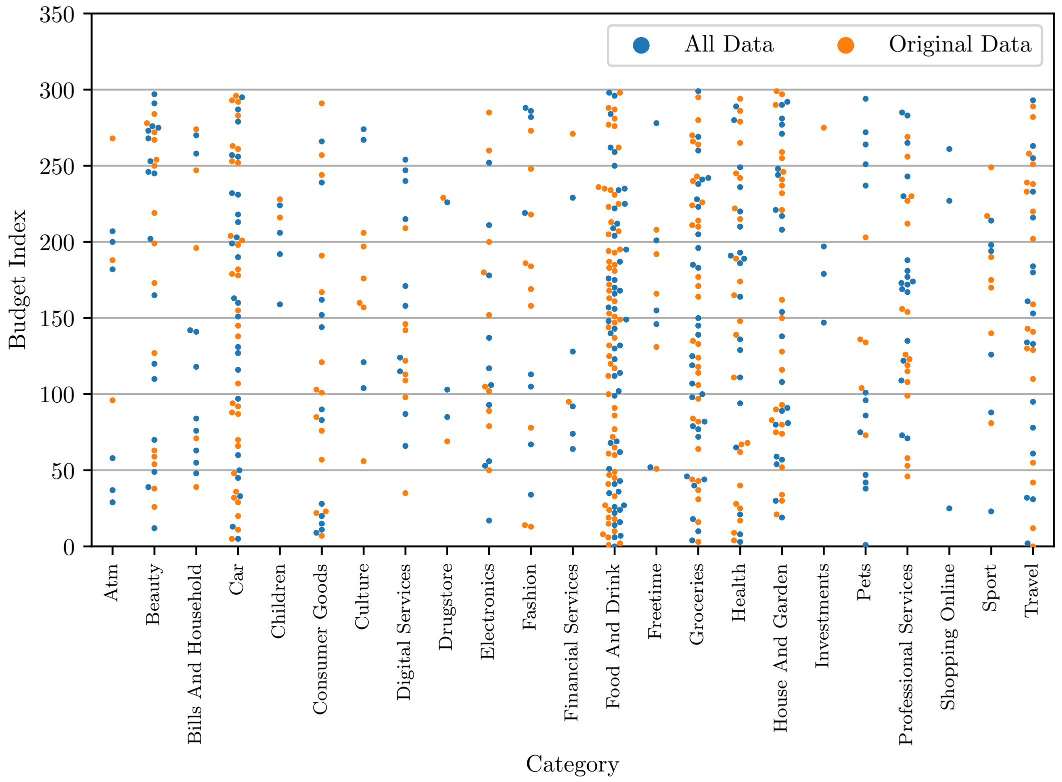
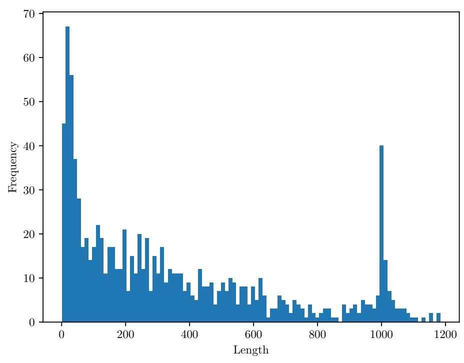


Figure 5.3: Data point selection swarm plot using xPAL.

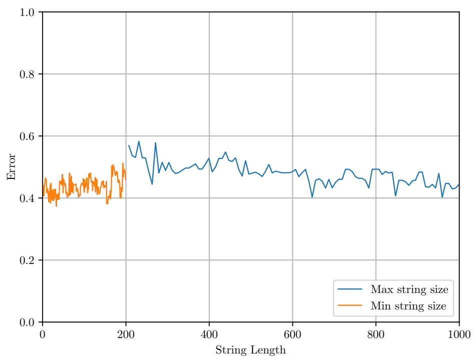
amounts of text. The spike here is a results from when we capped the non English data text to 1000 characters so that we could translate all of our data using the Azure translation services.

We imported the data and either selected a minimum number of characters or we altered the maximum number of characters allowed and created a new dataset. For each run we selected the data based on this criteria and then built the TF-IDF array. For the minimum string size tests we incremented the string size by 1 character. While for the max string size tests we decremented the string size by 10. We again used a train test split of 25% which has been our standard for testing throughout our experiments. We found that around the 200 character mark we would filter out too much data and would not have a minimum representation (2 data points) for all the categories. The results for this experiment are shown in Figure 5.4b.

We also tested with a minimum text length and a maximum text length constraint implemented together but this combination did not yield any obvious gains. This naive approach to filtering the data did not yield any obvious improvements in the test error. At best it may have filtered out some bad data and provided a small improvement in the test error. However, when implementing xPAL we hope to have it filter out the bad data in a more calculated manner.



(a) Distribution of text length for all data in 100 bins.



(b) Test error results for best LinearSVC with varying text length requirements.

Figure 5.4: Text length experiments data and results.

5.4 Testing with Fewer Categories

In this section we will briefly look at the PWC with xPAL and LinearSVC performance using progressively fewer categories. We will use all available data and remove the category from the data set if it has less than the minimum number of samples. We assume that reducing the number of categories decreases the test error. Intuitively, this should be the case because as we reduce the number of categories we are reducing the number of classes that the classifier has to learn and classify. This should make the classification task easier and therefore the test error should decrease. However, we have a lot of data in the 'Food and Drink' and 'Groceries' categories and we have seen that the classifiers struggle to classify these categories correctly. Results from some tests are shown for the PWC with xPAL in Figure 5.5.

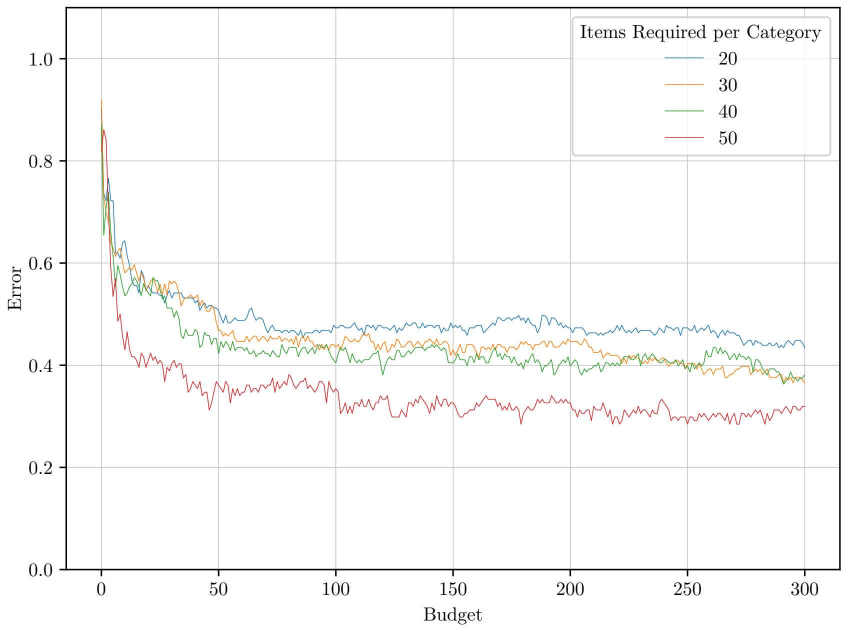


Figure 5.5: PWC with xPAL with category reduction on all data.

Dumais and Chen [2000] discusses the issue of reducing the number of categories in web content classification in their paper. They note that reducing the number of categories can improve the accuracy and efficiency of the model by reducing the complexity of the classification problem. However, they also note that reducing the number of categories can reduce the specificity of the classification and make it more difficult to distinguish between similar categories.

Looking at the results from the xPAL and PWC tests in Table 5.5 we can see that we have generally have reduction in test error except between the 30 and 40 category minimum tests. This table also shows us the categories that were used in the classification. This might tell us that 'Consumer Goods', 'House and Garden', and 'Professional Services' are easily linearly as the change in test error after 300 samples was small.

Review these results it seems that 'Food and Drink' and 'Groceries' are making up a large portion of the test error and if there was better way to classify these categories it would improve the overall test error.

Table 5.2: LinearSCV performance with category reduction on all data.

Category Minimum	Error	Categories
20	0.359756	[Beauty, Car, Consumer Goods, Fashion, Food And Drink, Groceries, Health, House And Garden, Pets, Professional Services, Sport, Travel]
30	0.362416	[Beauty, Car, Consumer Goods, Food And Drink, Groceries, Health, House And Garden, Professional Services, Travel]
40	0.320896	[Beauty, Car, Food And Drink, Groceries, Health, House And Garden, Travel]
50	0.234783	[Car, Food And Drink, Groceries, Health, Travel]

Conclusion

Our goal was to understand the entire process including the web scraping, translation, storing, and performance of the selection strategies and classifiers. This analysis provided some insight for our partner and allowed them to learn from our tests and experiments.

The scraping and data collection process was an exercise in itself. We initially wanted to dockerize the entire project but this was more time consuming and cumbersome than expected so we abandoned it. We used setup Scrapy to take a list of websites as input and then navigate the main webpage and scrape the html. We then processed the html and saved the text locally in a Postgres database.

After the text was collected and stored we realized we had some issues because we assumed more of the text would be in English. At this stage, after inspecting the data we realized we had 9 categories with 2 or less samples and a total of 275 data points for 23 categories. However, we had a large amount of unused data that we needed to figure out how to use. We experimented with a number of API's and other tools for collecting English text but ultimately ended up using the Azure API for translation, which allowed us to have a bit larger data set of text to work with.

One issue we struggled with was the quality of the collected data. We used some statistical methods to analyze the most frequent words and sometimes found non english words as being influential keyword for a category. This emphasized a few different things. First, was that maybe scraping text data from just a websites homepage isnt enough and experiments should be run with additional pages from the site tree. Second, that we were lacking in quality train data as a result of our raw text scrubbing and preprocessing methods were not optimal. Finally, we could have explored better web scraping tools to collect more data from the websites. However, at a certain point the scraper was performing well enough and we decided to move on to the next step to keep with the timeline.

Our next task was to start experimenting with Scikit-Learn and TensorFlow classifiers and see how they performed on our data. We used a number of different classifiers and found that the linear support vector classifier performed well with the data. However, we only scratched the surface with TensorFlow and more testing could be done with it.

We also used the Parzen Window Classifier from the Probalistic Active Learning GitHub repository from the "Toward optimal probabilistic active learning using a Bayesian approach" paper by Kottke et al. [2021]. This repository provided a number of different sampling strategies and we modified the repository to fit our needs and use with our data. We found that the xPAL sampling strategy was the best for our data and was able to reduce the testing error the most compared to the other available sampling strategies in the repository.

The linear support vector classifier also performed well using the original and all useable data sets. The Probabilist Active Learning repository was setup with the PWC so that when new data was added the classifier could be updated quickly and only where there was a change. This caused us issued as we tried to implement LinearSVC with xPAL as we would naively have to retrain the entire model for every new data point.

Improvements

To improve the results of the active learning classifier we would suggest making a number of changes. One of the first changes would be to find a better way to profile a website and make sure the quality of the text data from the websites were better. For example, a stronger web scraper would have allowed us to avoid potential IP address restriction issues and scrape data from social media websites that refused to allow our scraper to collect any data and resulted in some unusable data. We could have also run our own tests regarding how the number of sibling pages could have fortified the data, as we discussed in the previous section.

The scraper could be designed to scrape multiple pages of a website, scrape social media pages, and possibly scrape other websites that are linked to the original website. This could improve the quality of the data and allow for more accurate classification. Prioritizing the quality of the data is one of the key points to improving the performance of the classifier. It also seems that a small amount of good text data is better than a large amount of poor quality text data. Another way we could have made the scraped data better for the classifier is to take out all non english words (post translation).

To be more thorough, we could have run exhaustive tests for *all* the available classifiers within Scikit-Learn using GridSearchCV and other ensemble methods to see if any more performance gains were attainable. We could have also explored the performance of TensorFlow RNN's and LTSM's with word embedding for text classification.

The current setup of the active learning xPAL process uses the PWC as it is fast (because it updates only parts of the classifier with each new data point) and relatively simple to implement. However, it is not the best method for classifying our data as we have seen from our experiments. From our experiments we assume that we could improve the performance of the classifier with fewer data points by implementing xPAL with the LinearSVC classifier.

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A. Attachments

Table A.1: Category counts of data. Orig. = Orig. English + Translated, is the data from the original set that had usable text. Orig. English is a subset of Orig. that was in English. Translated is a subset of Orig. that was not in English. Add. is the newly collected data, translated if needed. All Useable = Orig. English + Translated + Add.

Category	Orig.	Orig. English	Translated	Add.	All Useable
Atm	4	2	2	4	8
Beauty	31	8	23	18	49
Bills And Household	9	4	5	10	19
Car	91	28	63	0	91
Children	4	0	4	5	9
Consumer Goods	28	5	23	7	35
Culture	10	1	9	6	16
Digital Services	16	12	4	4	20
Drugstore	3	2	1	5	8
Electronics	15	6	9	5	20
Fashion	22	6	16	6	28
Financial Services	4	0	4	6	10
Food And Drink	262	110	152	0	262
Freetime	8	2	6	8	16
Groceries	75	21	54	9	84
Health	64	14	50	8	72
House And Garden	44	11	33	3	47
Investments	2	1	1	5	7
Pets	18	6	12	8	26
Professional Services	32	15	17	5	37
Shopping Online	2	2	0	5	7
Sport	14	2	12	7	21
Travel	58	17	41	7	65
TOTALS	816	275	541	141	957

Table A.2: Variable importance, top 20 words from the vectorizer and all useable data.

	Importance
hotel	0.078177
hair	0.046888
car	0.045024
auto	0.017192
services	0.014782
station	0.013815
flower	0.010145
spa	0.010054
search	0.009680
energy	0.009531
internet	0.009404
parking	0.009226
barber	0.007874
service	0.007823
stations	0.007491
beauty	0.007353
hairdresser	0.007080
rental	0.006944
banking	0.006849
mobile	0.006536

Table A.3: Best LinearSVC model classification report using original data.

	precision	recall	f1-score	support
Atm	0.00	0.00	0.00	1.00
Beauty	0.75	0.38	0.50	8.00
Bills And Household	0.00	0.00	0.00	2.00
Car	0.63	0.55	0.59	22.00
Children	0.00	0.00	0.00	1.00
Consumer Goods	1.00	0.29	0.44	7.00
Culture	0.00	0.00	0.00	2.00
Digital Services	1.00	0.50	0.67	4.00
Drugstore	0.00	0.00	0.00	1.00
Electronics	0.50	0.25	0.33	4.00
Fashion	1.00	0.40	0.57	5.00
Financial Services	0.00	0.00	0.00	1.00
Food And Drink	0.49	0.94	0.64	64.00
Freetime	0.00	0.00	0.00	2.00
Groceries	0.50	0.21	0.30	19.00
Health	0.73	0.53	0.62	15.00
House And Garden	0.50	0.45	0.48	11.00
Investments	0.00	0.00	0.00	0.00
Pets	1.00	0.50	0.67	4.00
Professional Services	0.50	0.14	0.22	7.00
Shopping Online	0.00	0.00	0.00	0.00
Sport	0.00	0.00	0.00	3.00
Travel	0.70	0.50	0.58	14.00
micro avg	0.55	0.55	0.55	197.00
macro avg	0.40	0.24	0.29	197.00
weighted avg	0.57	0.55	0.51	197.00

Table A.4: Set of parameters used to test all other Scikit-Learn classifier shown in Figure 4.5.

Classifier	Parameters
LinearSVC	{'C': 1.0, 'class_weight': None, 'dual': True, 'fit_intercept': True, 'intercept_scaling': 1, 'loss': 'squared_hinge', 'max_iter': 10000, 'multi_class': 'ovr', 'penalty': 'l2', 'random_state': 42, 'tol': 0.0001, 'verbose': 0}
KNeighborsClassifier	{'algorithm': 'auto', 'leaf_size': 30, 'metric': 'cosine', 'metric_params': None, 'n_jobs': None, 'n_neighbors': 8, 'p': 2, 'weights': 'uniform'}
MLPClassifier	{'activation': 'relu', 'alpha': 0.0001, 'batch_size': 'auto', 'beta_1': 0.9, 'beta_2': 0.999, 'early_stopping': False, 'epsilon': 1e-08, 'hidden_layer_sizes': 500, 'learning_rate': 'constant', 'learning_rate_init': 0.001, 'max_fun': 15000, 'max_iter': 100, 'momentum': 0.9, 'n_iter_no_change': 10, 'nesterovs_momentum': True, 'power_t': 0.5, 'random_state': 42, 'shuffle': True, 'solver': 'adam', 'tol': 0.0001, 'validation_fraction': 0.1, 'verbose': False, 'warm_start': False}
SVC	{'C': 1.0, 'break_ties': False, 'cache_size': 200, 'class_weight': None, 'coef0': 0.0, 'decision_function_shape': 'ovr', 'degree': 3, 'gamma': 'scale', 'kernel': 'rbf', 'max_iter': -1, 'probability': False, 'random_state': None, 'shrinking': True, 'tol': 0.001, 'verbose': False}
GaussianNB	{'priors': None, 'var_smoothing': 1e-09}
LogisticRegression	{'C': 1.0, 'class_weight': None, 'dual': False, 'fit_intercept': True, 'intercept_scaling': 1, 'l1_ratio': None, 'max_iter': 1000, 'multi_class': 'auto', 'n_jobs': None, 'penalty': 'l2', 'random_state': 42, 'solver': 'lbfgs', 'tol': 0.0001, 'verbose': 0, 'warm_start': False}
RandomForestClassifier	{'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': None, 'max_features': 'sqrt', 'max_leaf_nodes': None, 'max_samples': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 200, 'n_jobs': None, 'oob_score': False, 'random_state': 42, 'verbose': 0, 'warm_start': False}

Table A.5: Data counts with 50 string character filter minimum.

	All w Str Filter	Original w StrFilter
Atm	8	4
Beauty	49	31
Bills And Household	19	9
Car	91	91
Children	9	4
Consumer Goods	35	28
Culture	16	10
Digital Services	20	16
Drugstore	8	3
Electronics	20	15
Fashion	28	22
Financial Services	10	4
Food And Drink	262	262
Freetime	16	8
Groceries	84	75
Health	72	64
House And Garden	47	44
Investments	7	2
Pets	26	18
Professional Services	37	32
Shopping Online	7	2
Sport	21	14
Travel	65	58

Table A.6: Cosine decay weights for each category.

	Weight
Shopping Online	1.000
Investments	0.996
Drugstore	0.983
Atm	0.963
Financial Services	0.934
Children	0.899
Freetime	0.857
Bills And Household	0.810
Culture	0.757
Sport	0.701
Electronics	0.642
Digital Services	0.581
Pets	0.519
Fashion	0.458
Consumer Goods	0.399
Beauty	0.343
Professional Services	0.290
House And Garden	0.243
Travel	0.201
Health	0.166
Groceries	0.137
Car	0.117
Food And Drink	0.104