Abstract

Information planning enables faster learning with fewer training examples. It is particularly applicable when training examples are costly to obtain. This work examines the advantages of information planning for text data by focusing on three supervised models: Naive Bayes, supervised LDA and deep neural networks. We show that planning based on entropy and mutual information outperforms random selection baseline and therefore accelerates learning.

1. Introduction

Information planning involves making decisions based on information measures (Cover & Thomas, 2006). Information planning is closely related to active learning (Settles, 2009), (Olsson, 2009) and optimum experiment design (Federov, 1994). In this framework, an active learner queries instances in the input space. In stream-based selective sampling and pool-based sampling. In membership query, the learner may request labels for any unlabelled instance in the input space. In stream-based selective sampling, the active learning is done sequentially as each unlabelled instance is added to the training set. In pool-based sampling, the entire set of unlabelled data is ranked and the most informative subset is labelled and added to the training set. In this work, we focus on pool based sampling as summarized in Algorithm 1.

The decisions whether or not to query instances of unlabelled examples are based on a measure of informativeness or a query strategy. The simplest and most commonly used query framework is uncertainty sampling (Lewis & Gale, 1994). In this framework, an active learner queries instances about which it is least certain about the label. For example, in a binary classification task, uncertainty sampling queries points near the decision boundary where the class probabilities are close to 1/2, i.e. highest entropy. Uncertainty sampling also works for regression problems, in which case the learner queries points with highest output variance in their prediction. In general, uncertainty sampling chooses a subset $x^*$ from a set of unlabelled examples $x \in D_{pool}$ that maximizes label entropy:

$$x^* = \arg \max_{x \in D_{pool}} - \sum_c p(y = c|x) \log p(y = c|x)$$

An alternative measure that not only looks at the uncertainty of the label but also at the informativeness is mutual information:

$$I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$

Algorithm 1 Generic Information Planning

1: Input: data $x \in \{D_{train}, D_{pool}\}$, model $M$, acquisition function $a(x, M)$
2: Output: trained model $M(T)$
3: for $t = 1, 2, ..., T$ do
4:  train $M^{(t)}$ on $D_{train}$
5:  select $x^* = \arg \max_{x \in D_{pool}} a(x, M^{(t)})$
6:  update $D_{train} = D_{train} \cup x^*$; $D_{pool} = D_{pool} \setminus x^*$
7: end for

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Other query selection strategies include ensemble methods such as query-by-committee (Seung et al., 1992) in which an ensemble of diverse and accurate models are trained on the labeled dataset. Each ensemble member is then allowed to vote on the labels of query candidates and the most informative query is considered to be an instance about which they most disagree. In this work, we focus on uncertainty sampling and mutual information as the primary query strategies.

In application to natural language processing, active learning has been successfully applied to information extraction (Scheffer et al., 2001), named entity recognition (Becker et al., 2005), text categorization (Tong & Koller, 2002), part-of-speech tagging (Ringer et al., 2002) and parsing (Becker & Osborne, 2002). In this work, we study the benefits of information planning for text data on three different tasks: text classification, supervised topic modeling and sentiment classification. Section 3 focuses on active learning with information planning in Naive Bayes model for text classification. Section 4 discusses the results and the paper is concluded in Section 6.

2. Naive Bayes

We consider the task of text classification using a Naive Bayes graphical model as shown in Figure 1.

Let $x_{ij}$ be Bernoulli random variables indicating the presence ($x_{ij} = 1$) or absence ($x_{ij} = 0$) of a word $j \in \{1, ..., D\}$ in document $i \in \{1, ..., n\}$, parameterized by $\theta_{jc}$, for a given class label $y_i \in \{1, ..., C\}$. In addition, let $\pi$ be a Dirichlet distribution representing the prior over the class labels. Thus, the total number of parameters is $|\theta| + |\pi| = O(DC) + O(C) = O(DC)$. Due to the small number of parameters, the Naive Bayes model is immune to over-fitting (Murphy, 2012).

The choice of Bernoulli Naive Bayes formulation is important because it leads itself to word-based information planning. By associating each word in the dictionary with a binary random variable, we are able to compute the influence of individual words on class label distribution.

Consider words $x_i$ in a single document $i$:

$$p(x_i, y_i | \theta) = p(y_i | \pi) \prod_{j=1}^{D} p(x_{ij} | y_i, \theta)$$

$$= \prod_{c=1}^{C} \pi_{c}^{[y_i = c]} \prod_{j=1}^{D} \prod_{c=1}^{C} p(x_{ij} | \theta_{jc})^{1[y_i = c]}$$

We can write-down the Naive Bayes inference algorithm by maximizing the log-likelihood objective:

$$\log p(D | \theta) = \log \prod_{i=1}^{n} p(x_i, y_i | \theta) = \sum_{i=1}^{n} \log p(x_i, y_i | \theta)$$

$$= \sum_{c=1}^{C} N_c \log \pi_c + \sum_{j=1}^{D} \sum_{c=1}^{C} \sum_{i: y_i = c} \log p(x_{ij} | \theta_{jc})$$

During test time, we would like to predict the class label $y$ given the training data $D$ and the learned model parameters. Applying the Bayes rule:

$$p(y = c | x_{i,1}, ..., x_{i,D}, D) \propto p(x_{ij} | y = c, D)$$

Substituting $p(x_{ij} | y = c, D)$ and taking the log, we get:

$$\log p(y = c | x, D) \propto \log p(y = c | D) + \sum_{j=1}^{D} \left( [x_{ij} = 1] \log \theta_{jc} + [x_{ij} = 0] \log (1 - \theta_{jc}) \right)$$

2.1. Information Planning

In entropy based planning we want to rank test documents according to the entropy of their class label. In the case of class distribution, the entropy can be computed in closed form: $H(y) = - \sum_{c=1}^{C} p(y = c) \log p(y = c)$. 

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1 all code is available on-line
In the case of mutual information, we need to choose the random variables we want to use for planning. Since we are interested in classifying documents, it makes sense to choose \( y_i \) (the class label for document \( i \)) as one of the variables. Our choice of the second variable depends on the quantity of interest. We can choose one of the global variables \( \theta_{jc} \) (probability that word \( j \) is present in class \( c \)) or \( \pi_c \) (probability of class \( c \)). In this example, we consider estimating \( I(y_i; \theta) \), i.e. we are interested in measuring the information gain about the word distribution \( \theta \) given the class label \( y_i \) for a test document. Since both variables are discrete, the mutual information can be estimated in closed form:

\[
I(y_i; \theta) = KL(p(y_i, \theta) || p(y_i)p(\theta)) = \sum_{y \in C} \sum_{\theta} p(\theta | y_i)p(y_i) \log \frac{p(\theta | y_i)}{p(\theta)}
\]

We can compute \( p(\theta) = \sum_{c \in C} p(x_j = 1 | y = c)p(y = c) \) for \( j \in \{1, \ldots, D\} \). In addition, we compute \( I(x_j; \pi) \) to measure how informative each word \( x_j \) is to the global label distribution \( \pi \).

We train our Naive Bayes classifier on a subset of the 20newsgroups dataset. In particular, we’ll restrict ourselves to 4 classes: space, graphics, autos and hockey. We’ll use a count vectorizer to produce a vector of word counts for each document while filtering stop and low frequency words. Figure 2 shows the posterior word distribution for the four classes.

Let’s visualize the test document ranking based on entropy and mutual information in Figure 3. In particular, we are interested in outliers, i.e. documents that have high entropy and mutual information. To visualize the difference between entropy and MI based planning, we can sort the documents according to entropy and use the same index to sort MI as shown in Figure 4. In Figure 4 documents that have high entropy but low MI are uncertain but not informative. Therefore, we expect MI to provide a better measure for information planning.

To evaluate the utility of information planning in comparison to random selection, we take a total of \( 1K \) documents and divide them into 100 labelled training documents, 700 unlabelled test documents, and holdout 200 documents for evaluating classification performance. We run the active learning pipeline, in which top \( K \) most informative documents are selected from the test set, labelled by annotators and added to the training set, at which point the model is re-trained from scratch and evaluated on the 200 holdout documents. Figure 5 shows the experimental results of this active learning pipeline. We can see a clear advantage of using information planning compared to random selection.

### 3. Supervised LDA

Latent Dirichlet Allocation (LDA) (Blei et al., 2003) is an unsupervised topic model that represents each document as a mixture of topics, where a topic is a distribution over words. The objective is to learn the shared topic distributions and their proportions for each document. However, it is often desirable to associate a quantity of interest (e.g. a score) with each document; this could be a five star rating for a movie review, a quality score of a report, or a number of times an on-line article is linked. Supervised LDA (sLDA) (Blei & McAuliffe, 2010) is designed to jointly learn the topics and the score variable associated with each document. The graphical model of supervised LDA is shown in Figure 6.

sLDA associates each word \( x_{id} \) with a topic label \( z_{id} \in \{1, \ldots, K\} \). Each document is associated with topic proportions \( \theta_d \) that can also be used as a measure of document similarity. The topics \( \beta_k \) represented by the Dirichlet distribution are shared across all documents. The hyper-

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**Figure 2.** Naive Bayes class-conditional posterior.

**Figure 3.** Violin plot showing the density of entropy and MI on test data.
parameters \( \alpha \) and \( \eta \) capture our prior knowledge of topic proportions and the topics, e.g., from past training of the model. Finally, \( y_d \) is the response variable that represents a score associated with each document. In this example, \( y_d \) is modelled as a regression between global coefficients \( w \) and a normalized histogram of topics present in a document: \( \bar{z} \).

Assuming a Gaussian distribution, \( y_d \) can be expressed as follows:

\[
y_d \sim N(w_1 \bar{z}_1 + \ldots + w_k \bar{z}_k, \sigma^2)
\]

(8)

\[
\bar{z} = \frac{1}{N} \sum_{n=1}^{N} z_n
\]

(9)

where \( z_n \) is a one-hot encoded topic assignment vector of size \( 1 \times K \). We use PyMC (Patil et al., 2010) Metropolis-Hastings sampler to infer the latent variables. Figure 7 shows the first 4 (out of 8) topics of sLDA model trained on the polarity sentiment dataset (Pang & Lee, 2004). Notice, that the addition of the score variable \( y_d \) influences topic inference due to the coupling between \( w \) and \( \beta_k \) introduced by the \( z_{i,d} \rightarrow y_d \leftarrow w \) and \( z_{i,d} \rightarrow x_{i,d} \leftarrow \beta_k \) v-structures.

### 3.1. Information Planning

We can use a sample based estimator to compute the entropy of the score variable \( y_d \):  

\[
H[y_d|x_d, D] = E[-\log p(y_d|x_d, D)]
\]

Assuming we have topic samples:

\[
\{ (z_{1d}^{(i)}, \ldots, z_{Nd}^{(i)}) \}_{i=1}^{M} \overset{MCMC}{\sim} p(z_{1d}, \ldots, z_{Nd}|x_d, D) 
\]

(10)

\[
p(y_d|x_d, D) = \sum_{z_{1d}} \ldots \sum_{z_{Nd}} p(z_{1d}, \ldots, z_{Nd}|x_d, D)p(y_d|z_d)
\]

\[
\approx \frac{1}{M} \sum_{i=1}^{M} p(y_d|z_d^{(i)}) = \hat{p}(y_d|x_d, D)
\]

(11)

Once we have a sample estimate \( \hat{p}(y_d|x_d, D) \), to compute entropy, we need to estimate the expectation:

\[
E[-\log \hat{p}(y_d|x_d, D)] = - \int p(y_d|x_d, D) \log \hat{p}(y_d|x_d, D) dy_d
\]

\[
\approx \frac{1}{M} \sum_{i=1}^{M} \log \hat{p}(y_d^{(i)}|x_d, D)
\]

(12)
where \( \{ (y_d^{(i)})_{i=1}^M \} \sim \text{MCMC} \).

To evaluate the utility of information planning in comparison to random selection, we start with a corpus of 100 documents, from which we allocate 15 documents for training, 35 for testing and holdout 50 documents for evaluating sLDA performance. Figure 8 shows the test MSE of the Gaussian score variable evaluated against the ground truth review score on the heldout set of 50 documents.

We can see that active learning selection achieves smaller MSE in comparison to random selection baseline.

4. Deep Neural Network

We consider information planning in the case of deep neural networks. In particular, we examine two architectures: LSTM and CNN in application to sentence sentiment classification (Goodfellow et al., 2016).

Recurrent Neural Networks (RNNs) provide a natural way of encoding a sentence as a sequence of words. Just as you are processing this sentence word by word while keeping a memory of what came before, RNNs maintain an internal model of the past and update it as soon as the new information arrives. Thus, RNNs contain an internal loop unrolled over the length of the input sequence. As a result, RNNs can capture more information in comparison to \( n \)-gram models. For example, in a \( n \)-gram language model (with \( n = 3 \)), we can predict the next word given the previous two:

\[
I_{\text{sent}} = \frac{1}{n} \log P(w_1, \ldots, w_n) = \frac{1}{n} \sum_{i=1}^{n} \log p(w_i|w_{i-1}, w_{i-2})
\]

(13)

The dependence in neural language model (LM) extends to the beginning of the sentence, i.e. \( p(w_i|w_{i-1}, \ldots, w_1) \), while in a \( n \)-gram LM the conditioning is only on the previous \( n \) words and as \( n \) grows larger, sparsity of training data becomes a problem. In both cases, the word conditional distribution greatly reduces the output space of possible words and enables learning of word representations based on their context (Mikolov et al., 2013).

A sentence can be encoded by an RNN (such as LSTM) as either the output of its last layer or via average pooling of its intermediate outputs. In both cases, the word position information is preserved in contrast to averaging of word vectors. Figure 9 shows the LSTM architecture used for sentiment classification. We use a bi-directional LSTM that concatenates sequence representations of forward and reverse LSTMs. This enriches order-sensitive representation of the sentence and leads to a slight increase in accuracy. In addition to output layer dropout, we use recurrent dropout that applies the same dropout mask at every time-step (in contrast to a dropout mask that varies randomly between time-steps that could harm the learning process) (Gal, 2016).

Convolutional Neural Networks (CNNs) offer computational advantages due to their parallel nature and comparable performance with time-series data, especially in cases when recent past is not more informative than the distant past (due to translation invariance of CNNs). The same properties that make convnets excel at computer vision also make them highly relevant for sequence processing. Time can be treated as a spatial dimension like the height or width of a 2D image. For example, 1D convolutions can be used to extract patterns from local 1D patch sub-sequences of the input sequence. Because the same transformation is performed on every patch, a pattern learned at a certain position in the sentence can later be recognized at a different position, making 1D convnets translation invariant. While a word-level conv-net operating on word embeddings with a kernel size of 5 should be able to recognize words or word fragments of length 5 or less, a character-level 1D conv-net is able to learn about word morphology. In addition, we can learn hierarchical patterns by stacking several convolutional layers. Figure 10 shows the CNN architecture used for sentiment classification. It consists of a word embedding layer followed by a stack of two convolutional layers separated by a dropout layer. Finally, the activations across each of the filters are pooled via global max pooling and fed into a Multi-Layer Perceptron (MLP) classifier.

For both LSTM and CNN models, we choose pre-trained word embeddings because in an active learning setting, there’s usually not enough training data to learn specialized word embeddings for a given task. In order to preserve the latent structure (that could otherwise be destroyed by large gradients from randomly initialized downstream layers), we configure the embeddings to be non-trainable. Both architectures use Glove pre-trained word embeddings (Pennington et al., 2014) based on word co-occurrence for dense representation of words.
4.1. Information Planning

As shown in (Gal & Ghahramani, 2016) dropout (Srivastava et al., 2014) and other stochastic regularization techniques can be used for approximate inference in deep neural networks. This is accomplished by using dropout at test-time and computing Monte Carlo integration (referred to as MC dropout):

$$p(y = c|x, D) = \int p(y = c|x, w)p(w|D)dw$$

$$\approx \int p(y = c|x, w)q_\theta(w)dw \approx \frac{1}{T} \sum_{t=1}^{T} p(y = c|x, \hat{w}_t)$$

where $\hat{w}_t \sim q_\theta(w)$ and $q_\theta(w)$ is a variational distribution that minimizes KL divergence to the true model posterior $p(w|D)$:

$$\arg \min_{\theta} KL(q_\theta(w)||p(w|D))$$

where $\theta$ are the variational parameters and $w$ are the neural network weights. Averaging forward passes with MC dropout during test time is equivalent to Monte Carlo integration over a Gaussian process posterior approximation (Gal et al., 2017).

We consider two acquisition functions: one based on entropy and one based on mutual information. An acquisition function $a(x, M)$ determines which measurements to take next, and it’s a function of the pool of unlabelled examples $x \in D_{pool}$ and the model $M$:

$$x^* = \arg \max_{x \in D_{pool}} a(x, M)$$

In the case of entropy, we want to choose data points that maximize:

$$H[y|x, D] = -\sum_c p(y = c|x, D) \log p(y = c|x, D)$$

In the case of mutual information, we want to choose data points that maximize the information gain between the predictions $y$ and the model parameters $w$:

$$I(y; w|x, D) = H[y|x, D] - E_{p(w|D)}[H[y|w, x, D]]$$

where $w$ in our case are the weights of the neural network and the expectation is computed using MC dropout. Thus, we are seeking data points $x$ for which the model is both marginally most uncertain about $y$ and most confident about the predicted label. Notice, that it’s easier to compute MI as written above (as opposed to its alternative version) because the entropies are computed in a discrete, low-dimensional output space. This interpretation allows reasoning about uncertainty in deep learning and the application of Bayesian methods to analyze existing deep learning frameworks.

We evaluate the effectiveness of information planning on Kaggle movie review sentiment dataset (Kaggle, 2015). The dataset consists of phrases from the Rotten Tomatoes dataset classified into 5 sentiment labels: negative, somewhat negative, neutral, somewhat positive and positive. Obstacles such as sentence negation, sarcasm, and language ambiguity make this a challenging task. We take the first 10K sentences, set aside 10% for training and holdout 10% for evaluating the performance. At each iteration, we select the top $K = 800$ most informative sentences to be annotated and added to the training set. Figures 15, 16, 17, 18 show active learning experimental results.

5. Discussion

In this section we discuss information planning results for each model.

5.1. Naive Bayes

Naive Bayes is the simplest model for studying information planning since all latent variables are discrete and information measures can be computed in closed form. By choosing the Bernoulli formulation of Naive Bayes we were able to do planning at the word level. In particular, the top-10 highest MI words as shown in Table 1 were found to be informative of the ground truth labels.

From Figure 5, we can see that we achieve about 10% accuracy increase when we use uncertainty sampling in comparison to random selection. All experimentes were repeated 10 times.
5.2. Supervised LDA

In supervised LDA model, the score variable is learned jointly with the topics. Figure 8 shows that smaller MSE is achieved with uncertainty sampling in comparison to random selection. We also note that sampling based inference for sLDA is more suitable to stream queries in which documents are queried one at a time due considerable time it takes to run sampling for the entire pool of unlabelled examples.

5.3. Deep Neural Networks

In deep neural network setting we assume that computational expense of re-training the model from scratch is justified by the cost of obtaining the labels. From the training and validation loss in Figures 11, 13, we see no signs of over-fitting due regularization with dropout and weight decay. The validation loss plateaus early in the training indicating that model capacity can be increased in an attempt to achieve higher classification accuracy. Figures 12, 14 show that CNN and LSTM model achieve comparable accuracy on the sentiment classification task with validation accuracy close to 55%. Figures 15, 17 show the benefit of information planning over the random baseline. We can see that we achieve close to 1% improvement in accuracy in the case of CNN and a relatively smaller improvement in the case of LSTM, even thought LSTM achieves 2% higher held-out test accuracy in the end. It’s also interesting to see, the decrease in test label entropy as shown in Figures 16, 18, where as expected the uncertainty sampling leads to highest reduction in entropy.

6. Conclusion

We examined two information measures: entropy and mutual information for active learning with text data. In particular, we focused on three supervised tasks: text classification with Naive Bayes model, supervised topic modeling with sLDA, and sentiment classification with deep neural net-
Information Planning for Text Data

works. In each case, we saw higher performance achieved with information planning in comparison to a random selection baseline. We hope the results of this work will encourage the use of information planning in settings where labels are expensive to obtain.

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