Task-Based Learning

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Abstract

This paper is about task-based learning. This is a draft.

Introduction

Prediction models have been widely used to facilitate decision making across domains, e.g., retail demand prediction for inventory control (Riemer et al. 2016), user behavior prediction for display advertisement (Yang, Zhu, and He 2017), and financial market movement prediction for portfolio management (Prado 2018), to name a few. These models are often trained using standard machine learning loss functions, such as mean square error (MSE), mean absolute error (MAE) and cross-entropy loss (CE). However, these criteria commonly used to train prediction models are often different from the task-based criteria used to evaluate model performance (Bengio 1997; Donti, Amos, and Kolter 2017). For instance, a standalone image classification model is often trained by optimizing accuracy or cross-entropy loss. However, when it is used to guide autonomous driving, we may care more about misclassifying a traffic sign vs. misclassifying a garbage can. In revenue surprise forecasting, financial institutes often train a regression model to predict the revenue surprise for each public company minimizing mean square error. However, they evaluate the model performance based on the Anchored Hit Rate (AncHR) and the Absolute Hit Rate (AbsHR) (see Fig.1) with respect to industry benchmarks (e.g. the consensus of the Wall Street analysts), which provide more value for downstream portfolio management. In credit risk modeling, banks often first train a classification model to predict the default probability of each loan application, and then optimize the probability threshold to accept/reject decisions. Eventually, they evaluate the model performance by aggregating the total profit made from those loans.

Despite the popularity of standard machine learning losses, models trained with such standard losses are not necessarily aligned with the task-based evaluation criteria and as a result may perform poorly with respect to the ultimate task-based objective.

One straightforward solution to this problem is to directly use the task-based evaluation criteria as the loss function. However, task-based evaluation criteria are often unfriendly to an end-to-end gradient-based training process due to the fact that often such performance objectives are not necessarily differentiable and may even require additional decision-making optimization processing. Existing works (Elmachtoub and Grigas 2017; Bengio 1997; Donti, Amos, and Kolter 2017; Wilder, Dilkina, and Tambe 2019; Perrault et al. 2019; Wilder et al. 2019) in this area mainly focus on deriving surrogate loss functions that differentiate from downstream evaluation criteria to the upstream prediction model via certain relaxations or KKT conditions. However, those derivations are mainly hand-crafted and task-specific. As a result, it requires a considerable amount of effort to find proper surrogate losses for new tasks, especially when the evaluation criteria are complicated or involve non-convex optimization. Moreover, hand-crafted sur-

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rogate losses are not optimized, which can hardly become the optimal choice. Therefore, a general end-to-end learning scheme, which can automatically integrate the task-based evaluation criteria, is still needed.

In this paper, we propose a generic end-to-end learning scheme, named Task-Oriented Prediction Network (TOPNet). It aims to automatically integrate task-based evaluation criteria into the learning process via a task-oriented estimator and directly learns a model with respect to the task-based goal. Specifically, (i) TOPNet learns a task-oriented estimator, which estimates the task-based loss that the predictions can obtain from the task-based evaluation criteria, given input features, the prediction, the ground-truth label and necessary contextual information. (ii) TOPNet learns a predictor that optimizes a loss function considering both the standard losses (or other differentiable surrogate losses) and the estimated task-based loss from the task-oriented estimator. The loss function of the predictor switches between the standard loss (or other differentiable surrogate losses) and the estimated task-based loss based on the estimation error of the task-oriented estimator.

We demonstrate the performance of TOPNet on two real-world financial prediction tasks: a revenue surprise forecasting task and a credit risk modeling task, where the former is a regression task and the latter is a classification task. Applying TOPNet to these two tasks, we show that TOPNet significantly boosts the ultimate task-based goal by integrating the task-based evaluation criteria, outperforming both traditional modeling with standard losses and modeling with differentiable (relaxed) surrogate losses.

Related Work

There is a growing body of research for integrating task-based evaluation criteria into the learning process under different names, such as task-based learning and decision-focused learning. The earliest work we found in the literature that is closely related to ours is the work of Bengio (1997), which uses a neural network to predict financial prices, and then optimizes the network based on returns obtained via a hedging strategy that employs it. Later, Kao, Roy, and Yan (2009) proposed Directed Regression, which directly trains a linear regression model that minimizes a convex combination of least square loss and a task-oriented loss obtained from the downstream evaluation criteria. In the context of task-based learning, TOPNet bridges not only the state-action (feature-label) information but also the label and all other necessary contextual information, which guides the upstream predictor to achieve better performance in the downstream evaluation.

The idea of the task-oriented estimator is inspired by the Q-network (Sutton 1988; Watkins and Dayan 1992, Lillicrap et al. 2015; Mnih et al. 2016; Sutton and Barto 2018), which is widely used in reinforcement learning (RL) to estimate the expected cumulative reward given the state and the action. However, the Q-network in reinforcement learning is used to foresee the future cumulative reward in a multi-step decision-making process given current state and action, while the task-oriented estimator is designed for approximating the non-differentiable task-based criteria to improve the predictive model. Moreover, the prediction tasks we consider in this paper naturally have labels as their direct supervision, which in general is not considered in reinforcement learning frameworks. Therefore, the task-oriented estimator in TOPNet bridges not only the state-action (feature-prediction) information but also the label and all other necessary contextual information, to better approximate the task-based evaluation criteria and guide the predictor to the task-based goal. In the context of task-based learning, TOPNet is the first work that automatically integrates the task-based evaluation criteria into an end-to-end learning process via a task-oriented estimator network.

Problem Formulation

We first formally define the task-based prediction problems that we study in this paper. We use \( x \in \mathcal{X} \subseteq \mathbb{R}^d \) and \( y \in \mathcal{Y} \) for the feature and label variables. In this paper, we mainly investigate classification tasks (\( \mathcal{Y} = \{0, 1, \ldots, l\} \)) and regression tasks (\( \mathcal{Y} \subseteq \mathbb{R} \)). Given training set \( D_{tr} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \) and test set \( D_{te} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\} \), our goal is to train a model \( f_{\theta} : \mathcal{X} \rightarrow \mathcal{Y} \) on \( D_{tr} \) that minimizes some task-based loss function (criteria) \( \frac{1}{n} \sum_{i=1}^n \ell_T(f_{\theta}(x_i), y_i, c_i) \) on \( D_{te} \). Note that, in this paper, we mainly consider tasks whose task-based performance objective can be decomposed into a point-wise loss function. We use \( \ell_T(f_{\theta}(x_i), y_i, c_i) \) to denote the point-wise task-based loss function, where \( y_i \) is the label, \( f_{\theta}(x_i) \) is our
prediction, and \( c_i \) is some necessary contextual information related to that criteria.

A key challenge of task-based learning comes from the fact that the task-based loss function \( \ell_T(f_\theta(x_i), y_i, c_i) \) is often non-differentiable and may even involve additional decision-making optimization processing. For instance, in revenue surprise forecasting, the task-based criteria evaluates a prediction \( f_\theta(x_i) \) based on both the true revenue surprise \( y_i \) and the prediction of the consensus of the Wall Street analysts \( c_i \), measuring whether the prediction is more directionally accurate than the Wall Street consensus and whether the prediction is significantly (50%) more accurate than the Wall Street consensus (We will present the detailed formula in our experiments). In credit risk modeling, the task-based criteria involve the prediction of the default probability of the \( i \)-th loan application \( f_\theta(x_i) \) as well as the probability threshold \( p_D \) to maximize the profit after approving all loan applications with a default probability lower than \( p_D \). In the following sections, we show how TOPNet addresses this challenge by automatically integrating the task-based loss via a task-oriented estimator.

### Task-Based Learning via Task-Oriented Prediction Network

Fig 2 depicts the end-to-end learning framework implemented in the Task-Oriented Prediction Network (TOPNet). A feature extractor \( G_1 \) is first applied to extract meaningful features from the raw input data \( x_i \). Then, a predictor network \( P \) takes the extracted feature \( G_1(x_i) \) to make prediction \( P(G_1(x_i)) = \hat{y}_i \). Given our prediction \( \hat{y}_i \), the ground truth label \( y_i \) and necessary contextual information \( c_i \) concerning the task, a task-oriented evaluation criterion, which potentially involves a decision-making optimization process, provides a task-based loss \( \ell_T(\hat{y}_i, y_i, c_i) \) measuring the predictive performance on the data point \( x_i \).

However, the real task-based evaluation criteria may be non-differentiable, and therefore the task-based loss \( \ell_T(\hat{y}_i, y_i, c_i) \) may not be used directly to guide the predictor. Existing works mainly focus on using a surrogate loss function \( \ell_S(\cdot) \) to guide the learning process, where practitioners can either choose standard machine learning loss functions, such as mean square error, mean absolute error and cross-entropy loss, or other differentiable task-specific surrogate loss functions [Bengio 1997] [Elamchitou and Grigas 2017] [Donti, Amos, and Kolter 2017] [Perrault et al. 2019] [Wild, Dilkina, and Lambe 2019] [Wilder et al. 2019] as the training loss, that is,

\[
\min_{G_1, P} \mathbb{E}_{(x_i, y_i) \sim D_{tr}} [\ell_S(P(G_1(x_i)), y_i, c_i)]
\] (1)

However, both standard machine learning losses and hand-crafted differentiable surrogate losses are designed manually. Moreover, finding a proper surrogate loss function requires a considerable amount of effort, especially when the evaluation criteria are complicated or involve non-convex optimization. Therefore, such approaches require considerable customization and do not provide a general methodology to task-based learning.
which is widely used in reinforcement learning (RL).

However, the Q-network in RL is used to foresee the future cumulative reward in a multi-step decision-making process, while the task-oriented estimator is designed for approximating the non-differentiable task-based criteria to improve the predictive model. Moreover, the setting of prediction tasks we consider in this paper is different from the setting of RL – we naturally have labels as direct supervision, and we only have a limited number of data points. In reinforcement learning, a universal Q-network can be learned by exhaustively exploring the environment using the simulator. Therefore, an action policy can be optimized only based on Q-network. In contrast, learning a universal task-oriented estimator in prediction tasks is very challenging, since we only have a limited number of data points in prediction tasks. Therefore, TOPNet hybridizes the surrogate loss function and the estimated task-based loss in a way that the predictor switches between the surrogate loss and the estimated task-based loss depending on the estimation error of the task-oriented estimator, bridging the supervision from both the labels and the task-based criteria. Intuitively, TOPNet utilizes the supervision from labels to “warm up” a reasonable predictor with the surrogate loss function, so that the task-oriented estimator only needs to estimate the task-based loss well when the predictor makes reasonable predictions, which is much easier than learning a universal estimator for arbitrary predictions. Conversely, a well-learned task-oriented estimator would also improve the predictor, which collaboratively forms a virtuous circle for the learning of both the task-oriented estimator network and the predictor network.

We summarize the pseudocode of our end-to-end learning scheme for TOPNet in Algorithm 1. Note that, TOPNet integrates a surrogate loss function \( \ell_S(\cdot, \cdot, \cdot) \) into the learning process, which can either be a designed task-specific surrogate loss or just a standard machine learning loss function. Here, we use an estimation error threshold \( \epsilon \) to switch the learning loss function between the surrogate loss and the estimated task-based loss, which enables TOPNet to "warm up" both the predictor \( P \) and the task-oriented estimator \( T \) using the designed surrogate loss at the early stage. The choice of the hyperparameter \( \epsilon \) depends on the scale of the task-based loss.

**Experimental Results**

TOPNet is a generic learning scheme that can be used in a variety of applications with task-based criteria. In this section, we validate its performance via datasets collected from two real-world applications in finance. The experiments are mainly designed to compare the benefit of using the proposed TOPNet over standard machine learning schemes or hand-crafted heuristics surrogate loss functions.

**General Experimental Setup:** For all models in our experiments, the training process was done for 100 epochs, using a batch size of 1024, an Adam optimizer (Kingma and Ba 2014) with a learning rate of 0.00003, and early stopping to accelerate the training process and prevent overfitting.

### Revenue Surprise Forecasting

Revenue growth is the key indicator of the valuation and profitability of a company and a major input for long-term value-based investment strategy. Large brokerage firms employ legions of stock analysts to publish forecast reports on companies’ earnings (revenue minus expense) over the coming quarters and compile the average or median estimates consensus. The consensus number can be adjusted at any time point before the actual revenue is announced. Due to the long tail distribution of revenue growth, the investment communities usually predict revenue surprise which is given by revenue growth minus consensus. Since revenue surprise is positively correlated to stock returns (Jegadeesh and Livnat 2006), it is widely used for investment decisions, such as stock selection and portfolio management. For instance, investors can determine to long/hedge a stock based on the direction (positive/negative) of the revenue surprise forecasts as well as the amount of investment on a stock based on the magnitude of revenue surprise. Despite the fact that revenues are published quarterly, daily forecasts of revenue surprise enable investors to adjust their portfolio in a granular way for return and risk analysis. To predict quarterly rev-

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**Algorithm 1** End-to-End learning process for TOPNet

**Input:** \( x_i, y_i \) and \( c_i \) are raw input features, label and corresponding contextual information sampled iid from the training set. \( \ell_S(\cdot, \cdot, \cdot) \) is the designed surrogate loss function or a standard machine learning loss. \( \epsilon \) is the maximal tolerance of the estimation error of the task-based loss. For ease of presentation, we use the update of one data point as an example.

1: Make prediction \( \hat{y}_i = P(G_1(x_i)) \)
2: Evaluate the prediction \( \hat{y}_i \) using task-based criteria given the label \( y_i \) and the contextual information \( c_i \), and get a task-based loss \( \ell_T(\hat{y}_i, y_i, c_i) \).
3: Encode the prediction \( \hat{y}_i \), the label \( y_i \) and the contextual information \( c_i \) into an embedding \( E(\hat{y}_i, y_i, c_i) \) via Encoder \( E(\cdot) \).
4: Encode the input features \( x_i \) into \( G_2(x_i) \) via feature extractor \( G_2(\cdot) \)
5: if \( \ell_T(\hat{y}_i, y_i, c_i) < \epsilon \) then
6: Update the predictor \( P \) and the feature extractor \( G_1 \) by: \( \min_{P, G_1} T([G_2(x_i); E(P(G_1(x_i)), y_i, c_i)]) \)
7: else
8: Update the predictor \( P \) and the feature extractor \( G_1 \) by: \( \min_{G_1, P} \ell_S(P(G_1(x_i)), y_i, c_i) \)
9: end if
10: Update the task-oriented estimator \( T \), the encoder \( E \) and the feature extractor \( G_2 \) by: \( \min_{T, E, G_2} (T([G_2(x_i); E(\hat{y}_i, y_i, c_i)]) - \ell_T(\hat{y}_i, y_i, c_i))^2 \)

Here, we use the formulation of regression tasks as an example. Similar formulation for classification tasks can be derived using equation (3) and equation (4).
Table 1: Statistics of the Revenue Surprise Forecasting dataset

<table>
<thead>
<tr>
<th></th>
<th>Starting time stamp</th>
<th>Ending time stamp</th>
<th>#data points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Set</td>
<td>01-01-2004</td>
<td>06-30-2015</td>
<td>3,267,584</td>
</tr>
<tr>
<td>Validation Set</td>
<td>07-01-2015</td>
<td>09-06-2016</td>
<td>465,383</td>
</tr>
<tr>
<td>Test Set</td>
<td>07-01-2017</td>
<td>06-30-2019</td>
<td>421,225</td>
</tr>
</tbody>
</table>


Revenue surprise at the daily level before their announcement, we collect information including quarterly revenue, consensus, stock price and various of their derivatives. The historical revenue and the consensus estimate is obtained from SEC 10K reports[3] and Yahoo! Finance[4], respectively. The data includes 1090 US public companies ranging from Jan 1st, 2004 to June 30th, 2019. Each data point is associated with a 10x12-dimensional feature vector describing up-to-date sequential historical information of the corresponding company. The label of each data point is a real number describing the revenue surprise of the corresponding company on that specific date. We split the whole dataset chronologically into training set, validation set and test set to validate the performance of models. Note that some companies only have a few data points due to their short history. Thus, we filtered companies to make sure that all remaining companies have enough (1,000) historical data points in the training set and end up using 902 companies in our experiments. Table 1 presents details of the dataset configuration.

Note that, even though we have about 4 million data points, on average each company only has about 3,600 training examples. Therefore, instead of learning a model for each company, we aim to use all data points to learn a company-agnostic prediction model. Though it is possible to build a multi-task learning framework for this specific task, it is out of the scope of this paper.

Task-based Criteria: In this regression problem, the task-based criterion is the total reward calculated based on the Anchored Hit Rate (AncHR) and the Absolute Hit Rate (AbsHR) with respect to the industry benchmark, consensus. To be specific,

\[
\text{AncHR}_i = \begin{cases} 
\alpha & \text{if } \text{sign}(\tilde{y}_i) = \text{sign}(\hat{y}_i) \\
-\beta & \text{if } \text{sign}(\tilde{y}_i) \neq \text{sign}(\hat{y}_i)
\end{cases}
\]

where \( \tilde{y}_i = \hat{y}_i - \text{median}(y) \), \( \hat{y}_i = y_i - \text{median}(y) \), \( \hat{y}_i \) (\( y_i \)) denotes predicted (true) revenue surprise of a public company at a specific date, \( \text{sign}(\cdot) \) denotes the sign function, and \( \text{median}(\cdot) \) represents the median of the predicted (true) revenue surprise of data points of all the companies within the same quarter as the \( i \)-th data point. The AbsHR is given by

\[
\text{AbsHR}_i = \begin{cases} 
\gamma & \text{if } \mid y_i - \hat{y}_i \mid < 0.5\mid y_i \mid \\
0 & \text{otherwise}
\end{cases}
\]

Here, we use AncHR\(_i\) and AbsHR\(_i\) to denote the Anchored Hit/Miss and Absolute Hit/Miss of data point \( i \), and \( \alpha, \beta \) and \( \gamma \) are 3 parameters denoting the reward/penalty of Anchored Hit, Anchored Miss, and Absolute Hit. In our experiments, \( \alpha = \$3.78 \), \( \beta = \$4.62 \) and \( \gamma = \$1.68 \) (those numbers are true values of the real application).

Intuitively, the AncHR measures the percentage of predictions among all the companies that are more directional accurate than the industry benchmark, which is critical for long/short investment decisions. The AncHR uses the median as the anchor to adjust both our prediction and the label in order to cancel the seasonal trend within a quarter. The AbsHR evaluates the percentage of predictions that are significantly (50%) more accurate than the industry benchmark, which is the essential input for optimizing the weight of stocks in a portfolio. Given AncHR\(_i\) and AbsHR\(_i\), the total task-based reward is,

\[
\frac{1}{m} \sum_{i=1}^{m} \text{AncHR}_i + \text{AbsHR}_i,
\]

which measures the average profit the model earned from all predictions. Since algorithm[1] minimizes the loss function, we use the negative of equation[6] as the task-based loss in TOPNet.

Benchmark Methods:

- Models that are trained with standard machine learning loss function: In this regression task, we selected mean square error (MSE) loss and mean absolute error (MAE) loss as candidates of standard machine learning loss functions.

- Models that are trained with heuristic surrogate loss functions: Given the task-based criteria, we observe that a proper surrogate loss function could be designed by approximating AncHR\(_i\) and AbsHR\(_i\) using \( \text{tanh}(\cdot) \), i.e.,

\[
\text{AncHR}_i \approx \alpha(1 + \text{sign}(\tilde{y}_i \cdot \hat{y}_i))/2 + \beta(1 - \text{sign}(\tilde{y}_i \cdot \hat{y}_i))/2 \\
\approx \alpha(1 + \text{tanh}(k \cdot \tilde{y}_i \cdot \hat{y}_i))/2 + \beta(1 - \text{tanh}(k \cdot \tilde{y}_i \cdot \hat{y}_i))/2
\]

\[
\text{AbsHR}_i \approx \gamma(1 + \text{sign}(0.5|y_i| - |y_i - \hat{y}_i|))/2 \\
\approx \gamma(1 + \text{tanh}(k \cdot (0.5|y_i| - |y_i - \hat{y}_i|))/2
\]

Here, \( k \) is a scale factor and we neglect some boundary situations such as \( \text{sign}(\tilde{y}_i) = \text{sign}(\hat{y}_i) = 0 \) and \( |y_i - \hat{y}_i| = 0.5|y_i| \). The key idea of this approximation is to approximate \( \text{sign}(x) \) with \( \text{tanh}(kx) \) since \( \lim_{k \to +\infty} \text{tanh}(kx) = \text{sign}(x) \). To saturate the performance of this surrogate loss function, we exhaustively explored the best scale factor \( k \) and found that it achieves the best performance with \( k = 100 \).

Experimental Setup: We use the Long Short-Term Memory (LSTM) networks [Hochreiter and Schmidhuber 1997] as the feature extractors and 3-layer fully-connected neural networks as the predictors for all models in our experiments. For a fair comparison, we explored the configuration of networks for all models to saturate their performance. For LSTMs and 3-layer fully-connected networks, the number of hidden units are chosen from \{64, 128, 256, 512, 1024\}. In TOPNet, the feature extractor \( G_2 \) is an LSTM with the

\[\text{https://www.sec.gov}\]
\[\text{https://finance.yahoo.com/}\]
same structure as the feature extractor $G_1$, and the encoder $E$, the task-oriented estimator $T$ are 3-layer fully-connected neural networks with hidden units 1024, 512, 256. More detailed implementation can be found in our code which will be shared upon paper acceptance.

**Performance Analysis:** We did 15 runs for all models with different random seed to compute the mean and the standard error of their performance. Since TOPNet also needs a surrogate loss function to “warm up” the predictor and the task-oriented estimator, we compared the performance of TOPNets with different surrogate losses (denoted as TOPNet_MAE, TOPNet_MSE, and TOPNet_Heuristic). As shown in Table 2, TOPNets significantly outperformed the standard machine learning models using either MSE or MAE as the loss function, boosting the average profit by 20%. Moreover, TOPNets further outperformed the model trained using the hand-crafted heuristic surrogate loss function, showing the advantage of using an optimized task-oriented estimator to automatically integrate the task-based criteria. Interestingly, we observe that TOPNet, which uses the heuristic loss function as the surrogate actually performed worse than TOPNet with either MSE or MAE. Our intuition to this phenomenon is: despite of the fact that the heuristic loss function alone performs much better than standard loss functions (MSE or MAE), the heuristic loss actually makes it harder to further improve the predictor with the task-oriented estimator. The same phenomenon can also be found in the next task.

### Performance Analysis

<table>
<thead>
<tr>
<th>Models</th>
<th>Average Profit per Prediction ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>$0.638 \pm 0.028$</td>
</tr>
<tr>
<td>MSE</td>
<td>$0.611 \pm 0.039$</td>
</tr>
<tr>
<td>Heuristic</td>
<td>$0.732 \pm 0.037$</td>
</tr>
<tr>
<td>TOPNet_MAE</td>
<td>$0.762 \pm 0.023$</td>
</tr>
<tr>
<td>TOPNet_MSE</td>
<td>$0.761 \pm 0.025$</td>
</tr>
<tr>
<td>TOPNet_Heuristic</td>
<td>$0.742 \pm 0.020$</td>
</tr>
</tbody>
</table>

Table 2: Task-based loss results for 15 runs of all models in the revenue surprise forecasting task. We compared the performance of TOPNets with different surrogate losses (TOPNet_MAE, TOPNet_MSE, and TOPNet_Heuristic), and the one with MAE (TOPNet_MAE) achieves the best performance. We show both the mean and the standard error of the performance of each model.

**Benchmark Methods:**

- **Models that are trained with standard machine learning loss function:** In this binary classification task, we selected cross-entropy loss as the standard machine learning loss function.

- **Models that are trained with heuristic surrogate loss functions:** Given the profit/loss of approving a loan application and the predicted probability of default $p_i$, a natural surrogate loss function is,

  $$ (1 - p_i) \cdot \text{profit/loss} + p_i \cdot 0, $$

  which measures the expected profit/loss given $p_i$.

**Experimental Setup:** We use 3-layer fully-connected neural networks with hidden units 1024, 512, 256 for the feature extractor of all models, and the predictors are linear layers. In TOPNets, the feature extractor $G_2$ as well as the encoder $E$ are also 3-layer fully-connected neural networks with hidden units 1024, 512, 256, and the task-oriented estimator $T$ is a linear layer.

In this task, the evaluation criteria would optimize the decision probability threshold $p_D$ to maximize the average profit via a validation set. Specifically, it would sort the data issued through its platform. The data includes over 200 factors, such as the loan status, the applicant’s information (e.g., asset, debt, and FICO scores) and the loan characteristics (e.g., amount, interest rate, various cost factors of default), etc. More details are given in the data dictionary of Lending Club.

We collected 1,305,080 personal loan applications from Lending Club and each of them is associated with an 88-dimensional feature vector (we filtered some irrelevant features) and a binary label denoting whether the loan application is defaulted or not. We split the whole dataset randomly into a training set (80%), a validation set (10%), and a test set (10%) to evaluate model performance.

**Task-based Criteria:** The Lending Club data provide information to compute the profit/loss of approving a loan application, i.e.,

$$ \text{Profit/Loss} = (\text{Received Principle} + \text{Received Interest} - \text{Funded Amount}) + (\text{Recovery Amount} - \text{Recovery cost}) $$

Note also that, the recovery happens only if the loan has defaulted and that if we reject a loan application, we simply earn $0 from it. Recall in credit risk modeling, the task-based criteria involve the prediction of the default probability $p_i$ of the $i$-th loan application as well as the probability threshold $p_D$ to maximize the profit after approving all loan applications with a default probability lower than $p_D$, i.e.,

$$ \frac{1}{m} \sum_{i=1}^{m} \text{Profit/Loss}_i \cdot I\{p_i < p_D\} + 0 \cdot I\{p_i \geq p_D\} $$

Here, we use $I\{\cdot\}$ to denote the indicator function.

**Credit Risk Modeling**

Credit is a fundamental tool for financial transactions and many forms of economic activity. The main elements of credit risk modeling include the estimation of the probability of default and the loss given default (Doumpos et al. 2019). In this study, we collect personal loan data for credit risk modeling from Lending Club. The company is a peer-to-peer lending company that matches borrowers with investors through an online platform and shares data about all loans

4https://www.lendingclub.com/

5http://resources.lendingclub.com
<table>
<thead>
<tr>
<th>Models</th>
<th>Average Profit per Loan ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross-Entropy</td>
<td>618.4 ± 0.3</td>
</tr>
<tr>
<td>Heuristic</td>
<td>770.4 ± 0.2</td>
</tr>
<tr>
<td>TOPNet_CE</td>
<td>783.3 ± 0.2</td>
</tr>
<tr>
<td>TOPNet_Heuristic</td>
<td>776.9 ± 0.4</td>
</tr>
</tbody>
</table>

Table 3: Task-based loss results for 15 runs of all models in the credit risk modeling task. We compared the performance of TOPNets with the heuristic loss and cross-entropy loss (TOPNet_Heuristic and TOPNet_CE), and the one with cross-entropy loss (TOPNet_CE) achieves the best performance. We show both the mean and the standard error of the performance of each model.

points based on the predicted default probability $p_i$ and optimize the threshold $p_D$ based on the cumulative sum of the profit/loss of approving load applications with $p_i < p_D$. Note that, TOPNet requires point-wise task-based loss as the feedback from the task-based criteria in the training phase. However, computing the task-based loss involves making decisions (approve/reject), which requires the decision probability threshold $p_D$ that is supposed to be optimized on the validation set. Noting that, the decision probability threshold $p_D$ is a relative value that depends on the predicted default probability $p_i$. Therefore, maintaining the order of predicted probabilities while shrinking or increasing them together does not affect the ultimate profit but leads to a different optimal threshold. Conversely, given a fixed decision threshold $p_D$ (e.g., 0.5), we can learn a predictor that predicts the default probability with respect to the threshold. Thus, in the learning process of TOPNet, we used a fixed decision threshold (0.5) to make decisions and provide task-based losses in Algorithm. During the test, we still apply the same threshold optimization process on the predictions made by TOPNet as other models.

**Performance Analysis:** We did 15 runs for all models with different random seed to compute the mean and the standard error of their performance. We evaluate the performance of TOPNets that use either cross-entropy loss or heuristic loss as the surrogate loss function (denoted as TOPNet_CE and TOPNet_Heuristic). As shown in Table, TOPNets significantly outperformed the standard machine learning models learned with cross-entropy, boosting the average profit by $164.9. Taking advantage of estimating the task-based loss using a task-oriented estimator network, TOPNets further boosts the profit by $12.9 per loan compared with the model trained using the heuristic loss function. Similar to the phenomenon in the revenue surprise forecasting task, the TOPNet using the heuristic loss function as the surrogate also performed a little bit worse than the TOPNet with cross-entropy loss.

**Conclusion**

In this paper, we proposed a generic end-to-end learning scheme, called Task-Oriented Prediction Network (TOPNet), which automatically integrates task-based evaluation criteria into the learning process via a task-oriented estimator and directly learns a model with respect to the task-based goal. Tested on two real-world financial prediction tasks, we demonstrate that TOPNet can automatically integrate the task-based evaluation criteria and significantly boost the ultimate task-based goal, outperforming both traditional modeling with standard losses and modeling with differentiable (relaxed) surrogate losses. Future directions include exploring how to integrate task-based criteria involving a strong connection among multiple data points.

**References**


