A Concept and Argumentation based Interpretable Model in High Risk Domains

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Abstract

Interpretability has become an essential topic for artificial intelligence in some high-risk domains such as healthcare, bank and security. For commonly-used tabular data, traditional methods trained end-to-end machine learning models with numerical and categorical data only, and did not leverage human understandable knowledge such as data descriptions. Yet mining human-level knowledge from tabular data and using it for prediction remain a challenge. Therefore, we propose a concept and argumentation based model (CAM) that includes the following two components: a novel concept mining method to obtain human understandable concepts and their relations from both descriptions of features and the underlying data, and a quantitative argumentation-based method to do knowledge representation and reasoning. As a result of it, CAM provides decisions that are based on human-level knowledge and the reasoning process is intrinsically interpretable. Finally, to visualize the purposed interpretable model, we provide a dialogical explanation that contain dominated reasoning path within CAM. Experimental results on both open source benchmark dataset and real-world business dataset show that (1) CAM is transparent and interpretable, and the knowledge inside the CAM is coherent with human understanding; (2) Our interpretable approach can reach competitive results comparing with other state-of-art models.

Introduction

For decision-making tasks in high-risk domains, machine learning (ML) methods are required to have high level of interpretability. Many feature importance based post-hoc explainable methods, such as SHapley Additive exPlanations (SHAP) (Lundberg and Lee 2017) and Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro, Singh, and Guestrin 2016), are proposed to explain black box models. However, (Slack et al. 2020) showed that feature importance based explanation can neither reflect the real behavior of the black model nor improve human understanding of the model. Thus, interpretable models have been an increasingly active research direction, and high order Generalized Additive Models (GAMs) such as Explainable Boosting Machine (EBM) (Caruana et al. 2015) and NODE-GAM (Chang, Caruana, and Goldenberg 2021) are purposed to provide analysis on individual features or interaction between two features toward the prediction target. Additionally, a line of researches have focused on the high-order features and feature grouping methods (Luo et al. 2019; Chen et al. 2022). However, the aforementioned methods are purely data-driven and did not include domain knowledge from expertise, and sometimes the resulted feature interactions from those methods are hard to be understood by humans.

To improve the interpretability of the above methods, argumentation-based methods are purposed to increase human understanding and trust of the model by injecting the human-level knowledge during decision-making stage. Because formal argumentation, as a formalism for representing and reasoning with knowledge (Baroni et al. 2018), are capable of providing various ways for justifying and explaining why a claim or a decision is made (Borg and Bex 2021; Prakken and Ratsma 2022). Among them, quantitative argumentation frameworks (QAF) has a greater advantage over qualitative argumentation when combined with data-driven methods. To construct the argumentative structure, majorities of the existing augmentation-based methods are bespoke to a specific problem (Chi et al. 2021; Chi and Liao 2022) and depend on the knowledge from in-domain expertise, which significantly limits the usage of these methods since the specific argumentation structures are hard to migrate to a new problem.

One approach to address the above issue is to automate the argumentation structure generation process with data miming techniques using orthogonal in-domain knowledge information from external data. For tabular data in high risk domain, data descriptions are one of the great resources for in-domain knowledge since in-domain expertise needs to make decisions depends on raw features value directly (Lakkaraju et al. 2019). In this paper, we propose a concept and argumentation based model (CAM) that generates human-understandable concepts by mining data descriptions automatically and representing the generated concepts and the reasoning paths with argumentation structure. To illustrate CAM, Fig. 1 shows a concrete example from a real word high risk application (Chen et al. 2018) : to explain the decision-making process, concept Installment is gener-
ated automatically from the two underlying features based on their similar data descriptions, and the processes are repeated twice to generate concepts *Delinquency* and *Inquiry*. On top of them, concept *risk* is generated to represent the final decision-making process. The resulted concept-based knowledge can be properly represented and reasoned using QAF: each concept can be viewed as an abstract argument, while the inter-concept edges can be understood as supports or attacks between arguments, and a quantitative argumentation-based field-wild leaning algorithm is designed to evaluate and filter the generated concepts.

With quantitative argumentation, CAM can be represented as stacked QAFs with weighted edges that represent the inter-concept relationship strength, and a quantitative argumentation-based method is designed as the reasoning machine inside the stacked QAFs to conduct knowledge reasoning by aggregating the strengths of lower-level concepts or features to the strengths of higher-level concepts. The reasoning machine can output a knowledge reasoning path that can be used as global model interpretation. As a result of it, CAM can be treated as an interpretable white-box model since the decision-making process is transparent to the users with the visualization of the reasoning path in form of dialogical tree.

**Our contributions.** To summarize, our contributions are listed as follows:

- Conceptually, we propose CAM to automatically generate and evaluate concepts from tabular data, and utilize quantitative argumentation to represent and reason on concepts. Furthermore, we provide explanation as the key reasoning path within CAM.
- Empirically, we conduct CAM on both open source benchmarks and real-world business datasets in high-risk domains. Experimental results show that (1) CAM is competitive compared to other ML models; (2) CAM is both global and local interpretable, and the knowledge inside the model is coherent with human understanding.

**Related work**

*Explainable artificial intelligence works for tabular data*  
For tabular data, a group of post-hoc methods explain models by computing or approximating the feature importance, such as LIME and SHAP. But, the explanation can be complex and difficult to be understood by humans because the granularity of the explanation is too fine (Ghorbani et al. 2022). Recently, researchers have focused on the interaction of features rather than individual features by constructing interpretable model. NODE-GAM and EBM are a class of interpretable model that can provide analysis on individual features or interaction between two features. These two methods apply neural network models and boosting tree models, respectively, to fit a functional relationship between a single feature or an interaction feature with the output. However, (Chang et al. 2021) argue that different fitting models can have different or even contradictory interpretations for the same data. This is because the fitting model model relies solely on data-driven and leads to overfitting. DANETs (Chen et al. 2022) are able to abstract higher-level tabular features by neural network. But the higher-level features only contribute to the classification performance. The semantic within them is not completely explicit, which may lead to confusing features.

*Interpretable Concepts Mining*  
Recent researches have focused on generating high-level human concepts from data. TCAV (Kim et al. 2018) and VCEC (Fang et al. 2020) produced estimation of how important a concept is for the prediction. ProtoPNet (Chen et al. 2019) is trained to learn visual prototype vector and calculate similarity for prediction. ACE (Ghorbani et al. 2019) proposed a method to automatically extract visual concept from certain class’s images. But all the above-mentioned methods are designed specifically for image data. Our goal is to make similar effort for interpretable tabular ML.

*Quantitative argumentation-based work in explainable artificial intelligence*  
Quantitative argumentation frameworks (QAF) are a knowledge representation formalism that can be used to solve decision problems in a very intuitive way by weighing up pro and contra arguments (Baroni et al. 2015). QAF are are based on Bipolar Argumentation Frameworks (BAFs) (Cayrol and Lagasquie-Schiex 2005) by quantifying the semantics of arguments and the relations between them. Many reasoning methods are proposed for evaluating their semantics, including DF-QuAD algorithm (Rago et al. 2016), O-QuAD algorithm (Chi et al. 2021), Multi-layer Perception (MLP)-based algorithm (Potyka 2021) and etc. These models have better performance in solving real life problems, such as fraud detection (Chi et al. 2021), opinion polling (Rago and Toni 2017), and review aggregation (Cocarascu, Rago, and Toni 2019). However, the argumentation model rely on a concrete knowledge structure. It can be the inherent structure of the data, such as the tree conversation structure in social media (Chi and Liao 2022), or constructed manually by human experts (Chi et al. 2021). To the best of our knowledge, existing works have not introduce a method that can automatically construct argumentative tree from tabular data.

**Concepts and argumentation based model**

**Knowledge definition and representation**

*Knowledge in tabular data*  
In tabular data, the knowledge may be divided into two categories: human-level knowledge and knowledge learned from data. The former can be data

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**Figure 1:** An example of concept abstraction from tabular data for risk estimation

| ID | MaxDelq | RecentDelq | NumInstall | PercentInstall | NumInquiry | RecentInquiry |
|----|---------|------------|------------|----------------|------------|--------------|
| 1  | 6       | 4          | 2          | 75             | 1          | 0            |
| 2  | 5       | 4          | 2          | 50             | 2          | 0            |
Represent knowledge in quantitative argumentation framework A QAF is a quadruple \((A, E, \beta, \omega)\) consisting of a set of arguments \(A\), edges \(E \subseteq A \times A\) between these arguments, a function \(\beta : A \rightarrow [0, 1]\) that assigns a base score \(\beta(a)\) to each argument \(a \in A\) and a function \(\omega : E \rightarrow \mathbb{R}\) that assigns a weight to each edge. Furthermore, for every argument \(a \in A\), we let \(\text{Att}(a) = \{(b, a) \in E \mid \omega(b, a) < 0\}\) and \(\text{Sup}(a) = \{(b, a) \in E \mid \omega(b, a) > 0\}\).

A concept tree rooted by concept with the global semantics \((c_a)\) can be represented in form of QAF as \(QAF_G : (A, E, \beta, \omega)\), each argument \(a \in A\) represents a concept \(c_a\) or a feature \(f\), edges \(E \subseteq A \times A\) between these arguments describe the positive and negative correlation between concepts and features, a function \(\beta : A \rightarrow [0, 1]\) that assigns a base score \(\beta(a)\) to each argument \(a \in A\) which represents a concept, and a function \(\omega : E \rightarrow \mathbb{R}\) that assigns a weight to each edge. \((\beta, \omega)\) are not defined now until the field-wise learning algorithm is introduced. It is worth noting that features as a unit of knowledge are also represented as arguments. However, in the QAF, the arguments representing features are at the leaf node positions, because the knowledge embedded in features has the finest granularity. In the tabular database, features have been mapped to the underlying data. Therefore the strength of the arguments representing the features can be obtained directly from the data without the need of the base score function to assign initial values. We denote features as \(f \in F\), and \(F\) is a set of features contained in tabular data.

Definition of concept From the perspective of knowledge representation, the knowledge contained in a concept can be represented as two characteristics of the concept: a semantic-based and an argumentation-based characterisation. The former one can be described in form of natural language for human or semantic vector for machine, representing the knowledge learned from data description. The other can be represented in form of QAF rooted by this concept, in which the nodes \(A\) and edges \(E\) in QAF are learned from data description. The other can be represent in form of QAF rooted by this concept, in which the nodes \(A\) and edges \(E\) in QAF are learned from data description and \(\beta\) and \(\omega\) are learned from underlying data.

Definition 1. Let \(C\) be a set of concepts, a concept \(c \in C\). A semantic-based characterisation of \(c\) is meaning \(m_c \in M\). An argumentation-based characterisation of \(c\) is \(QAF_c \subseteq QAF_G\), where \(M\) is a finite set of meanings of concepts, and \(QAF_c\) is the subtree of \(QAF_G\).

A concept \(c\) consists two characterisations \((m_c, QAF_c)\),

\[\text{Figure 2: The overall workflow of CAM. In CAM, we first mine semantic knowledge as concepts from data description and represent them in QAFs. Then, the quantitative knowledge is mined from underlying data for concept quantification and evaluation. Repeating these two step, we can built } QAF_G \text{ by stacking concepts in form of QAF for decision-making.}\]
m_c represents the semantic information and QAF_c describes its argumentative information. As shown in Fig. 1, we take concept 'Installment' as an example.

Example 1. concept c.Installment have the meaning m.Installment as 'installment is a sum of money due as one of several equal payments for something, spread over an agreed period of time'. And its argumentative information can be decoupled into two processes: (i) semantic knowledge mining, and (ii) quantitative knowledge mining, as shown in Fig. 2. Semantic knowledge mining is designed for automatically searching lower-level knowledge units (such as features and lower-level concepts) with similar meanings and abstract higher-level concepts from them. Then, quantitative knowledge mining is designed for mining the correlations between concepts and their children.

Semantic knowledge mining To simulate the process of abstracting concepts in human cognitive learning, we need to combine features with similar meaning and extract the same characteristics as the meaning of the generated concepts. To achieve this goal, three main procedures are necessary in Semantic knowledge mining: 1) Vectorization. 2) Grouping. 3) Abstraction.

Vectorization transfers the natural language information into vector space with the leverage of pretrained multilingual language model. In that way, the meaning of features or concepts is embedded into vector from natural sentences. And then Grouping process the semantic vectors into several groups by combine the features or concepts with high similarity. (In our task, every group contains two elements which can be features or concepts). Finally, in Abstraction process, the similar descriptive part of the natural statements in each group is extracted and vectorized as the meaning of newly generated higher-order concept. To be noticed, the structures of the new concepts are also mined in this process, which can be represented in form of A and E in their QAFs.

For example, in Fig. 1, m.Installment of f.Installment in description of dataset is ‘number of trades with installment, installment is one of several equal payments for something, spread over an agreed period of time’. And m.PercentInstall is described as ‘percents of trades with installment, installment is...’. Through procedures of Vectorization and Grouping, f.Installment and f.PercentInstall are grouped together. Then, c.Installment is abstracted from them, and the meaning of c.Installment is represented as ‘installment is one of several equal payments for something, spread over an agreed period of time’. To make machine understand, m.Installment will also be the semantic vector. Also, A and E of QAF.Installment is captured as showed in Example 1.

Quantitative knowledge mining After the process of semantic knowledge mining, as shown in Fig. 2, assuming that we obtain t concepts from n features, and the structural information of them. In this part, the quantitative knowledge from underlying data need to be mind and attached to the generated concepts. Logistic regression (LR) is a suitable choice. First, it is the most widely used interpretable model, and fast for inference. Second, the parameters in LR model contains the same semantic with QAF. However, the LR model only learn from the features to the prediction target, and the strength of the concept nodes and the strength of the associated edges are not directly accessible. Therefore, we propose a field-wise learning algorithm to learn values of all nodes and edges in QAF:

The field-wise learning algorithm runs in two steps. In First step, we train a LR model to learn the strength of nodes and edges of QAF_G as original arguments (without the newly generated concepts in last process) to concept with global semantics c_g. QAF_{org}^G is denoted as a QAF rooted with c_g and the children only contain original arguments. In second step, we link the newly generated concept c_i and its children as a sub-tree to QAF_{gen}^G, and delete the edges which link children of c_i directly to c_g, thus we get a new QAF_{gen}^G by adding the structure of a new generated concept c_i and remove the repeated arguments. Then we use a net which has the same structure with QAF_{gen}^G to learn the unknown strength of nodes and edges of QAF_{gen}^G. The same parts of QAF_{org}^G and QAF_{gen}^G has been learned in the first step, thus the net only learn strength of edges and node related to c_i. Hence, the learning process is ‘field-wise’. We repeat the second step, until all the strength of edges and nodes related to newly generated concepts are mined. And we obtain a list of fully learned QAF (QAF_{org}^G, ..., QAF_{gen}^G).

Formally, denote original arguments set as A_{org} = \{a_1, ..., a_q\}, where a may be features or concepts. Specially, in the first round of concept mining, a only represents features. Denote children of a newly generated concept c_i as \{a_j, a_k\}. In first step, LR model can be described as:

\[
S(c_g) = \varphi\left( \sum_{a_i \in A_{org}} w_i \times a_i + b_g \right)
\]

(1)

where \(\varphi(z) = \frac{1}{1 + \exp(-z)}\) is the logistic function, \(w_i \in (w_1, ..., w_k)\) is the weight and \(b_g\) is bias.

To represent the knowledge learned from data in form of QAF, edges between arguments and concept with global semantics c_g are represented as E = (a_1, c_g), ..., (a_q, c_g), \(w_i \in (w_1, ..., w_k)\) is the strength of edge (a_i, c_g), thus function \(\omega\) in QAF_{org}^G is instantiated as \(\omega((a_i, c_g)) = w_i\), where \(w_i \in (w_1, ..., w_k)\) and \(a_i, c_g \in E\). b represent the initial score of c_g. But in QAF, \(\beta(c_g) \in [0, 1]\), thus we define \(\beta(c_g) = \varphi(b_g)\). In second step, a net model can be described as:

\[
S(c_g) = \varphi\left( \sum_{a_i \in A_{org}} \sum_{a_j \in A_{gen}} w_i \times a_i + b_g + w_{c_g} \times \varphi(w'_j \times a_j + w'_k \times a_k + b_{c_g}) \right)
\]

(2)

where in sum function \(w_i \in A_{org} \setminus \{a_j, a_k\}\), and \(w_i\) is learned in last step thus we fix \(w_i\) as a constant score during net model training process. \(w_i\) is the weight of newly generated concept c_i, w_j, w_k are new weights of a_j and a_k, cause their structure has changed. b_{c_g} is bias of c_i.
weights and biases can be represented in $QAF_{G}$ to instantiate $\omega$ and $\beta$ function.

**Knowledge reasoning: quantitative argumentation-based method**

To ensure the consistency of the strength in QAF in the learning process and inference process, we define a Net-based reasoning method as our quantitative argumentation-based method to complete knowledge reasoning. In Net-based reasoning algorithm, we have a strength $s(a) \in [0, 1]$. $s(a)$ is the strength value of argument $a$. The strength values are then updated by doing the following two steps for all $a \in A$ from down to top until the concept with global semantics:

**Aggregation:** $\alpha(a) := \sum_{(b,a) \in E} \omega(b, a) \times s(b)$

**Combination:** $s(a) := \varphi(\ln(\frac{\beta(a)}{1 - \beta(a)}) + \alpha(a))$

An instance is denoted as $x = [x_1, ..., x_n]$, corresponding to all features in dataset. It is worth noting that the $x$ is preprocessed, such that $x_i \in [0, 1]$. For the sake of simplicity of presentation, we take the outputs of the first round of concept mining as an example to illustrate the reasoning process of QAF. Thus, in $QAF_{G}^{org}$, the children of concept with global semantics $c_g$ are all features, represented as $A_{org} = \{f_1, ..., f_n\}$, and the edges are denoted as $E = (f_1, c_g), ..., (f_n, c_g)$

$$s(c_g) = \varphi(\ln(\frac{\beta(a)}{1 - \beta(a)}) + \sum_{(f_i, c_g) \in E} \omega((f_i, c_g)) \times x_i)$$

where $\omega$ and $\beta$ function are instantiated by field-wise learning algorithm in previous process.

By completing the inference for all samples in the evaluation dataset using the quantitative argumentation-based method, we can use resulting metrics Area-Under-Curve (AUC) to evaluate the performance of $QAF_{G}^{org}$. When the process of concept mining can generate new concepts, the reasoning method can evaluate whether the concepts are useful for decision making and thus filter out the irrelevant concepts. The process is described as follows.

If $\text{AUC}(QAF_{G}^{org}) \geq \text{AUC}(QAF_{G}^{org})$, then keep $c_i$.

If $\text{AUC}(QAF_{G}^{org}) < \text{AUC}(QAF_{G}^{org})$, then drop $c_i$.

When the evaluation is over, the kept concepts and features not grouped for concept mining enter the knowledge mining process as a new round of input. CAM performs concept mining method and quantitative argumentation-based method repeatedly to generated all the import concepts from tabular data for decision making task as shown in Fig. 2. Until the concept mining method can not mining a new concept, the output of it is $QAF_{G}$. In $QAF_{G}$, every layer of important concepts are stacked until the concept with global semantics. In this case, quantitative argumentation-based method will not perform evaluation, but only act as a reasoning machine. Then, CAM are constructed by combining $QAF_{G}$ and reasoning machine. Thus, CAM can make decisions base on human-level knowledge.

**Dialogical explanation within CAM**

CAM are capable of providing the underlying structure for generating dialogical explanations for users. A user may interact with CAM by requesting an explanation of an argument (concepts or features).

**Definition 2.** Given a $c_g$ of an instance $x$, and its $QAF_{G}(A, E, \beta, \omega)$, an argumentation dialogue between a user and CAM consists of explanation requests $Q(a)$ for $a \in A$ from user, to which CAM responds with explanation $\mathcal{X}(a)$.

Inspired by (Cocarascu, Rago, and Toni 2019), we provide a simple argument dialogue as follows.

Let $r_1^+, r_1^-, r_2^+, r_2^-$ be functions giving positive primary, negative primary, positive secondary and negative secondary, for any argument $a \in A$:

- $r_1^+(a)$ = because the supporting argument $a$ is $s(a)$;
- $r_1^-(a)$ = because the attacking argument $a$ is $s(a)$;
- $r_2^+(a)$ = and the supporting argument $a$ is $s(a)$;
- $r_2^-(a)$ = and the attacking argument $a$ is $s(a)$;

For any $S \subseteq A$, if $S = \emptyset$, let $\text{max}(S) = \emptyset$; else, let $\text{max}(S) = \text{argmax}_{a \in S} (\omega(a) \times s(a))$, $\text{sec}(S) = \text{argmax}_{a \in S \setminus \text{max}(S)} (\omega(a) \times s(a))$, where $\text{argmax}$ refers to the argument $a$, at which the value of $(\omega(a) \times s(a))$ is as large as possible. Then, an argumentation dialogue is such that for any $a \in A$:

- if $a = c_g$ and $s(c_g) \leq 0.5$ and $\exists b \in \text{Att}(a)$:
  - $Q(a) = \{\text{Why is } a \text{ evaluated as } s(a)\}$
  - $\mathcal{X}(a) = r_1^-(\text{max}(\text{Att}(a))) + r_2^-(\text{sec}(\text{Att}(a)))$;
- if $a = c_g$ and $s(c_g) > 0.5$ and $\exists b \in \text{Sup}(a)$:
  - $Q(a) = \{\text{Why is } a \text{ evaluated as } s(a)\}$
  - $\mathcal{X}(a) = r_1^-(\text{max}(\text{Sup}(a))) + r_2^+(\text{sec}(\text{Sup}(a)))$;

Our intuition here is that the dialogical explanation is simpler than but consistent with CAM by giving at most two paths which contributed most to concepts with global semantics. The explanation of $c_g$ may consist of its supporter or attackers which have significant impacts on $c_g$, depending on whether $c_g$ is accepted or not. This dialogue is fairly repetitive traced down other important arguments in support of the result.

**Experiments**

**Introduction of dataset**

We evaluate CAM with two real-world high risk application benchmark datasets denoted as Fico and Mimic3 and two
Table 1: Summary of datasets

| Source Type | Name   | Domain   | #Samples | #Features | Positive rate |
|-------------|--------|----------|----------|-----------|---------------|
| Benchmarks  | Fico   | Banking  | 9871     | 23        | 52.03%        |
|             | Mimic3 | Healthcare | 27348   | 57        | 9.83%         |
| In domain Dataset  | data 1 | E-commerce | 96452   | 33        | 3.2%          |
|              | data 2 | E-commerce | 98936   | 65        | 2.0%          |

Table 2: Experimental results for four datasets conducted by CAM and other machine learning approaches using AUC(%) metrics.

|                          | Interpretable models | Black-box model |
|--------------------------|----------------------|-----------------|
|                          | CAM mean | std mean | std | EBM mean | std mean | std | NODE-GA2M mean | std mean | std | MLP mean | std mean | std | XGB mean | std mean | std |
| Fico                     | 88.20     | 0.99    | 79.74 | 1.14 | 80.09     | 0.87 | 77.22     | 0.81    | 77.22     | 0.81    | 79.88     | 0.78    |
| Mimic3                   | 79.76     | 0.49    | 77.66 | 0.60 | 90.71     | 1.18 | 82.22     | 0.64    | 72.71     | 2.16    | 82.99     | 1.21    |
| data 1                   | 93.12     | 0.23    | 86.04 | 0.49 | 94.96     | 0.12 | 92.78     | 0.66    | 82.61     | 1.85    | 97.13     | 0.40    |
| data 2                   | 96.16     | 0.24    | 83.94 | 4.15 | 96.17     | 0.20 | 96.87     | 0.14    | 71.34     | 12.78   | 97.14     | 0.25    |
| Average                  | 87.31     | 0.49    | 81.85 | 1.64 | 87.06     | 0.59 | 90.17     | 0.36    | 78.02     | 4.40    | 93.84     | 0.66    |

in-domain anti-fraud datasets collected from two Alibaba e-commerce applications denoted as data1 and data2. These datasets are medium-size with 10-100K samples and Table 1 summarizes these datasets. And the detail about the datasets will be described in Appendix.

The setting of experiment
We use 80-20 splits for training and evaluation set and we repeat the experiments with five random seeds. All the datasets are for binary classification, and we use AUC as the evaluation metrics. CAM is compare against the interpretable methods of LR, EBM and NODE-GA2M, and the black-box models of MLP and xgboost (XGB)(Chen and Guestrin 2016). The compared models are selected as they are commonly used classification tools for tabular data. And among them, XGB is widely regarded as the classification model with excellent performance, and EBM and NODE-GA2M are considered as the state-of-the-art in interpretable models in recent years. In Appendix, we provide the detail about data preprocessing and the hyperparameter selections for the models.

Analysis on Classification results
In Table 2, we present the comparative results among the proposed CAM, LR, EBM, NODE-GA2M and MLP, XGB models in terms of mean and std of AUC. The best experimental results are in bold font. The results shows that CAM achieve best mean value of AUC in Fico dataset, while XGB performs best in other three datasets. In average, CAM ranks third behind the XGB and EBM. And EBM only has a small lead over CAM. As for the std value of AUC, CAM performs best in Mimic3, EBM achieve best score in data1, and NODE-GA2M runs most stably in Fico and data2. In average, CAM outperform other models as the most consistent model. Overall, the results show that CAM can competitive performance among all the interpretable and black-box models, and it has high stability.

Mean is the average value of the 5 experimental results indicating the average performance of the model, and std is the variance of the 5 results indicating the stability of the model.

Figure 3: A visualization of showing the global CAM for Fico dataset. The color of the node indicates the relation of the node to the concept risk, while the color of the edge denotes the relation of the child node to the parent node. Red and blue color indicates support and attack respectively.

Interpretability Analysis on Fico Dataset
Here we interpret the CAM instantiated in terms of risk prediction for Fico dataset. Fico dataset contains 10K credit bureau reports of consumers that used for predicting their loan defaulting risk. We provide the details in Appendix.

First, we analyze the interpretability of the global model from both semantic and argumentative perspectives. We can see that the top layer of the concept tree has 11 nodes, of which 6 concepts are generated by grouping and abstracting 18 features, and each concept can be treated as a risk factor. From the semantic perspective, Taking concept inquiry as an example, the two child concepts MSinceMostRecentInqExcl7days and NumInquiry describes different aspects of inquiry, and features NumInqLast6MExcl7days and NumInqLast6M describe different aspects of NumInquiry as well. The resulted semantic tree for inquiry is reasonable since all related features are grouped into concepts with different granularities. Additionally, We can see that in grouping, irrelevant features or concepts are not mixed in and the abstraction process makes the semantics of the nodes more general. From an argumentative perspective, in Fig.3, the red and blue nodes represent the supporters and attackers to
concept risk respectively. It means that as the strength of the blue node increases, the value of the concept risk decreases. The opposite is true for the red nodes. To be specific, we can see that when the values of feature NumInqLast6Mexcl7days and NumInqLast6M increase, then the value of concept NumInquiry increase, and the value of concept Inquiry increase, finally the value of concept Risk increase. Combined with the semantic information in description, our observation is reasonable as it can be summarized as ‘when the lending institution pulled a consumer’s credit bureau report more frequently, the consumer’s risk of defaulting on a loan increase’. Similarly, we can obtain other observations in line with human intuition such as ‘when the consumer’s revolving balance increase, the consumer’s risk of defaulting on a loan increase’, ‘when number of credit agreements on a consumer credit bureau report with on-time payments (satisfactory) increase, the consumer’s risk of defaulting on a loan decrease’ and etc.

Second, we start with a local example showed in Fig. 4, and CAM gives the result of the reasoning and an explanation in form of dialogical tree which is showed as follows.

user: Why is Risk evaluated as 0.92?
CAM: Because the supporting argument Installment is 0.69; and the supporting argument TradeRecord is 0.40.

user: Why is Installment evaluated as 0.69?
CAM: Because the supporting argument FractionInstall is 0.54; and the supporting argument InstallTrade is 0.30.

user: Why is FractionInstall evaluated as 0.54?
CAM: Because the supporting argument FractionInstallBurden is 1.0; and the supporting argument PercentInstallTrade is 0.22.

user: Why is FractionInstallBurden evaluated as 1?
CAM: Because in this case, FractionInstallBurden is 471%.

Users can end the conversation at any time, depending on their understanding of CAM, and he key reasoning path we can get from the above conversation is that: 

\[ s(FractionInstallBurden) = 471\% \rightarrow s(FractionInstall) = 0.54 \rightarrow s(Installment) = 0.69 \rightarrow s(Risk) = 0.92. \]

With this description, we can understand the reasoning paths as ‘in this case, installment balance of the the consumer is 471% of his original loan amount, which leads the fraction of installment risk factor increases by 68.7%. The significantly increased fraction of installment risk factor leads the installment risk factor increases by 25% since the fraction of installment is significantly higher than other individuals. Finally, with the highest feature weights, installment risk factor contributes to the risk decision mostly’. This explanation is very intuitive and easy for human to understand.

**Conclusions and future Work**

In this work, we have proposed CAM as an interpretable model for tabular data in high-risk domains. CAM consists of a concept mining method to automatically acquire human-level knowledge as concepts in the form of QAF from both data descriptions and underlying data, and a quantitative-argumentation based method to evaluate the discovered concepts. We have also provided explanations for decisions by showing a dominated path for each reasoning process within CAM in the form of a dialogical tree.

In our experiment, we have applied CAM on four datasets in high-risk domains. The results of classification indicate that CAM can reach competitive results comparing with other state-of-the-art models. And the results of interpretation show that CAM is a global interpretable model and able to provide explanations. The knowledge inside the model is coherent with human understanding.

As a new attempt in the direction of combining knowledge mining and quantitative argumentation in interpretable research for tabular data, some aspects of this articles are still preliminary. First, the abstraction of concept names still relies on human by providing abstracted descriptions of concepts. Second, CAM has been applied in Alibaba applications and helped users to understand the decisions, but we did not collect and evaluate users’ feedback. In our future work, we are going to collect data about the feedback of the users who receive answers and explanations of their queries, and use it to our empirical study.
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Appendix

A: Details in Experiments

Preprocessing and acquisition of datasets For all datasets used in the experiment, we use 80-20 as our train-val splits, and we split all datasets with five random seeds. After that, a standardization scaler will be applied to three datasets respectively. For FICO dataset, we fill the missing values with the mean values and drop entirely empty rows. Link information of experiments benchmark datasets is listed in Table 3.

For CAM training with tabular data, we target encode categorical features, apply quantile transform for all features and encode the binned features with one-hot encoder. For data description data, we first remove all special characters from the text and use pretrained multi-lingual sentence embedding models from Sentence-bert package (Reimers and Gurevych 2020).

Hyperparameters Selection For CAM, we use cosine distance to calculate the similarities between data descriptions and set threshold to 0.55 to generate potential concepts. For the augmentation-based field-wise filter, we freeze the models weights of the original model and fine-tune the augmentation-based model with 5 epochs. For the Logistic Regression backbone model, we use LBFGS (LIU and NOCEDAL 1989) as the optimizer and train the model with one single large batch.

For XGB, we select the hyperparameters from Node-GAM to make sure the model is fully converged.

For LR, we use l2 regulation and the default regulation weights from the sklearn learn package.

For EBM, we use the default parameters and set up the batch normalization (Ioffe and Szegedy 2015) and use LeakyReLU(Xu et al. 2015) as the activation function.

For NONE-GA2M, we use the second-order interaction mode and use default values for all other hyperparameters.

B: Details in Fico dataset

The dataset contains 23 financial features that includes trade, inquiry, delinquency, satisfactory, and utilization information. Every credit agreement between the consumer and a lending institution is represented by a separate line of information called a trade line, and is often truncated to the term ‘trade’. An ‘inquiry’ is also a line of information, but captures when a lending institution has pulled a consumer’s credit bureau report in order to make a credit decision. The term ‘delinquency’ refers to a payment received some period of time past its due date. This is typically measured in 30-day intervals, such as 60 days delinquent or 90 days delinquent. NumSatisfactoryTrades counts the number of credit agreements on a consumer credit bureau report with on-time payments (satisfactory). NumTradesWithHighUtilization counts the number of credit cards on a consumer credit bureau report carrying a balance that is at 75% of its limit or greater. The ratio of balance to limit is referred to as ‘utilization’. The data description is list in Table 4.

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