Human-in-the-Loop Feature Selection

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Outline

What Is It?

- **Human-in-the-Loop (HITL) – a model that requires human interaction.**
  - Allows for the identification of problems and requirements that may not be easily/automatically identified.
- **Feature Selection – the process of selecting a subset of relevant features (variables, predictors, etc) for use in model construction.**
  - Often done to simplify models (for explainability), shorten training times, avoid the curse of dimensionality, and enhance generalization by reducing overfitting.

Motivation

- **Clearly feature selection is useful**
- **Currently, feature selection is mostly a manual process done by consulting human experts about the most important features for a problem.**
  - But this process is time-consuming and expensive.
  - Also, the experts with this knowledge are rarely the ones building the actual machine learning models.
- **Some automatic feature selection can be done, but these methods only generate a single subset of features for all examples.**
- **Ideally, feature selection should be influenced and reinforced by user feedback**

Goals

- **Automate the feature selection process**
- **Involve model designers, domain experts, and users in the feature selection process**
- **Simplify the model by only considering a subset of the most important features**
- **Improve model performance/accuracy by utilizing feedback**
- **Provide per-example explanations of predictions**

This Paper's Approach

1) Have experts manually identify the most important features for a few examples

2) Use that feedback to model the probability of selecting each feature given an example

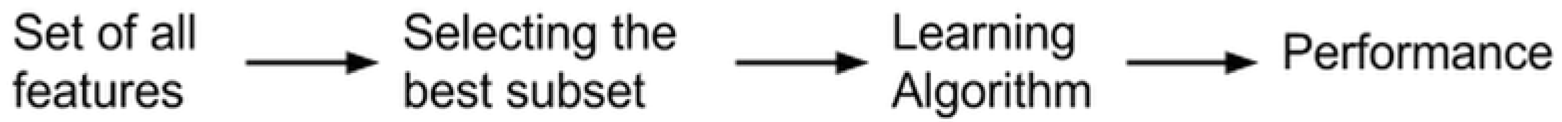
3) Derive a RL policy that produces a new feature subset for each example in the dataset.

- This policy is learned through policy gradient methods that minimize both the loss function of the learning algorithm and the dissimilarity of model-chosen and human-chosen feature subsets

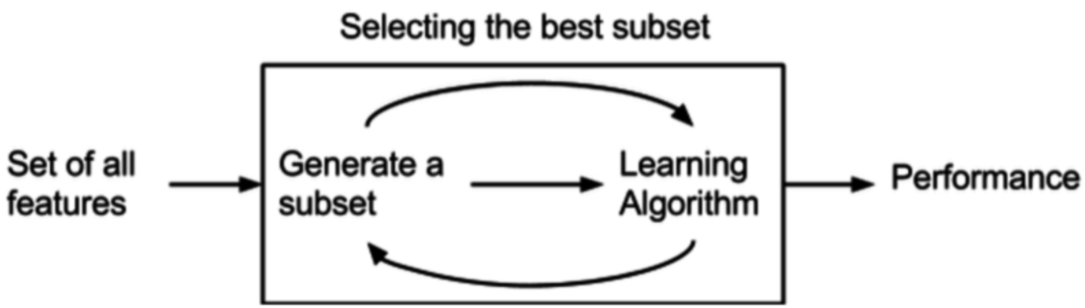
Related Work

Feature selection/elimination methods:

- <u>Filters</u> – consist of a preprocessing step where the top-k features are selected by ranking them against some score function, such as the mutual information between input and target variables (Tyagi and Mishra 2013)

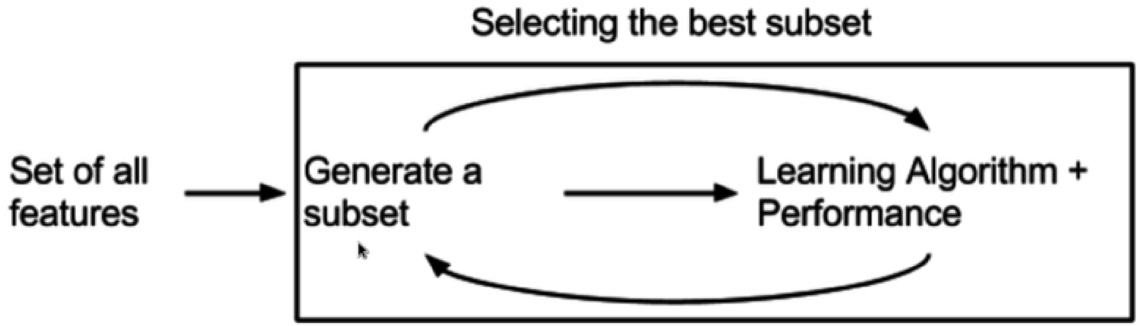


- <u>Wrappers</u> – rank feature subsets following some performance measure such as the accuracy in the training data (Kohavi and John 1997)



Related Work

- Embedded Methods – similar to wrappers, but different in that feature selection is performed while training the learning algorithm (Guyon and Elisseeff 2003)
  - The approach in this paper is an embedded method, since the feature selection and learning algorithms are jointly trained via gradient descent



  - This method reduces the significant computation time of wrapper methods, since the learning algorithm is only trained once

Related Work

Per-example Feature Selection:

- A filter-based method utilizing mutual information was proposed in (Avdiyenko, Bertschinger, and Jost 2012), however:
  - It is deterministic and completely data-driven, whereas the model in this paper includes human feedback
  - It builds feature subsets sequentially, while this paper's model does so in a single step

Attention Mechanisms:

- By attributing weights to different hidden states in a neural network, attention mechanisms are also selecting the most relevant features to minimize the model's cost function
- The work of this paper applies these ideas in HITL framework
- More info: (Xu et al. 2015; Bengio, Leonard, and Courville 2013; Bahdanau, Cho, and Bengio 2015)

Framework

- **In this framework, expert annotators provide the ground truth and select the most relevant features that influenced their decision**
  - This selection is modeled with a binary mask a that is applied element-wise to filter out the irrelevant features of an example x, where $x \in \mathbb{R}^d$ and each dimension corresponds to a feature x_j

$$\begin{cases} a_j = 1, \text{ if } x_j \text{ is used for example } x \\ a_j = 0, \text{ otherwise.} \end{cases}$$

  - The input to the learning algorithm then becomes $x' = x \odot a$
  - The cost function $C(x', y, \theta)$ must be differentiable w.r.t. the function that defines a if we hope to minimize the cost using gradient descent

Framework

- However, it is not differentiable if a is an indicator variable
- So we model the probability of a given x instead.
- We do so by associating each component $a_j \in \{0,1\}^d$ with a Bernoulli distribution parameterized by $\hat{q}_j$ and obtain:

$$\pi(a|x) = \prod_{j=1}^{d} \hat{q}_j^{a_j} (1 - \hat{q}_j)^{(1-a_j)}$$

- The goal then is to concentrate the mass of the distribution $\pi(a|x)$ on values of a that minimize the loss function $C(x', y, \theta)$
  - $\pi(a|x)$ should then tell us the best set of features given any input
  - The probability $\hat{q}_j$ of each feature being selected can be approximated by a neural network with parameters ψ :

$$\hat{q}_\psi = (\hat{q}_1, \hat{q}_2, ..., \hat{q}_d) = h(x; \psi)$$

Framework

Human-Like Feature Selection:

- We've discussed how expert feedback can be modeled and used to learn the feature selection algorithm, but the framework can also be used to mimic the feature selection of users.
  - Let's denote the user feedback by q (the learned model gives $\hat{q}$)
  - Intuitively, if either q_j or $\hat{q}_j$ are close to 1, then feature j is determinant to predict $\hat{y}$ and is negligible otherwise.
- We can define a similarity measure between q_j and $\hat{q}_j$ (which also serves as the cost function $C_f(x, q, \psi)$) to measure how well a model fits user feedback:
  - Euclidean distance: $\mathcal{C}_f(x, q, \psi) = \mathbb{E}_x \, ||q_i - \hat{q}_i||^2 = \mathbb{E}_x \, ||q_i - h(x;\psi)||^2$
  - Cosine distance: $$C_f(x, q, \psi) = 1 - \frac{q\,\hat{q}}{||q||_2\,||\hat{q}||_2} = 1 - \frac{q\,h(x;\psi)}{||q||_2\,||h(x;\psi)||_2}$$

Framework

- With the similarity measure $C_f(x, q, \psi)$ defined, we simply add it to the final cost function, which we'll denote by C:

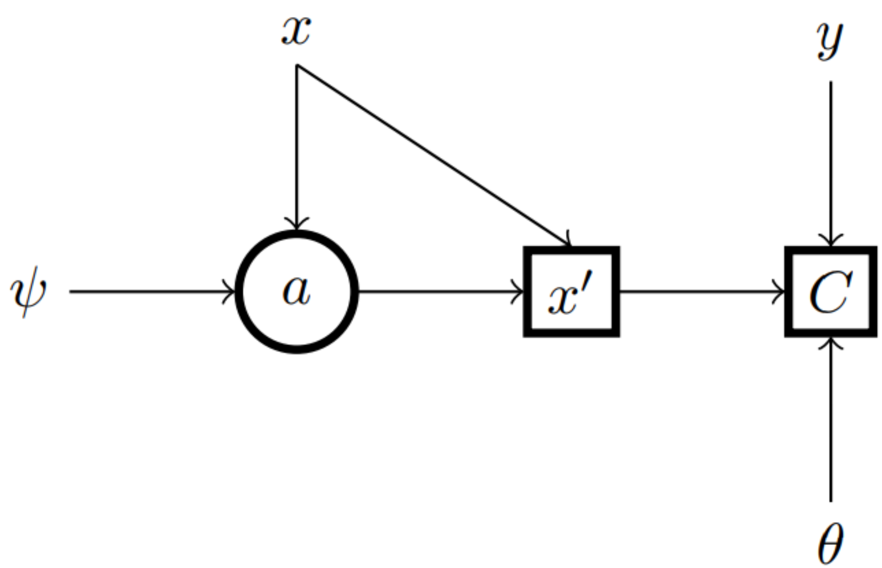
$$\mathcal{C} = \mathcal{C}(x, y, q, \theta, \psi) = \mathcal{C}(x', y, \theta) + \lambda \mathcal{C}_f(x, q, \psi)$$

  where λ is a hyperparameter that balances the tradeoff between these two signals

  - Intuitively, this cost function encourages the agent to achieve good performance at the machine learning task while mimicking human feature selection, which serves as a bias of sorts.
  - For examples with no human feedback available, $C_f(x, q, \psi) = 0$

Stochastic Computation Graphs

- a is stochastic and we need to sample it before making a prediction, so we can frame the model as a stochastic computation graph



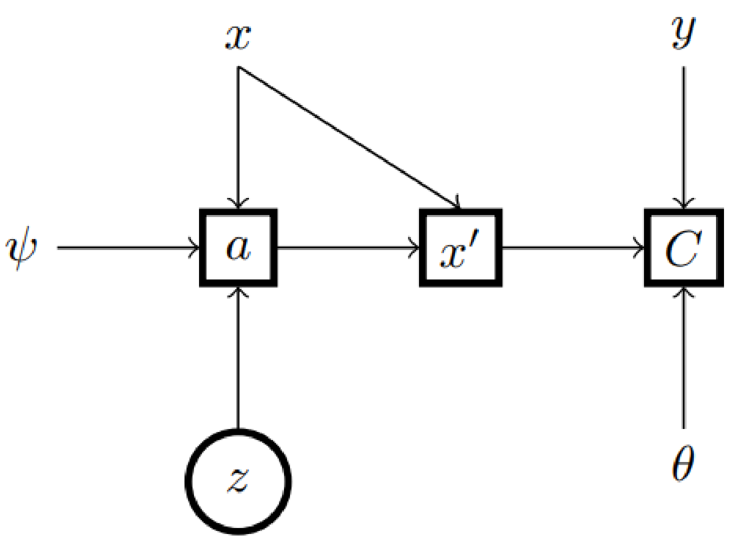
- Square nodes are deterministic and round ones are stochastic
- Inputs and parameters are represented by their vector names

Stochastic Computation Graphs

- The challenge here is that $C(x', y, \theta)$ is non-deterministic and non-differentiable w.r.t the parameters ψ, so we can't use the standard backpropagation algorithm in gradient descent
- Instead we need to somehow estimate $\nabla_{\psi} \mathrm{E}_a[C]$, the gradient of the expected loss w.r.t ψ
  - Two solutions are to use the ***Score Function*** (SF) (Williams 1992) or ***Pathwise Derivative*** (PD) estimator (Schulman et al. 2015)
- Using the ***Score Function*** estimator entails rewriting $\nabla_{\psi} \mathrm{E}_a[C]$ as $\mathrm{E}_a[C \nabla_{\psi} \log(\pi(a|x, \psi))]$ and minimizing a surrogate cost function defined as: $C' = C \log(\pi(a|x, \psi)) + C$
  - This cost function is then regularized to encourage both sparsity in the number of features selected and high variance in the feature subsets selected across examples

Stochastic Computation Graphs

- The *Pathwise Derivative* estimator is also known as the reparametrization trick and was made popular by variational autoencoders (Kingma and Welling 2014)
  - This method entails sampling from $\pi(a|x)$ by first sampling a latent variable z from a known fixed probability distribution $p(z)$ and transforming it, using some function to recover a
  - In variational autoencoders, z is usually sampled from a Gaussian distribution, but the process can be extended to categorical variables by sampling instead from a Gumbel-softmax distribution (Jang, Gu, and Poole 2017; Maddison, Mnih, and Teh 2015)
  - Notice how in the graph a is no longer a stochastic node



Stochastic Computation Graphs

- Assuming K different states, a_{jk} is the probability of assigning state k to feature j :

$$a_{jk} = \frac{exp((log(\hat{q}_{jk}) + g_k)/\tau)}{\sum_{l=1}^{\mathcal{K}} exp((log(\hat{q}_{jl}) + g_l)/\tau)} \text{ for k in } 1, ..., \mathcal{K},$$

  where $g_0, g_1, \ldots, g_k$ are samples from Gumbel(0,1) and τ is a hyperparameter that controls how close the distribution is to the argmax function

  - During training time, $\tau > 0$ ensures that this function is differentiable
    - τ Is gradually decreased as the model reaches convergence
  - At test time, we set $\tau = 0$ to recover the argmax function so that a is once again an indicator variable
  - Now $a \in \mathbb{R}^{d \times K}$, so we must recover the mask before multiplying it by x
    - We do so multiplying a by $w \in \mathbb{R}^K$ so that $aw \in [0,1]^d$ ($w = [0,1]^T$ for $K = 2$)
- PD does not require a surrogate cost function or regularization like SD does, but it does introduce the τ hyperparameter

Experimental Results

Experiment details:

- Models were developed using Tensorflow and run on a GPU
- Refer to the paper for model parameter information

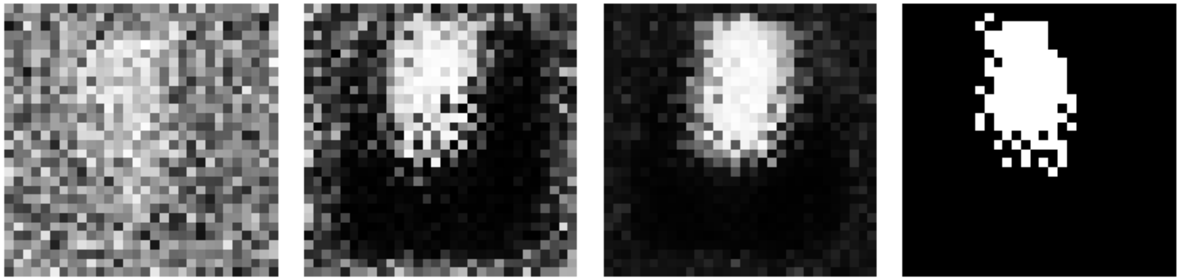
Image Classification Task (proof of concept):

- They used an augmented MNIST handwritten digit dataset
  - Source code and details: github.com/AlCorreia/Human-in-the-loop-Feature-Selection
- In this experiment, user feedback is simulated:

(a) (b)

Experimental Results

- A baseline NN model achieves 92.23% accuracy in the test
- Both SF and PD estimators achieve similar accuracy (88% to 92% after feedback is introduced)
- The figure below shows how the feature selection evolves:
  - Increased sharpness of $\hat{q}$ in (d) shows the effect of the feedback



(a) Beginning (b) 25 epochs (c) 50 epochs (d) feedback

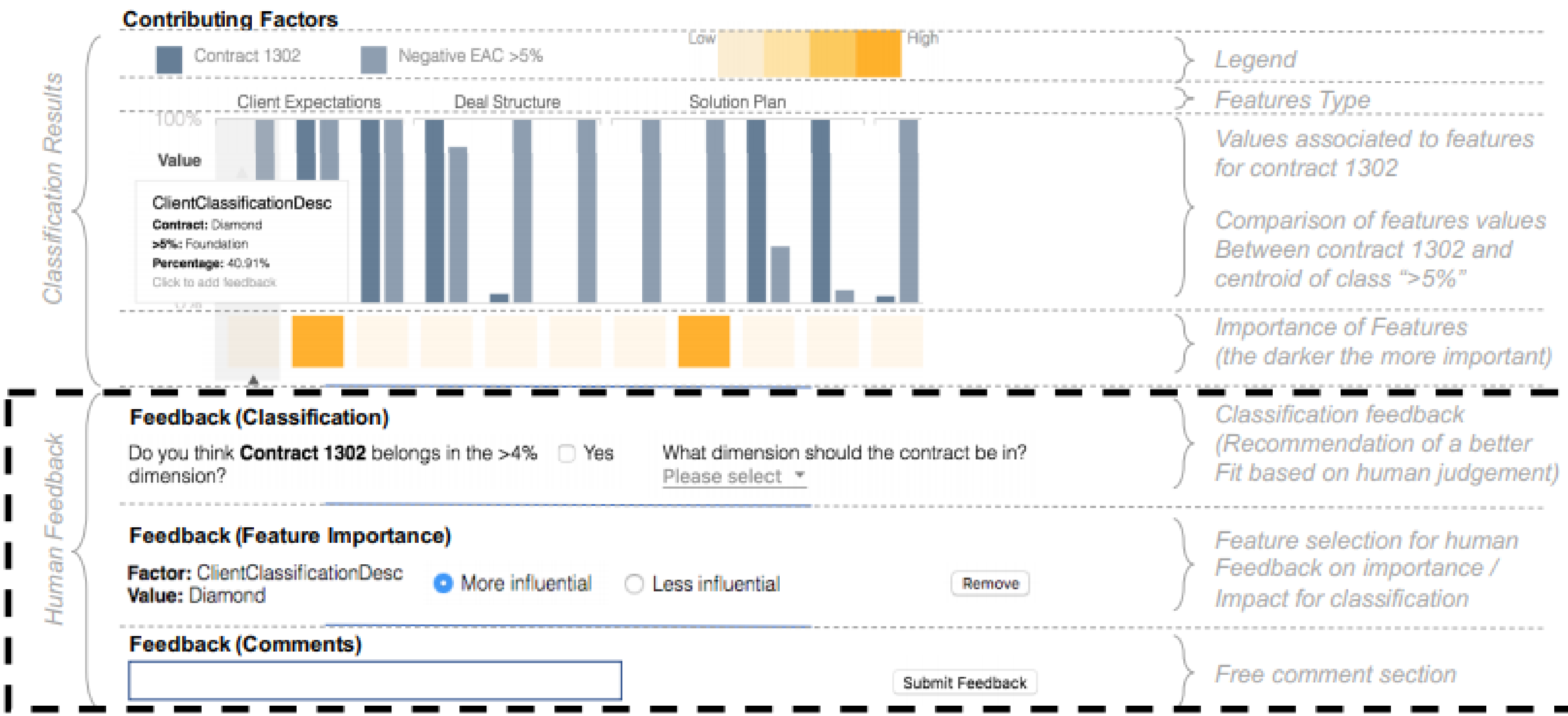
- For PD, a temperature value $\tau = 1.0$ achieved the best results
  - This value presumably balances policy exploration vs feedback exploitation

Experimental Results

Project Risk Classification (PRC) Task:

- The method was also tested on 4 years of project risk profiles
  - The data consists of 349,324 projects across 97 features and is classified among 5 categories, from high to no financial risk)
  - They collected 613,916 pieces of feedback (labels, important features, and comments) on 87,657 active contracts from 114 business experts over a period of 6 months
- This is an interesting test of the model for various reasons:
  - Baseline approaches reach a (low) max accuracy of 31.45% (random forest)
  - PRC is a highly human-curated task that relies on feedback from human experts
  - Completely data-driven approaches would require very large amounts of data

Experimental Results



The user interface for PRC (human feedback in dashed zone)

Experimental Results

- Both SF and PD estimators show significant improvements:

Feedback / Estimator	SF	PD
Before Feedback	29.53	**29.99**
Cosine Feedback	**82.49**	77.51
MSE Feedback	80.11	78.44

- After training with feedback, the models selected a relatively low number of features: 2 to 12 with $\mu: 4.6, \sigma: 1.5$
- Additional observations:
  - The SF estimator does not respond well to dropout, while PD does
  - The estimator used is independent of the architecture, so multiple estimators can be tested and the best for the application can be used
  - The influence of the dissimilarity distance (MSE/cosine) did not affect much, but might vary with the application

Conclusions

- The authors addressed the problem of human-in-the-loop per-example feature selection as a stochastic computation graph.
- They demonstrated that the model could identify the most relevant features of each example in the image classification dataset.
- With the PRC dataset, they showed that the model utilized human feedback to dramatically improve accuracy (31.15% to 81.87%) while also providing business -driven insights.

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