Data Storytelling Methods: Extraction, Reorganization, and Narrative

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Date: 2024-03-12T00:00:00+00:00

Abstract

Purpose/Significance: Data storytelling methods that integrate interpretability results provide a new strategy for addressing challenges in data cognition, interpretation of prediction results, and the credibility of model decisions. Method/Process: This study systematically reviews the explanation forms of model-agnostic local interpretability techniques, the narrative structures of data stories, and the methods currently employed in data storytelling research. Based on interpretability theory and data storytelling implementation patterns, we construct a data storytelling model characterized by 'extraction—reorganization—narration', define an element tuple-based data story mapping process, and identify the key technologies essential for storytelling model design. Results/Conclusion: Guided by the theoretical framework of data storytelling model design, this research proposes a 'fan-shaped' storytelling implementation pathway oriented toward interpretation results and an interactive framework that integrates interpretation results with storytelling model elements. Through case studies, we validate the practical value of the data storytelling method in result interpretation. By constructing a systematic methodological framework for data storytelling based on interpretability results, this work provides novel insights for expanding storytelling pathways endowed with data perception and cognition capabilities to support intelligent decision-making.

Full Text

Data Storytelling Method: Extraction, Reorganization, and Narrative

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Abstract

[**Purpose/Significance**] The data storytelling method that integrates interpretability results provides a new strategy for addressing challenges such as difficult data cognition, incomprehensible predictions, and low trust in model decision-making. [**Method/Process**] This study systematically reviews the interpretation forms of model-agnostic local interpretability techniques, the narrative structures of data stories, and the methods currently employed in data storytelling research. Based on interpretability theory and data storytelling implementation patterns, we construct an "extraction-reorganization-narrative" data storytelling model, define the data story mapping process using element tuples, and identify the key technologies for implementing storytelling model design. [**Result/Conclusion**] Guided by the theoretical framework of data storytelling model design, this research proposes a "fan-shaped" storytelling implementation path oriented toward interpretable results and an interactive framework that integrates interpretability results with storytelling model elements. Through case studies, we validate the practical value of the data storytelling method in result interpretation. By constructing a systematic framework for data storytelling methods based on interpretable results, this study provides new insights for expanding storytelling pathways that possess data perception and cognition capabilities and can assist in intelligent decision-making.

Keywords: data storytelling; interpretability; model-agnostic; local interpretability; narrative
Classification Number: G203

1 Introduction

Insight presentation and result interpretation represent two critical research directions in the era of big data. How to present, communicate, and deliver data analysis and interpretation results to users in an understandable manner constitutes a significant research question. The integration of data storytelling methods with interpretability techniques offers a novel solution to these challenges, enhancing data cognition and supporting decision-making. On one hand, explaining complex model outcomes through interpretability techniques requires non-experts to comprehend the operational principles of model decisions. However, due to their lack of domain-specific expertise, algorithmic models assisted solely by interpretability techniques struggle to gain trust from non-professionals. Presenting interpretable results through storytelling methods proves more accessible for audiences without technical backgrounds. On the other hand, data storytelling possesses characteristics that facilitate memory, cognition, and experience, helping users make decisions by generating easily understandable data stories[1]. Traditional data storytelling focuses on presenting data analysis results; by introducing interpretability techniques to reveal the rationale behind model decisions, we can add depth and application value to data stories. Therefore, presenting interpretability results in the form of data stories achieves complementary advantages, preserving the benefits of interpretability techniques in enhancing transparency and facilitating debugging while leveraging the accessibility and strong interactivity of data storytelling narratives.

Based on existing literature analysis, current research on data storytelling primarily concentrates on concepts, processes, models or structures, and applications[1,2,3,4,5], while research on data storytelling methods remains in the exploratory stage. The data storytelling method proposed in this study represents a general research approach aimed at exploring data insights, facilitating the transition from data perception to data cognition, and assisting decision-making[1]. This method finds broad application in scenarios requiring the interpretation of prediction results for any model (model-agnostic) on single sample points (local interpretation) and communication with non-technical audiences, such as credit score explanation in finance, disease prediction interpretation in healthcare, customer behavior analysis in e-commerce, and course recommendation systems in education. Analysis reveals that existing data storytelling methods suffer from strong subjectivity, insufficient integration with domain knowledge, and over-simplification of important information. To address these issues, introducing objective interpretation results based on data and model behavior—rather than the narrator' s subjective judgment—during story generation can enhance story objectivity and reliability. Furthermore, transforming model-agnostic local interpretability results into understandable data stories can help non-professional audiences comprehend data analysis outcomes, thereby broadening the integration pathways between data stories and professional knowledge. Additionally, since existing data storytelling methods lose important information through over-simplification, local interpretability results preserve more complexity and crucial details by demonstrating model behavior and decision rationale, ensuring story accessibility. Thus, data storytelling methods that integrate interpretability techniques help fully realize their potential in mining data insights, enhancing data understanding, and providing deep-level cognition, thereby achieving the goals of communicating, explaining, persuading, or engaging target audiences[6].

To explore the integration pathways between interpretability results and narrative structures in data storytelling methods, this study systematically reviews the presentation forms of model-agnostic local interpretability results, the narrative structures of data stories, and existing data storytelling methods. From the perspective of data storytelling models, we define and represent the elements of the "extraction-reorganization-narrative" storytelling model, propose a data story mapping process based on element tuples, discuss and analyze the "fan-shaped" storytelling implementation path oriented toward interpretable results and the interactive fusion framework, and validate the proposed data storytelling method and model through a "bank loan credit risk prediction" case study.

2 Related Research

This study aims to achieve the integration of model-agnostic local interpretability results and data storytelling models. Specifically, it first extracts key data based on model information and interpretation result content, matches them with data storytelling model elements, then performs contextualized sequencing of data events based on story objectives and user behavior, and finally realizes the storytelling narration of interpretation results. In light of this, this section focuses on investigating the presentation forms of model-agnostic local interpretability results, the narrative structures of data stories, and existing data storytelling methods.

2.1 Presentation Forms of Model-agnostic Local Interpretability Results

In interpretable machine learning, "model-agnostic" and "local interpretation" refer to "applicable to any model" and "interpreting a single sample point," respectively[7]. Model-agnostic local interpretability methods can explain the prediction results of a single sample point in any model, aiming to help users understand and trust model decisions. Different interpretability methods produce varying output forms, such as feature importance scores, feature weight lists, interpretable rules, and visual charts, as shown in Table 1 .

Table 1 The Presentation Form of Different Model-agnostic Local Interpretability Results

Model-agnostic Local Interpretability Technique	Interpretation Result Description
Feature Importance Score	Calculates the Shapley value for each feature, sorted by impact magnitude. Positive values (red) indicate prediction increases to the right, while negative values (blue) indicate decreases to the left.
Local Surrogate Model	Using the LIME method, identifies the top 6 features with the greatest contribution to the decision of an islanding detection model, producing a feature weight list.
Local Perturbation Method	Perturbs superpixels in the original image and calculates their impact scores across different hidden layers to help identify the most influential training images.

Model-agnostic Local Interpretability Technique	Interpretation Result Description
Visualization Technique	Employs Partial Dependence Plots (PDP, red line) and centered Individual Conditional Expectation (c-ICE, black line) charts to identify the direction of relationships between input variables and model outputs.
Counterfactual Explanation	Sample point x has two paths, A and B, crossing the decision boundary to change the prediction result (valid counterfactuals), but path A is the shortest, representing the minimal counterfactual.
Interpretable Text	Uses Anchor rules to explain the output of a "recidivism prediction model," showing that African American males with supervision duration greater than 8 years and ages between 25-31 have higher recidivism risk. Uses a hierarchical relevance propagation-based method to visualize defect images, fits the model into a decision tree, and converts prediction results into human-interpretable text.

In summary, model-agnostic local interpretability techniques exhibit diverse interpretation forms due to technological differences. These techniques play a crucial role in enhancing model transparency and assisting users in understanding model decision-making behavior. However, the vast majority of explanations interpret model outputs based on feature vector dimensions, which often requires corresponding domain knowledge and professional expertise to comprehend, making them unfriendly for non-professional users. Compared to traditional interpretation forms, adopting data storytelling to present and communicate interpretation results not only provides users with richer and more intuitive data insights but also offers significant advantages in improving data understanding and the effectiveness of result interpretation. This user-centered storytelling approach compensates for the shortcomings of traditional interpretability techniques that are not user-friendly for non-professionals, opening new avenues for enhancing data understanding and result communication, and demonstrating unique research and application value.

2.2 Narrative Structure of Data Stories

Constructing data stories relies on two core elements: narrative structure and story content, which respectively serve as the "skeleton" and "muscle" of data stories. Narrative structure is responsible for building the story framework, ensuring that the story unfolds along a clear path and covering key stages such as beginning, development, climax, and ending, thereby providing a coherent thread for the story. Meanwhile, story content is enriched by core elements including characters, plot, emotion, and dialogue, which imbue the story with emotional depth.

In research exploring narrative structures for data stories, various storytelling frameworks have been proposed to accommodate different narrative purposes and audience needs. For instance, Segel E and Heer J introduced the martini glass structure, interactive slideshow structure, and drill-down structure[15], which balance creator intentions and audience exploration needs. Yuan STD et al. adopted a three-act structure of "background exposition, conflict, and solution" [16] to motivate service innovation in micro-enterprises through narrative advertising. Freytag' s pyramid structure[17] and Dykes' data storytelling arc model[18] focus on driving business decisions through data stories. Campbell' s "Hero' s Journey" [19] emphasizes personal growth and transformation, while Hoey' s "problem-solution" pattern[20] provides a narrative strategy focused on problem resolution. These studies demonstrate the diversity and richness of data story narrative structures, highlighting the importance of pursuing user attraction, emotional resonance, and problem-oriented plot development. Different narrative structures possess distinct characteristics and application scenarios based on their frameworks, objectives, and target audiences. For example, the "problem-solution" pattern suits problem-focused narratives, while the "Hero' s Journey" framework emphasizes depicting personal growth and transformation. These multi-perspective narrative structures provide rich expressive forms and depth for data stories, ensuring that each story can be presented in the most suitable manner for its content and purpose.

2.3 Existing Data Storytelling Methods Research

In exploring data storytelling methods, this study conducts an in-depth analysis from four dimensions: story flow direction, segmented story description, compositional elements, and temporal dimension, as shown in Table 2 . (1) Analysis of story flow direction reveals three core methods of data storytelling: creator goal-driven, audience behavior-driven, and co-participation of creators and audiences. This provides an important insight for this study: effective data storytelling requires balancing creator intentions and audience engagement. This balanced thinking guides the creation of this study' s data storytelling implementation model, ensuring that stories align with creator goals while arousing audience interest and emotional resonance. (2) The methodology of segmented story description provides structural support for this study' s implementation model. By dividing the storytelling process into different stages, such as "modeling-generation-presentation" or "deconstruction-reorganization-narrative," this study adopts similar segmented logic. This segmented approach not only helps systematically extract key elements from interpretability results but also effectively presents data insights by reorganizing these elements and adopting appropriate narrative structures. (3) Analysis of compositional elements emphasizes the importance of matching data analysis results with story elements and the necessity of orderly arranging story elements. This study' s storytelling model adopts the structure of extracting key elements, reorganizing them to conform to narrative logic, and narrating stories, which exactly reflects this principle. (4) Analysis from the temporal dimension, i.e., storytelling as a process of describing events chronologically, emphasizes the role of timelines in constructing logical and compelling stories in data storytelling implementation models, particularly in contexts requiring consideration of event sequences and emotional development.

Table 2 Classification and Application of Data Storytelling Methods

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
Story Flow Direction	Creator Goal-Driven	SPSN Model	Explores earthquake frequency and evolution processes based on the SPSN (Situation—Problem—Solution—Next steps) model, constructing earthquake data stories comprising situational analysis, problems to be solved, solutions, and follow-up actions[21]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
		Pyramid Structure	Applies Freytag's pyramid to stories extracted from 103 data videos, proposing a design space composed of narrative patterns, data flow, and visual communication[22]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
		SUCCESs Model	Applies the SUCCESs model to library instruction: presents the library’ s mission in a Simple manner, guides students to use Unexpected strategies to find library resources, introduces how to locate articles on specific topics through Concrete databases, uses statistics to ensure students use Credible information sources, stimulates student attention and engagement through Emotional appeals, and motivates students to conduct research through Stories[23]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
	Audience Behavior-Driven	Drill-down Structure	Proposes a narrative visualization method with interactive slideshows, where users explore at different granularity levels through drill-down paths and decide whether to click for deeper exploration or shift to other related components[24]
		Interactive Story Generation Model	Proposes a data story modeling method based on user interaction behavior by extracting three story elements: data content, logical relationships, and storytelling probability, where users and their interaction data serve as story protagonists and story content, respectively[25]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
	Creator and Audience Co-participation	Martini Glass Structure	Designs a martini glass visualization composed of story synthesis, narrative visualization, and animation layering. Creates data stories based on hierarchical and scroll-based storytelling techniques, where stories begin with explanation or narration (creator-driven) and rely on users' exploratory and interactive operations to determine displayed content (audience-driven)[26]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
		Interactive Slideshow Structure	Gapminder uses three demonstration graphics—histograms, scatter plots, and bar charts—to present global income and health trends in human development research. Each chart is constructed step-by-step with animated transitions, single-frame modeling, and interactive explanations for each stage, allowing users to complete personalized navigation across multiple slides[15]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
Segmented Story Description	Modeling-Generation-Presentation	Abstract Layer Model	Uses storyboards to model media types through operations such as page access and data retrieval in web information systems, generates media types through extended views, and finally presents activities in storyboards in layers[27]
	Deconstruction-Reorganization-Narrative	"Deconstruction-Organization-Scene Reproduction" Structure	Designs a storytelling process with "deconstruction-organization-scene reproduction" as the main thread to promote knowledge discovery and services for open collection resources[28]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
		"Integration, Aggregation, and Narrative" Structure	Introduces a three-act structure to complete the integrated overview, aggregated reconstruction, and summarizing narrative of public appeal information for storytelling description methods of public appeals[29]
	Exploration-Narrative	Data Exploration, Data Narrative Two Stages	Constructs an analytical model, story type, and narrative model with narrative strategies through data exploration and data narrative processes to provide cognitive interpretation and value transformation of educational data elements[30]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
Compositional Elements	Multi-element Narrative	Three-Element Model	Applies story templates to three selected diseases to demonstrate how narrative techniques support visual communication and promote understanding of medical data for general audiences[31]
		5W1H Model	Applies the 5W1H framework to news story writing: What identifies an event, Who determines the people or groups associated with the event, When describes when the event occurred, Where reports the location of the event, Why explains the news information, and How determines how an event occurred[32]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
		Five-Element Model	Uses text maps to explain content details and explicitly states that narrative story retelling components should include five elements: characters, setting, plot, conflict, and solution[33]
Temporal Dimension	Storyline Based on Emotional Change	"Boy Meets Girl" Story Model	Plots a G-I (Good fortune–Ill fortune) axis to depict a person' s emotional change curve of good and bad events throughout a day. Above the curve' s average represents prosperity and health, while below represents death, extreme poverty, and disease[34]

Analysis Dimension	Storytelling Method	Story Model/Structure	Application Case
		Multimodal Story Composition	Creates a multimodal narrative architecture to express multimodal data as hierarchical multimodal stories through five modules: data embedding, topic modeling, storyline generation, story draft generation, and story evaluation[35]

In summary, the data storytelling methods listed above demonstrate commonalities in narrative structure, target audience, emotional elements, interactivity, and data visualization, all emphasizing the importance of narrative, audience needs, emotional resonance, increasing user engagement through interactive methods, and presenting data through visualization tools. Different storytelling methods exhibit differences in narrative models and structures, driving approaches, application domains, and narrative elements. Considering that this study' s objective is to apply model-agnostic local interpretability results to data storytelling models, a segmented data storytelling method is appropriate: extracting key elements from algorithmic models and interpretability results, matching them with story elements, and presenting stories through specific narrative structures. Therefore, this review identifies result features, story elements, and segmented data stories as critical to implementing data storytelling methods.

3 Design of Model-agnostic and Local Interpretable Storytelling Model

Constructing a storytelling model constitutes the core step in implementing data storytelling methods. Based on the analysis in Section 2.1, model-agnostic local interpretability results primarily focus on sample features as parameters, where differences in feature values directly affect model outputs. Therefore, establishing connections between interpretability result features and data story elements represents a crucial component of building data storytelling models.

3.1 Theoretical Basis of Model Design

The data storytelling model designed in this study requires support from multiple theories, including interpretable machine learning, data storytelling patterns, narrative transportation mechanisms, cognitive science, and human-computer interaction. Among these, interpretability theory manifests in aspects such as interpretability properties, interpretation effects, and tool development, specifically encompassing model-agnosticism, local interpretability, feature importance, causal relationships, result comprehensibility, and interpretability tools. Interpretability theory guides the practical process from prediction results to interpretable results. Data storytelling implementation patterns have generally evolved through three developmental stages: three-act narrative structure[16], narrative arc theory[36], and screenwriting theory[37], with progressively refined story development content, collectively guiding the generation process from story elements to story products. Meanwhile, narrative transportation mechanisms emphasize users' immersive experiences and emotional resonance in data stories; cognitive science helps understand how people comprehend, process, and remember information, which is crucial for designing memorable and deeply cognitive data stories; human-computer interaction theory emphasizes the interaction methods between stories and users, facilitating the establishment of user feedback mechanisms and the generation of personalized data stories. To highlight the model-agnostic and local interpretability characteristics of this study' s data storytelling method, we should focus on the guiding roles of interpretable machine learning theory and data storytelling implementation patterns in storytelling model construction, as shown in Figure 1 [Figure 1: see original paper].

Figure 1 The Storytelling Model Design Dominated by Interpretability Theory and Narrative Patterns

In the design of the data storytelling model, this study constructs a hierarchical "extraction-reorganization-narrative" data story generation model: First, result features are extracted from interpretable results, aiming to obtain event information based on interpretable results to prepare for story narration; then, result features are reorganized into story elements, with the goal of establishing connections between interpretability results and story elements and achieving the mapping of result features within narrative structures; finally, the pathway from story elements to data stories relies on narrative structures to concretize the storytelling model. The underlying logic of the entire "extraction-reorganization-narrative" data storytelling model is data authenticity and narrative quality. Real business data serves as the foundation for generating data stories, while story-oriented narrative techniques and visual design deepen users' understanding of the data.

To validate the effectiveness and efficiency of the storytelling model designed based on multiple theories, this study first analyzes the model' s constituent elements and their representation methods, and proposes a data story mapping scheme based on the extracted elements. Finally, we validate the data storytelling method that integrates interpretability results and storytelling models through specific cases, including: extracting key feature information from interpretability result data (extraction), logically reorganizing result feature information (reorganization), and effectively telling stories to audiences (narrative).

3.2 Model Element Identification and Representation Based on Model-agnostic Local Interpretability Results

To establish a robust connection between interpretability results and data story elements, we first obtain the element sets of interpretability results and story events separately based on model-agnostic local interpretability results, and then closely associate the two sets according to specific narrative structures, thereby completing the "extraction" and "reorganization" operations of the data storytelling model. Among these, interpretability result elements serve as the raw material for data stories, specifically including prediction result probability values, key feature values, new sample sets for training surrogate models, interpretable feature weight values, etc. Data story elements, conversely, serve as the synthetic material for data stories, referring specifically to story background and objectives, narrative structure, characters, events, plot, etc.

Sample features constitute the core indicator that best reflects result elements, while events act as the bridge mapping interpretability result elements to data stories. Researchers hold varying perspectives on events: (1) From the element composition viewpoint, events include four elements: role, behavior, time, and space, where the role represents the implementer and receiver of event behaviors, behavior denotes the interactive actions of roles in the narrative process, and time and space represent the spatiotemporal attributes of events[28]. (2) From the event association perspective, each event is represented using general event information, empirical data related to the event, the event' s time and location, links to its sub-events, and causal links to other events[38]. (3) From the domain-specific perspective, events in data journalism constitute a set of news documents reporting the same news event in different ways[39], where event occurrence time and participating entities are key to distinguishing event types. Events in archives can be described using 12 different attributes: start and end time, location, agent, activity, art historical period, value, genre, style and movement, object, value, material, dimension, and theme. These attributes were derived from discussions with museum partners and based on event schema analysis[40]. This study defines events as a type of story point led by characters (the sample to be interpreted), involving modification behaviors of sample feature values based on feature weights, while simultaneously calculating the distance to the sample to be interpreted. The number and type of events are unlimited, with appropriate events selected for presentation based on story interpretation objectives.

The data representation method that integrates the concepts of sample features and events establishes model-agnostic local interpretable data storytelling element tuples (hereinafter referred to as "element tuples"). These tuples aim to establish associations between result elements and story elements, utilizing model information from result elements to obtain data story background information and story objectives, and using sample information to obtain data story characters, events, and other elements. By connecting elements, relationships, and attributes, audiences can better understand the contextual information output by interpretability results.

(1) Element Tuple Definition

By considering event composition elements, element tuples include three main elements: subject, predicate, and object. The subject represents local information from interpretability results, the object includes specific elements of data stories, and the predicate represents the linking method from interpretability results to story elements. This method takes forms such as elaboration, scanning, exchange, reversal, dialogue, and drill-down, ultimately defining the element tuple structure in the form of (interpretability result, story element, link).

(2) Element Tuple Representation

We now introduce some notation and formally describe the tuple structure of this study. Given an interpretability result element set D = {D1, D2, ···, Di, ···}, where Di is existing or newly generated single-sample feature information in the sample set, comprising four components: feature and prediction result, feature variation magnitude, score metric indicating feature importance, and distance to the desired target. Associated with this is the story event element set E = {E1, E2, ···, Ej, ···}, where Ej is a single story point (event), correspondingly containing four components: character, behavior, variation basis, and spatial location. The objective of this study is to connect all interpretability result elements with data story elements to form story groups S = {S1, S2, ···, Sk}, where each story S = (E, L) contains a set of events E and a set of links L. The relationship between events E1 and E2 within an event group can be directed or undirected links. The set representation is shown in Figure 2 [Figure 2: see original paper], where the universal set U contains the interpretability result element set D and the story event element set E, generating individual stories based on the regularized arrangement of events.

Figure 2 Set Representation of Element Tuples

Based on the "result element—story element"form, this has practical value for constructing model-agnostic local interpretable data storytelling models, guiding model event generation, and achieving storytelling presentation of interpretability results. The link information in element tuples ensures the traceability of storytelling presentation, facilitating reasoning and intelligent decision-making in data storytelling. By analyzing element tuples, insights about relationships between elements can be generated, thereby better supporting the audience's decision-making process.

3.3 Data Story Mapping Based on Element Tuples

As described in Section 2.1, although model-agnostic local interpretability results exhibit diverse output forms, extracting story-usable feature elements from interpretability results constitutes the key to achieving data story mapping. On this basis, result elements are reorganized into elements required for data stories, and story generation and presentation are conducted according to specific narrative structures. The data story mapping based on element tuples is illustrated in Figure 3 [Figure 3: see original paper]. By extracting key elements from interpretability results and their prediction models and establishing associations between extracted elements and data storytelling, data story products are obtained through story modeling, generation, and presentation steps, thereby achieving the mapping from interpretability results to data stories.

Figure 3 Storytelling Presentation Design for Model-agnostic Local Interpretable Results

3.4 Key Technologies for Implementing Storytelling Model Design

Designing data storytelling models requires covering the complete path from model interpretation to story generation and integrating relevant technologies and methods to enhance story comprehensibility and interactivity. The core of model design lies in constructing a storytelling implementation framework that not only reveals the internal logic of model decisions through interpretable machine learning techniques but also leverages result element extraction technology and data story generation methods to achieve the transformation from interpretability results to data stories. This research method particularly emphasizes the conversion process from local interpretability result elements (prediction result probability values, key feature values, interpretable feature weight values, etc.) to story elements (i.e., story background and objectives, characters, events, plot, and narrative structure), as well as the role of LIME technology in generating interpretability results. Figure 4 [Figure 4: see original paper] illustrates the storytelling model design process that integrates four types of technologies.

Figure 4 Technical Process for Designing Data Storytelling Models

(1) Interpretable Machine Learning Technology: Model-agnostic local interpretability techniques represented by the LIME algorithm can output feature weight lists, helping users identify features that play critical roles in model decisions. By identifying and explaining key features, data support is provided for story event generation.

(2) Result Element Extraction Technology: Interpretability models provide probability values of prediction results and actual values of key features, which can be directly transformed into story background (the context in which the model makes predictions), story objectives (desired prediction probabilities), and characters (sample points containing feature values and prediction results).

Feature weight values obtained through LIME technology reveal feature contributions in the model decision-making process. These weight values can serve as the basis for driving plot development, i.e., how to adjust different features (events) to achieve desired prediction results (story objectives).

(3) Natural Language Generation (NLG) Technology: NLG technology can convert complex data analysis and model interpretations into natural language-based text stories. This process includes not only data description but also integrating interpretation results into storylines and transforming storylines into interpretive texts to enhance story readability. Additionally, NLG can generate customized texts according to users' specific needs, and this personalized text generation helps improve user engagement with data stories.

(4) Data Visualization Technology: Combined with story narration, data visualization techniques (such as feature importance charts, decision path diagrams, etc.) are used to graphically present the model's decision-making process and interpretation results. This enhances the intuitiveness and interactivity of stories, enabling audiences without technical backgrounds to gain in-depth understanding.

The innovation of this research method lies in its focus not only on explaining prediction results from a technical perspective but also on how to convert these interpretable results into meaningful, easily understandable stories. Through local interpretation techniques such as LIME, this study can extract corresponding story elements from the model' s local decisions, such as events (sample predictions driven by feature changes) and conflict (inconsistency between model prediction probability and desired prediction probability). In summary, this study' s data storytelling model design method, by integrating interpretable machine learning, result element extraction technology, NLG, and data visualization, provides a comprehensive framework for transforming complex data.

4 Data Storytelling Method Integrating Interpretation Results and Narrative Structure

The data storytelling method that integrates interpretation results and narrative structure aims to organically combine model interpretability results with narrative structures. The core steps for implementing this data storytelling method include extracting key interpretability elements, integrating interpretability elements, constructing narrative structures, and storytelling narration. Therefore, this section delves into the storytelling implementation path and the interactive fusion framework between interpretation results and model elements, and validates the feasibility of the data storytelling method through case studies.

4.1 Storytelling Implementation Path Oriented Toward Interpretation Results

The data storytelling method proposed in this study can narrate and present interpretation results for specific samples in any model, thereby achieving "model-agnostic" and "local interpretation" functions. The storytelling implementation path oriented toward interpretation results is shown in Figure 5 [Figure 5: see original paper]. Starting from model-agnostic local interpretability results, it sequentially extends outward through the result layer, element layer, association layer, and story layer. The layers are closely interconnected: the operation from result layer to element layer is extraction, from element layer to association layer is reorganization, and from association layer to story layer is narrative. The specific content of each layer exhibits different characteristics based on its functional differences.

Figure 5 The "Fan-shaped" Storytelling Implementation Path Based on Interpretable Results

The result layer comprises interpretability result elements, the element layer extracts result features, the association layer associates content from the element layer according to story objectives or plot development, and the story layer coordinates various story elements supported by narrative structures.

4.2 Interactive Fusion Framework Between Interpretation Results and Storytelling Model Elements

Implementing model-agnostic local interpretable data storytelling methods requires establishing an interactive fusion framework between interpretation results and data stories, as shown in Figure 6 [Figure 6: see original paper]. This interactive fusion framework is divided into the result layer, story layer, and interaction layer. The result layer represents the process of generating interpretability results. Since this study focuses primarily on the storytelling presentation of interpretation results, the training and testing of prediction models and interpretability models are not the research emphasis. The story layer contains the story element system, which first clarifies story objectives based on story background and user expectations, then constructs storytelling model elements centered on narrative structures driven by story objectives. The interaction layer connects interpretability result elements with story elements through element tuples. Through such an interactive fusion framework, users can be guided to explore the relationships between model elements and interpretability results, thereby gaining deeper understanding of the model' s decision-making process.

Figure 6 A Storytelling Implementation Framework Integrating Interpretability Results and Narrative Structures

4.3 Application of Model-agnostic Local Interpretable Storytelling Method: A Case Study of "Bank Loan Credit Risk Prediction"

To validate the practicality of the proposed data storytelling method in result interpretation, we conduct a case study on "bank loan credit risk prediction." The business background involves training a classification model based on a dataset identifying default status to predict default risks for unknown users. The selected "Bank Loan Credit Risk Analysis" dataset[41] is an open-source dataset from Kaggle' s official website for classification model training, with quality and size meeting training requirements and possessing good accessibility and usability. Sample diversity represents different types of loan cases, and its practical application value lies in extracting key feature information from the dataset as the basis for result interpretation and using storytelling methods to demonstrate how the model utilizes the dataset for credit assessment. Therefore, from the perspectives of dataset reliability, feature richness, and case relevance, this dataset is representative for this study.

In the data preparation phase, to avoid privacy infringement and algorithmic bias as much as possible, data preprocessing operations removed sensitive features such as customer age, education level, and annual income. In the model training phase, a logistic regression model was trained based on this dataset for prediction. The story background involves user u (marked as sample 0) with 4 years of service, address feature value of 0, debt-to-income ratio of 9.7, and credit debt ratio of 0.2, whose output result in the prediction model is [0]. Model-agnostic local interpretability techniques are employed to interpret the prediction results, with the aim of further interpreting the interpretable results using data storytelling methods.

(1) Rationale for Interpretability Technique Selection

The LIME algorithm is a model-agnostic, locally interpretable method that can explain prediction results for single sample points in any model. Moreover, this interpretability algorithm can output weight lists and weight charts representing feature importance, which can serve as constituent elements of the storytelling model. Therefore, the LIME algorithm meets the interpretation requirements of model-agnostic local interpretable data storytelling methods.

(2) Visualizing Sample Distribution

The new sample set for training surrogate models is one of the key elements of interpretation results. To ensure that the surrogate model constructed by the LIME algorithm more accurately fits the original model, the newly generated dataset through perturbation should maintain the same distribution as the initial training data when training the surrogate model. One condition for constructing surrogate models is perturbing to generate new sample sets for model training. For example, 99 sample points (IDs: 1-99) are generated in the neighborhood of a specific sample (ID: 0). Euclidean distance formula is used to calculate distances between new samples and the specific sample, which are used as sample weights to plot a data distribution map centered on the sample to be explained, based on weight magnitude and result clustering. Nodes connected in red and blue represent sample sets with prediction results of "1" and "0," respectively, and line length indicates distance, as shown in Figure 7 [Figure 7: see original paper]. Given that sample 0' s prediction result is "1," by visualizing the distribution of the new sample set and achieving clustering based on results, we can observe that sample 0 tends to cluster with the sample set whose prediction result is "1." This also provides a preliminary explanation of the prediction result from the perspective of sample distribution.

Figure 7 Sample Point Distribution Map Based on Weight Size and Prediction Category

(3) "Extracting" Result Features Based on Interpretability Results

LIME output results can provide support for storytelling models regarding prediction result probability values, key feature values, interpretable feature weight values, and other elements. The feature list output by the LIME algorithm is shown in Table 3 .

Table 3 List of Feature Weights Output by the LIME Algorithm

Feature Value Range	Weight
CreditCardDebt <= 0.37	-0.162433
Address <= 3.00	0.084595
3.00 < YearsOfService <= 7.00	0.054726
8.50 < DebtRatio <= 13.90	0.031019

LIME Prediction Probability: [0.281117]
Original Model Prediction Probability: [0.292807]

As shown in Table 3, compared to the original model, the surrogate model trained based on the LIME algorithm demonstrates good fitting in result prediction and provides weight magnitudes of key features' impact on prediction results, which is crucial for adjusting feature directions to obtain desired results. Positive and negative weights represent positive or negative impacts on prediction results.

(4) Reorganizing Story Elements Based on Result Features

Based on the definition and representation of element tuples in Section 3.2, and under the premise of extracted result features, the features and interpretation results of user u (sample 0) in the model are reorganized into story elements. The element correspondence can be represented as:

```
{
"YearsOfService: 4, Address: 0, DebtRatio: 9.7, CreditCardDebt: 0.2, Prediction Result: [0]"
"Increasing CreditCardDebt can make prediction probability closer to original model" $\right
```

```
"CreditCardDebt weight: -0.162433, Address weight: 0.084595" $\rightarrow$ "Variation Basis'
"Distance difference to desired target: 0.011690" $\rightarrow$ "Spatial Location"
}
```

(5) Implementing Narrative Based on Story Elements

Reorganizing story elements helps clarify story background, objectives, characters, events, and plot. Based on the element tuple representation of user u, an event tree for a specific character is constructed according to sample feature value changes, consisting of a set of events and their relationships. Assigning corresponding story identifiers to the event tree generates a data story. The data story tree represented by user u is shown in Figure 8 [Figure 8: see original paper]. The story background is that user u' s prediction result is [0.292807], and the local prediction result based on the LIME algorithm is [0.281117]. The story objective is to explain the reasons for this prediction result through storytelling methods. The specific operational approach involves sequentially adding key features according to the LIME feature weight list and observing the gap between the prediction result after feature addition and user u' s prediction result. A decreasing distance indicates positive feature contribution. The tree depth is determined by the number of key features. For example, sample 0 has 4 key features, so a 4-layer tree is displayed. Each branch division in the tree is based on sample feature weight magnitude and feature value distribution range within that feature column, with larger feature weights having priority division rights. The red line in the figure identifies the explanation process of the explanation algorithm for sample 0. The results show that as key features are added, the distance to the sample to be explained gradually decreases. A series of story points composed of Sample 0 → Event 1-1 → Event 2-1 → Event 3-2 → Event 4-2 constitutes a storyline for user u, which can also be considered the simplest data story.

Figure 8 Data Story Tree Led by User u (Sample 0)

As shown in Figure 8, different feature ranges have varying contributions to prediction results. As features of different importance levels are added to model prediction, the distance to the initial sample point gradually decreases until reaching 0.011690, indicating good fidelity between interpretability results and original model prediction results. Figure 8 only demonstrates the storytelling interpretation process for a single sample point (story protagonist). Further reasoning suggests that presenting storytelling processes for multiple characters can compose a story forest, where trees maintain certain connections. Each story tree consists of multiple logically connected events, and the event sequence on a single path from root node to leaf node constitutes a plot or story. The plot represents a reasonable mapping of important events in story development and explains relationships between events from the perspective of feature changes. The case analysis results demonstrate that the data storytelling method proposed in this study, including the storytelling model, implementation path, and interactive fusion framework, is feasible and practical when facing result interpretation for single sample points in any model, with good interactive experience and generalization capability.

5 Conclusion

This study proposes a novel data storytelling method aimed at bridging the gap between model-agnostic local interpretability results and data storytelling. By transforming complex interpretation results into stories containing profound insights, this method integrates key feature interpretation with narrative structures, combining multiple technologies including data visualization, data analysis, storytelling modeling, natural language generation, and story presentation to more effectively deliver data information, explain prediction results, and share knowledge with audiences. The research value of this method lies in: (1) **Filling research gaps**: Addressing the insufficient exploration of data storytelling methods, we construct a data storytelling model supported by interpretability theory and data storytelling theory, thereby strengthening the integration of model-agnostic local interpretability results and data storytelling. (2) **Innovating story generation models**: By developing an "extraction-reorganization-narrative" data story generation framework, we effectively achieve the transformation from interpretation results to story elements, providing a structured framework for narrative construction. (3) **Exploring the "fan-shaped" storytelling implementation path**: We propose a storytelling implementation path based on interpretability results and validate the effectiveness of this path and storytelling method through applications with real datasets.

Although this research has made significant progress in the field of data storytelling, challenges remain, particularly regarding the optimization of data element extraction methods for interpretability results and the automated generation of story trees. Future research will focus on in-depth exploration of these areas and evaluation studies of storytelling models, aiming to continuously improve the accuracy, efficiency, and user experience of data storytelling methods. Through these efforts, this study aims to provide powerful tools for data scientists to explain complex data in accessible ways, revealing the stories and insights behind data for decision-makers and story audiences.

Author Contribution Statement: Jin Qingwen: Proposed research ideas, designed experimental protocols, collected and analyzed data, drafted and revised the paper.

Supporting Data: Supporting data is openly accessible at https://www.kaggle.com/datasets/atulmittal19917 risk-analysis-for-extending-bank-loans.

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Note: Figure translations are in progress. See original paper for figures.