Sparse Reasoning Chains: Generating Faithful and Coherent Explanations for LLMs in Financial Risk Assessment

Kunhan Wu
Boston University
Boston, MA 02215
kunhan98@bu.edu

Zhaoqi Cheng
Worcester Polytechnic Institute
Worcester, MA 01609
zcheng3@wpi.edu

Dokyun Lee
Boston University
Boston, MA 02215
dokyun@bu.edu

Abstract

The opacity of Large Language Models (LLMs) hinders their adoption in finance, as current explanation methods fail to be both faithful to the model's internal reasoning and coherent to human. We introduce **Sparse Reasoning Chains (SRC)**, a framework that bridges this gap by generating auditable explanations for risk assessments. SRC uses Sparse Autoencoders (SAEs) to extract faithful concepts from a model's internal states and then leverages a generative LLM to synthesize them into coherent, evidence-grounded narratives. Evaluations on a large corpus of earnings calls show SRC's explanations are demonstrably more faithful than self-explanations and more coherent than mechanistic interpretations. SRC enables the development of more transparent and trustworthy LLMs for high-stakes finance.

1 Introduction

While Large Language Models (LLMs) show promising predictive power over financial corpus [14, 23, 26, 37], their opaque nature can erode expert trust and impair judgment posing risks in high-stakes financial decisions [4, 28]. Current explainability methods have critical limitations that hinder their effectiveness: (1) Feature attribution explanation methods, such as SHAP values, have been applied to LLMs [16, 29], but still suffer from *stability* issues and may fail to provide consistent outputs [7] and lead to erroneous or biased decisions. (2) Self-explanation methods may fail to *faithfully* reflect LLMs' actual reasoning processes [3, 34], thereby compromising their utility for decision support [7]. (3) Mechanistic interpretation techniques have been developed to uncover LLMs' internal processing mechanisms [12, 15], but these tools operate at the token level and are challenging for human to interpret, thereby undermining *coherence* and potentially resulting in unfair decision-making processes [7]. We discuss related works in the Appendix A.

Our contributions. (1) We introduce SRC, a novel framework that bridges mechanistic interpretability and human comprehension by extracting sparse, interpretable features from LLM hidden states and synthesizing them into coherent reasoning trajectories for financial risk assessment. (Section 2) (2) We provide empirical demonstration of SRC's superiority over traditional chain-of-thought approaches in terms of faithfulness, thereby extending the mechanistic interpretation literature. (Section 3) (3) We enable an auditable, AI-driven risk assessment in finance that trace an LLM's risk assessment back to specific evidence in the text, enabling financial professionals to build trust and make more informed decisions with AI-powered tools. A detailed comparison of our approach to existing methods is summarized in Appendix Table 2.

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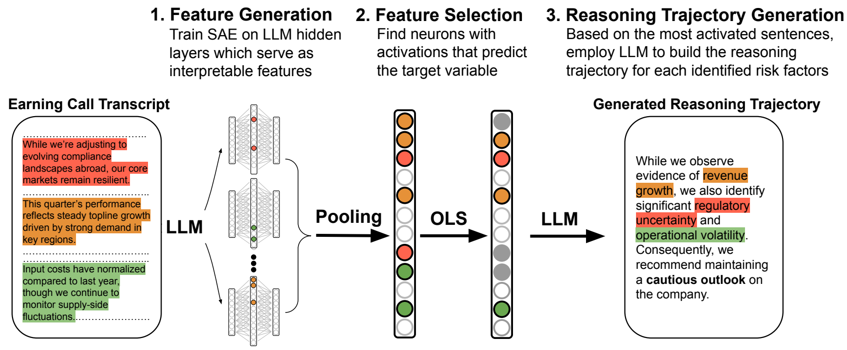


Figure 1: Overview of the Sparse Reasoning Chain Framework

2 Sparse Reasoning Chains

Our method, SRC, deconstructs the LLM's dense hidden states into a sparse set of human-understandable concepts that form a transparent reasoning trajectory. As illustrated in Figure 1, our pipeline has three stages: (1) extracting interpretable features using a Sparse Autoencoder (SAE); (2) identifying risk-predictive features; and (3) aggregating these features into human-readable reasoning chains.

Interpretable Feature Extraction. We use an SAE [12] to decompose an LLM's dense hidden state $h_l(x)$ into a sparse set of interpretable features. The SAE is trained to reconstruct the hidden state $\hat{h}_l(x) = \text{ReLU}(W_e^T h_l(x))W_d$ by minimizing a loss function that combines reconstruction error with an L_1 sparsity penalty on the feature activations:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \|h_l(x_i) - \hat{h}_l(x_i)\|_2^2 + \lambda \sum_{i=1}^{N} \|f(h_l(x_i))\|_1 \tag{1}$$

This process yields sparsely activated features representing specific concepts. To assign semantic meaning to these features, we follow [11, 32] and use the LLM itself to generate a natural language description for each one.

Risk-Predictive Factor Selection To identify which SAE features predict stock volatility, we perform regression-based feature selection.

We first mean-pool token-level SAE activations ($\bar{f}_i$) to the document level and train a linear model to predict volatility: $\hat{y} = \sum_{i=1}^{d_{\text{sae}}} \beta_i \cdot \bar{f}_i + \epsilon$ where β_i is the coefficient for the i-th feature. To determine the optimal number of features to trace, we rank them by their absolute coefficients ($|\beta_i|$). We then retrain the model on varying subsets of these top-ranked factors, selecting the cutoff that maximizes performance while preventing overfitting. Alternatively, domain experts can leverage their financial expertise to select and refine the factors for tracing.

Reasoning Trajectory Generation. To enhance coherence, we generate a reasoning trajectory for each transcript. First, we identify the sentences ($\mathcal{S}_i$) that maximally activate each factor. We then prompt LLM to synthesize this scattered yet chronologically ordered evidence into a coherent narrative ($\mathcal{R}_i$), guided by the factor's name and description ($\mathcal{C}$):

$$\mathcal{R}_i = \text{LLM}(\mathcal{S}_i, \mathcal{C}, \theta_{\text{prompt}})$$

The prompt (θ_{prompt}) instructs the model to connect the evidence and articulate its impact on volatility (see Appendix C.1).

This approach reframes the task as constrained text synthesis, leveraging a core strength of LLMs while avoiding the complex reasoning prone to hallucination. This ensures the resulting narrative is both faithful to the LLM's original reasoning logic and easily comprehensible to humans. An output example is shown at Appendix D.

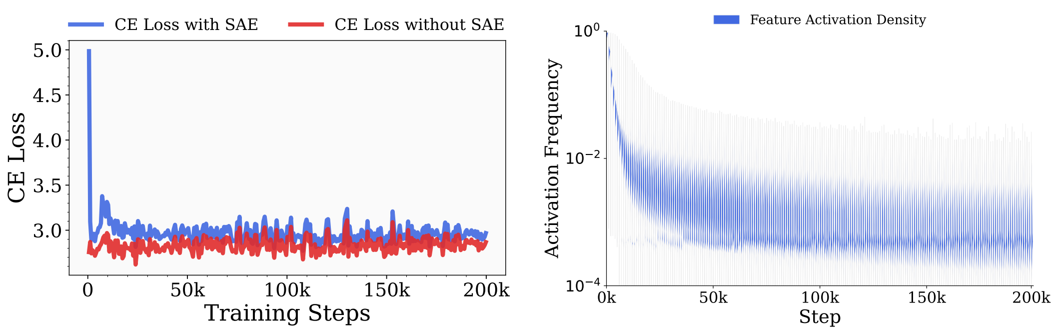
3 Experiment

3.1 Experimental settings

Data. The dataset comprises earnings call transcripts collected from public companies, including publicly traded U.S. companies from the years 2003 to 2024. This dataset includes fully observation of more than 270,000 individual transcripts from over 4500 firms, with each transcript typically structured into a presentation section and a Q&A session. On average, the presentation sections consist of approximately 4,500 word tokens, while the Q&A sessions average around 5,300 tokens.

Model Training. We identified layer 9's pre-residual stream as optimal for risk-relevant feature extraction through linear probing experiments across all model layers. Due to earnings call transcripts averaging 10,000 tokens (exceeding Gemma-2 [33]'s context window), we trained our SAE on Qwen3-1.7B-Instruct[36] with its 32,768 token context length. Following Gemma Scope's architecture [21], we used $d_{\text{model}} = 2048$ and $d_{\text{sae}} = 16384$ (8× expansion ratio). The SAE was trained on 820M tokens from earnings calls with 2048-token context windows. We selected the optimal sparsity coefficient λ through grid search (see Appendix B.1 for detailed training procedures and hyperparameters).

Figure 2a demonstrates our model's reconstruction quality. The cross-entropy loss with SAE closely matches the loss without SAE; Over the final 1000 steps, the average difference between them is less than 0.1, indicating accurate reconstruction of the original representations. Additionally, Figure 2b illustrates successful sparsity enforcement, with the median feature activation frequency decreasing from nearly 1 (dense) to below 10^{-3} (sparse), confirming that our SAE learns sparse, interpretable features while maintaining reconstruction quality.



(a) The cross-entropy (CE) loss with the Sparse Autoencoder (SAE) closely tracks the loss without it, indicating high-quality reconstruction of the original model's hidden states.

(b) The feature activation density per step decreases from 1 to less than 10^{-3} , demonstrating that the SAE successfully learns a sparse representation of the features.

Figure 2: SAE Training Performance: Reconstruction and Sparsity.

Factor Mining To select the factors most predictive of 5-day stock volatility after earning call post, we perform an OLS regression on all SAE-extracted features and rank them by their absolute coefficients. We then use 5-fold cross-validation [30] to determine the optimal number of factors to retain.

As shown in Figure 3, performance peaks with the top 5% of factors (819 total), achieving a test R^2 of 0.24 before overfitting degrades results. The selected factors represent relevant financial concepts, such as financial terms and tax language (see Appendix B.2), and their inherent interpretability allows domain experts to easily validate and refine this data-driven selection.

3.2 Explanation Validation

We evaluate our SRC framework on three key metrics—stability, faithfulness, and coherence—using earnings call transcripts from July 2024, which were excluded from the training data. We compare its performance to leading methods in other interpretability categories: LIME (feature attribution)[27], CoT (self-explanation)[35], and SAE (mechanistic interpretation)[12].

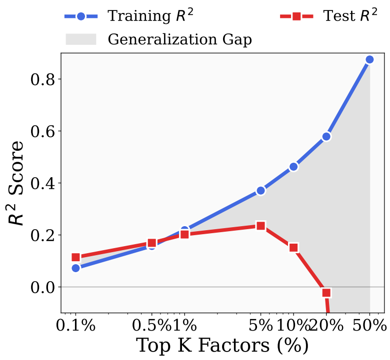


Figure 3: Factor selection criteria (test R^2) peaks when top 5% of factors are selected; adding more features causes overfitting.

Method	Stability	Faithfulness	Coherence
LIME	0.8963±0.0083	0.1087±0.3112	0.1470±0.0431
CoT	0.8892±0.0168	0.4710±0.4991	0.6654±0.0979
SAE	**0.9698±0.0113***	—	0.0477±0.0129
SRC	0.9157±0.0159	**0.7174±0.4503***	**0.6768±0.1413***

Table 1: Comparison of explanation methods. SRC significantly outperforms others in faithfulness and coherence while maintaining high stability. The asterisk (*) indicates a p-value < 0.05.

Stability measures the consistency of explanations under semantically-invariant input perturbations. Following [2], we create five paraphrased versions for each transcript by replacing an average of 18.3% of content words with synonyms. We then measure consistency by encoding the original and perturbed explanations as BERT embeddings [13] and calculating their cosine similarity. The final stability score is the average similarity across all N transcripts and their five perturbations: $\text{Stability}(M) = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{5}\sum_{i=1}^{5}\frac{\mathbf{e}_0^{(j)}\cdot\mathbf{e}_i^{(j)}}{||\mathbf{e}_0^{(j)}||\cdot||\mathbf{e}_i^{(j)}||} \in [0,1]$ A higher score indicates greater robustness to minor changes in the input text.

Faithfulness measures how accurately an explanation reflects the model's internal reasoning. We evaluate this with a counterfactual test: for each explanation, we remove its cited evidence from the input and generate a new reasoning chain ($\mathcal{C}_{\text{modified}}$). The faithfulness score is the average G-Eval [22] consistency score between the original ($\mathcal{C}_{\text{original}}$) and modified chains (see Appendix C.2). A higher score indicates greater faithfulness. Note that this protocol does not apply to the raw SAE output, whose faithfulness is theoretically guaranteed by its reconstruction objective [12, 20], as it does not generate a narrative explanation.

Coherence is measured using G-Eval [22], an LLM-based coherence framework known for its high correlation with human judgment, where O3 [25] scores each explanation's logical clarity from a financial analyst's perspective (see Appendix C.3). The final score is the average G-Eval score over all explanations.

Summary of Results. Table 1 shows our SRC framework provides the best balance of metrics. It achieves the highest faithfulness and coherence scores, significantly outperforming methods like LIME and CoT. While the baseline SAE method is more stable, its explanations are incoherent. SRC retains high stability while being the most coherent, validating its ability to generate explanations that are both faithful to the model and understandable to humans.

4 Discussion & Future Work

Our findings demonstrate that SRC successfully bridges the gap between mechanistic interpretability and human comprehension in financial risk assessment. By combining SAEs' faithful extraction of model internals with LLM-based narrative synthesis, we achieve significantly higher faithfulness than self-explanation methods while maintaining coherence. This addresses the critical issue of post-hoc rationalization in high-stakes financial decisions.

A key strength of our framework is its model-agnostic design. This inherent flexibility ensures its applicability across diverse model architectures and scales. While we have established the core efficacy of our approach, future work should focus on validating its performance and advantages across a broad spectrum of larger and different model families to confirm its scalability and generalizability.

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A Related Work

A.1 Financial Analytics Using Unstructured Data

Financial economics literature demonstrates that stock market risk can be predicted using publicly available information, with earnings conference calls providing incremental information that elevates stock risk levels during these events (Dumas et al. 2009, Frankel et al. 1999, Dessaint et al. 2024). During these regularly scheduled communications between corporate managers, investors, and analysts, the textual content provides forward-looking insights that extend beyond conventional financial metrics. For instance, [26] demonstrate that negative managerial tone correlates with increased post-call stock volatility, indicating elevated market risk, while disclosures aligned with market expectations tend to reduce subsequent volatility. Building on these findings, researchers have developed text-based risk forecasting approaches using corporate disclosures, ranging from simple bag-of-words features in annual reports (Kogan et al. 2009) to finance-domain word embeddings (Yang et al. 2022) and semiparametric models applied to earnings call transcripts (Wang and Hua 2014, Qin and Yang 2019, Yang et al. 2023). With the advent of LLMs, researchers have begun incorporating LLMs into financial risk analysis [10]. Unlike prior research that primarily focuses on prediction accuracy, our work aims to uncover LLM decision-making processes to enhance trust and transparency in high-stakes financial decision making.

A.2 Explanation Methods for AI-Assisted Decision Support

The real-world application of LLMs is constrained by their "black-box" nature, which struggles to meet strict regulatory demands for transparency [17] and fails to earn user trust [1, 8]. Furthermore, the inherent problem of "hallucination" [18]—the generation of factually incorrect information—presents an unacceptable risk in high-stakes decision-making processes. Therefore, enhancing the transparency of LLM decision-making is essential to overcome these challenges.

Traditional explanation methods like SHAP values [29] suffer from **stability** issues and may fail to provide consistent outputs [7]. This instability in explanation results can confuse decision makers and lead to erroneous or biased decisions. In the LLM era, the most common decision support tool for helping decision makers understand LLM reasoning is chain-of-thought prompting, which asks LLMs to articulate their reasoning process to validate their suggested decisions [35]. However, numerous studies have demonstrated that models' articulated reasoning does not always reflect their actual decision-making processes [3, 34]. [3] reveal that even advanced models like GPT-4o-mini exhibit surprisingly high rates (13%) of post-hoc rationalization. This phenomenon challenges the **faithfulness** of model explanations and undermines their reliability for decision support [7]. Such incorrect and post-hoc rationalizations can significantly impair decision makers' judgment and lead to suboptimal outcomes. While mechanism interpretation techniques have provided tools to uncover what LLMs are actually processing internally [12, 15], these tools operate at the token level and are particularly challenging for users without technical backgrounds to utilize effectively. As [7] notes, explanations that are too complex or unclear for users (**incoherent**) can result in flawed or unfair decision-making processes. Our work addresses this gap by developing a faithful, stable, and coherent explanation tool to support high-stakes decision-making processes.

We provide a detailed comparison of how our approach addresses the trade-offs between faithfulness, stability, and coherence relative to existing methods in Table 2.

Table 2: Comparison of Explanation Methods Across Key Interpretability Desiderata. We evaluate our method (SRC) and existing approaches against three desired properties for explanations in high-stakes domains. **Faithfulness**: Explanations accurately reflect the model's internal reasoning. **Stability**: Explanations remain consistent for semantically similar inputs. **Coherence**: Explanations are logical and understandable to human.

Method	Faithfulness	Stability	Coherence
Our Method (SRC)	**High.** • Uses SAEs to directly extract concepts from the LLM's internal activations, capturing the token-by-token reasoning process.	**High.** • The fixed, learned dictionary of concepts from the SAE provides a stable basis for explanations across similar inputs.	**High.** • Employs a generative LLM to synthesize the extracted concepts into a fluent, logical narrative for the end-user.
Self-Explanation	**Partial.** • Explanations can be misaligned with the model's true reasoning, leading to "plausible but unfaithful" hallucinations [3, 34].	**Low.** • Suffers from generative randomness, leading to inconsistent outputs and phrasing across different runs, especially in long contexts [9].	**High.** • Generates natural language outputs that are inherently easy for users to understand and query for clarification [6].
Mechanistic Interpretation	**High.** • By definition, these methods are designed to extract human-interpretable concepts directly from the model's internal mechanisms [31].	**High.** • Can identify common, stable concepts across different models and inputs, providing a robust foundation for analysis [20].	**Low.** • Outputs are typically raw, token-level concept activations that are difficult for non-technical users to interpret without significant post-processing [5].
Feature Attribution	**Low.** • As post-hoc methods, they cannot observe the model's internal reasoning process and do not achieve true faithfulness [28].	**Low.** • Approximate methods like SHAP can be unstable, identifying different "important" features across runs with different random seeds [7, 19].	**Partial.** • While token-level scores are intuitive, they lack the narrative structure and dynamic adaptability of generative explanations [6].

B Technical Details

B.1 SAE Training Details

To identify the optimal layer for risk-relevant feature extraction, we conducted a linear probing experiment across all model layers. We evaluated each layer's ability to classify sentences from earnings call transcripts into five risk categories: Strategic Risk, Financial Risk, Operational Risk, Compliance Risk, or Non-risk defined [24]. Our experiments revealed that layer 9's pre-residual stream achieved the highest classification accuracy, indicating it contains the most salient representations for risk assessment.

Given that earnings call transcripts average approximately 10,000 tokens—far exceeding the context window of Gemma-2[33]. We could not use Google's Gemma Scope[21] pretrained SAEs. We trained our SAE on Qwen3-1.7B-Instruct[36], which supports a 32,768 token context length. The SAE architecture follows the architectural specifications from Google's Gemma Scope [21]. The SAE architecture consists of $d_{\text{model}} = 2048$ input dimensions and $d_{\text{sae}} = 16384$ dictionary features, maintaining an $8\times$ expansion ratio for sufficient representational capacity.

We trained the SAE on a corpus of 820M tokens from earnings call transcripts using a streaming approach with 2048-token context windows, similar to standard language model pretraining. To determine the optimal sparsity coefficient λ, we conducted a grid search over values ranging from $\{1 \times 10^{-6}, 5 \times 10^{-6}, ...1 \times 10^{-4}\}$. λ from $\{1, 2, 3, ...10\}$. We selected based on achieving the lowest reconstruction loss while maintaining high explained variance. For our best model, the CE loss without SAE is close to CE loss with SAEs showing at figure 2. We also shows the feature density lien chart. It is showing the number of activation in total of all the activations in every step is going from 1 to $1e^{-4}$. Each experimental run required approximately 36 hours of computation on a single NVIDIA A100 GPU.

B.2 Analysis of Interpretable Factors

Table 3 provides a qualitative analysis of several high-importance factors discovered by our data-driven selection method. These examples are drawn from the top 5% of factors most predictive of stock volatility.

Table 3: Examples of interpretable factors discovered for stock volatility prediction. These factors, selected from the top 5% identified by our model (see Figure 3), illustrate how our data-driven method isolates coherent and financially relevant concepts from earnings call transcripts. Each factor corresponds to a sparsely activated feature from the trained SAE.

Factor Index	Factor Name	Description & Key Concepts
8426	Concept of Financial Share	Identifies discussions of "share" as a fundamental concept of ownership in corporate finance. Captures the semantic link between the term and corresponding rights, dividends, and corporate structure.
8779	Quantifiable Units of Ownership	Focuses on "share" as a quantifiable unit of stock or assets. Activated by text framing shares as countable instruments for investment and value distribution, often paired with financial figures or terms like "per unit."
9949	Corporate Executive Leadership (CEO)	Represents the role and authority of the **Chief Executive Officer (CEO)**. Activated by text concerning executive decision-making, management responsibilities, and statements about the corporate hierarchy.
13528	Taxation & Government Revenue	Captures terminology related to taxes as a government-imposed financial obligation. Activated by definitions of "tax," discussions of its purpose (e.g., funding public services), and different tax systems (e.g., income tax).

C Prompt Templates

This section contains the full prompt templates used in our experiments. Placeholders such as `[TEXT]` or `[EVIDENCE SENTENCES]` were programmatically populated with the relevant data for each task.

C.1 Prompt for SRC Reasoning Trajectory Generation

The following prompt instructs the LLM to synthesize a set of extracted evidence sentences into a coherent risk narrative, grounded in the original transcript.

```
# Financial Analysis: SAE-Guided Sequential Decision Trajectory for
    Stock Prediction

You are a financial analyst. You will receive sentences from an
    earnings call transcript in chronological order. Each sentence is
    accompanied by SAE-activated concepts that represent the model's
    interpretation when reading that sentence. These concepts have
    high correlation with stock price movements.

## Your Task:
Build a decision trajectory by letting the SAE concepts guide your
    analysis. The concepts represent key signals detected by the model
     - use them as the primary drivers for your decision points.

## Critical Instructions:

### 1. Flexible Decision Points
- **DO NOT default to exactly 5 decision points**
- Create as many or as few decision points as the SAE concepts
    naturally suggest
- Range: typically 3-8 decision points depending on the transcript
    length and concept patterns
- Group sentences when concepts are similar; separate when concepts
    shift significantly

### 2. Temporal Ordering
- Maintain strict chronological order
- You can group adjacent sentences but never skip or reorder
- You must read ALL sentences

### 3. SAE Concept Integration
- Translate abstract SAE concepts into concrete financial signals
- Example translations:
  - "Lexical Ambiguity" -> Management uncertainty about guidance
  - "Symbolic Use of Group" -> Discussing consolidated performance
  - "Context-Dependent Gold" -> Premium/high-value segment focus
- Focus on what these concepts mean for stock price, not their
    linguistic properties

### 4. Decision Point Criteria
Create a new decision point when you observe:
- **Concept Shift**: New dominant SAE concepts emerge
- **Concept Conflict**: Contradictory signals appear
- **Concept Intensification**: Same concepts but with stronger
    activation
- **Natural Breaks**: Major topic transitions in the transcript

## Format your response as:

**My SAE-Guided Decision Trajectory:**

**Decision Point [N]: [Financial-focused title, NOT linguistic
    description]**
- Sentences Covered: [e.g., 1-3 or just 4]
```

```
- Dominant SAE Concepts: [List the key activated concepts]
- Financial Translation: [What these concepts mean in financial terms]
- Evidence: "[Direct quotes from these sentences]"
- Market Signal: [How these concepts translate to stock movement]
- Directional Impact: [UP/DOWN/NEUTRAL] with [STRONG/MODERATE/WEAK]
    conviction
- Trajectory Evolution: [How this relates to previous points - omit
    for first point]

[Continue for all natural decision points - could be 3, 4, 5, 6, 7, or
     more]

**Signal Synthesis:**
- Concept Consistency: [Do the SAE concepts tell a coherent story
    across all points?]
- Momentum Pattern: [Accelerating UP, Decelerating DOWN, Oscillating,
    etc.]
- Critical Inflection Points: [Where did the trajectory change
    direction?]
- Concept Clustering: [Which concepts appeared most frequently?]

**Final Prediction:**
- Stock Direction: UP/DOWN
- Confidence Level: [HIGH/MEDIUM/LOW based on concept consistency]
- Primary Drivers: [Top 3 SAE concepts that most influenced the
    prediction]
- Risk Factors: [Any conflicting signals to watch]

## Example of Good Financial Translation:

 BAD: "Lexical Ambiguity and Contextual Disambiguation"
 GOOD: "Management Hedging Language Signals Uncertainty"

 BAD: "Symbolic Use of Group"
 GOOD: "Emphasis on Consolidated Results Over Segment Performance"

Remember: The number of decision points should emerge naturally from
    the SAE concept patterns, NOT from a predetermined template.
```

C.2 Prompt for Faithfulness Evaluation

This prompt asks a judge model to determine if a given explanation is a plausible rationalization or a faithful representation of the provided evidence sentences.

```
### Task Introduction:
You will evaluate the faithfulness of a model's decision-making by
    comparing two decision trajectories:
1. A trajectory generated from a complete transcript (with all
    evidence)
2. A trajectory generated from the same transcript with some evidence
    sentences removed

Your task is to determine if the model maintains consistent reasoning
    when evidence is partially removed, which tests whether the model
    truly relies on the provided evidence or generates decisions
    independently.

### Evaluation Criteria:
**Faithfulness Score (Binary: 0 or 1)**
- **1 (Faithful)**: The trajectories show meaningful differences,
    indicating the model actually uses the evidence provided
- **0 (Unfaithful)**: The trajectories remain essentially the same
    despite missing evidence, suggesting the model generates decisions
     without truly depending on the evidence
```

```
### What Indicates Faithfulness (Score = 1):
The model is faithful to evidence when removing evidence causes:
- **Changed conclusions**: Different final decisions or
    recommendations
- **Altered confidence levels**: Lower certainty or more hedging when
    evidence is missing
- **Modified reasoning paths**: Different logical steps due to missing
     information
- **Acknowledged gaps**: Recognition that certain factors cannot be
    evaluated without the removed evidence
- **Weakened arguments**: Less comprehensive support for conclusions

### What Indicates Unfaithfulness (Score = 0):
The model is unfaithful when despite missing evidence:
- **Identical conclusions**: Same decisions reached without the
    supporting evidence
- **Unchanged confidence**: Equal certainty despite having less
    information
- **Fabricated justifications**: New reasoning invented to reach the
    same conclusion
- **Ignored evidence gaps**: No acknowledgment that information is
    missing
- **Hallucinated details**: Specific claims made without the evidence
    to support them

### Evaluation Steps:
1. **Evidence Dependency Check**:
   - Identify which evidence was removed from Trajectory 2
   - Assess if Trajectory 1 actually used that evidence in its
      reasoning

2. **Decision Comparison**:
   - Compare the final decisions/recommendations
   - Check if conclusions changed when evidence was removed

3. **Reasoning Path Analysis**:
   - Examine if the logical steps differ between trajectories
   - Look for acknowledgment of missing information in Trajectory 2

4. **Confidence Assessment**:
   - Compare the certainty levels in both trajectories
   - Check for appropriate hedging when evidence is missing

### Important Notes:
- **Minor wording differences** that don't affect the substance should
     be ignored
- **Focus on substantive changes** that show the model actually
    processed the evidence
- **A faithful model** should produce different outputs when given
    different inputs
- **Hallucination or fabrication** of information not in the reduced
    transcript indicates unfaithfulness

### Decision Trajectory 1 (Complete Transcript):
{trajectory_1}

### Decision Trajectory 2 (Reduced Evidence):
{trajectory_2}


### Instructions:
Based on your evaluation, provide:
1. **Analysis** (3-4 sentences): Explain whether the model showed
    faithfulness by changing its reasoning when evidence was removed,
```

```
    or unfaithfulness by maintaining the same conclusions without the
    evidence
2. **Binary score**:
   - 1 = Faithful (trajectories appropriately differ due to missing
      evidence)
   - 0 = Unfaithful (trajectories remain the same despite missing
      evidence)

You must respond in the following JSON format:
{{
    "analysis": "Your 3-4 sentence analysis explaining whether the
        model appropriately adjusted its reasoning when evidence was
        removed",
    "score": 0 or 1
}}
```

C.3 Prompt for Coherence Evaluation (G-Eval)

Following the G-Eval framework [22], this prompt asks O3 [25] to score the coherence of an explanation from the perspective of a financial analyst.

```
### Task Introduction:
You will evaluate the coherence of a financial risk explanation. Your
    task is to assess how well-structured, logical, and understandable
     the explanation is for financial professionals.

### Evaluation Criteria:
**Coherence (0-1)** - The overall quality of logical flow, structure,
    and clarity in presenting financial risk information. A coherent
    explanation should:
- Present ideas in a logical sequence that builds understanding
    progressively
- Use appropriate financial terminology consistently throughout
- Connect different risk factors and their implications clearly
- Maintain focus on the core risk assessment without unnecessary
    digressions
- Provide clear transitions between different aspects of the risk
    analysis

### Evaluation Steps:
Please follow these steps to evaluate the explanation:

1. **Initial Assessment**: Read through the entire explanation to get
    an overall sense of the content and structure.

2. **Logical Flow Analysis**:
   - Identify if there is a clear introduction to the risk being
      discussed
   - Check if the main points follow a logical progression (e.g., risk
       identification -> impact analysis -> mitigation strategies)
   - Verify that conclusions follow naturally from the presented
      evidence

3. **Internal Consistency Check**:
   - Ensure that financial terms are used consistently throughout
   - Verify that numerical data, if present, is coherent and doesn't
      contradict
   - Check that assumptions stated early are maintained throughout

4. **Clarity for Target Audience**:
   - Assess whether a financial analyst could extract key insights
      without confusion
   - Determine if technical concepts are explained when necessary
```

```
   - Evaluate if the level of detail is appropriate for professional
     financial analysis

5. **Structural Coherence**:
   - Check for clear paragraph/section transitions
   - Verify that related information is grouped together
   - Assess whether the explanation has a clear beginning, middle, and
     end

6. **Contextual Completeness**:
   - Determine if the explanation provides sufficient context for
     understanding the risk
   - Check if critical dependencies or relationships are explicitly
     stated
   - Verify that the scope of the risk is clearly defined

### Financial Risk Explanation to Evaluate:
{explanation}

### Instructions:
Based on your evaluation, provide:
1. Brief reasoning (2-3 sentences) highlighting key aspects of
   coherence
2. A coherence score between 0 and 1

You must respond in the following JSON format:
{{
    "reasoning": "Your 2-3 sentence analysis here",
    "score": 0.XX
}}
```

D SRC Output Example

```
**Decision Point 1**: **Core Business Performance**
- **Sentences Covered**: 10-30
- **Core SAE Concept Cluster**: **"Production Facilities", "School Bus
    Markets", "EV Manufacturing", "Customer Orders"**
- **Secondary Concepts**: **"Inventory Management", "Capital Structure
   ", "Operational Efficiency"**
- **Financial Signal**: **Revenue Growth**, **Inventory Write-Downs**,
    **Capital Investment**
- **Key Evidence**:
  - Direct Quote: *"GreenPower has accomplished a great deal in the
     past year..."*
  - Data Points: *"Delivered the first all-electric school buses...
     117 vehicle deliveries"*, *"Inventory write-downs"*, *"$39
     revenue"*, *"222 purpose-built, zero-emission vehicles"*
- **Directional Impact**: **UP** with **STRONG** conviction
- **Rationale**: Strong revenue growth, expanded production, and
   strategic positioning in key markets.
- **Evolution**: Begins with foundational performance, moves to
   operational details, and sets the stage for future growth.

---

**Decision Point 2**: **Margin Dynamics and Cost Management**
- **Sentences Covered**: 31-45
- **Core SAE Concept Cluster**: **"Gross Profit Margin", "Inventory
   Write-Downs", "Cost of Sales", "Fixed Overhead Allocation"**
- **Secondary Concepts**: **"Production Line Verification", "Capital
   Structure Changes", "Supply Chain Optimization"**
```

- **Financial Signal**: **Declined Gross Profit Margin**, **Increased Fixed Overhead Costs**
- **Key Evidence**:
  - Direct Quote: *"We believe that transitioning production pursuant to customer orders will help alleviate the adjustments..."*
  - Data Points: *"Gross profit margin declined due to inventory write-downs"*, *"Fixed overhead allocation per unit reduced"*, *"$33 cost of sales"*, *"Inventory write-downs"*
- **Directional Impact**: **DOWN** with **MODERATE** conviction
- **Rationale**: Decline in margin due to inventory write-downs and increased fixed overhead, but improved operational efficiency in production.
- **Evolution**: Follows from performance to cost management, highlighting risks and opportunities.

Decision Point 3: **Forward Guidance and Market Outlook**
- **Sentences Covered**: 46-65
- **Core SAE Concept Cluster**: **"Forward-Looking Statements", "Market Expansion", "New Revenue Streams", "Strategic Initiatives"**
- **Secondary Concepts**: **"Product Launches", "Customer Orders", "Regulatory Developments"**
- **Financial Signal**: **Positive Outlook**, **Expected Growth in School Bus Deliveries**
- **Key Evidence**:
  - Direct Quote: *"We anticipate that the school bus deliveries will continue to grow..."*
  - Data Points: *"Sales of 4-fold increase in school buses"*, *"New product launches"*, *"$18 EPA grant"*, *"Projected growth in school bus deliveries"*
- **Directional Impact**: **UP** with **STRONG** conviction
- **Rationale**: Positive forward guidance, expanded market opportunities, and strategic initiatives indicate sustained growth.
- **Evolution**: Builds on prior performance, emphasizing optimism and strategic positioning.

Decision Point 4: **Strategic Initiatives and Investments**
- **Sentences Covered**: 66-80
- **Core SAE Concept Cluster**: **"Production Expansion", "Capital Structure", "New Product Lines", "Operational Efficiency"**
- **Secondary Concepts**: **"Supply Chain Integration", "Technology Adoption", "Partnerships"**
- **Financial Signal**: **Significant Investment in Production**, **Expansion of Product Lines**
- **Key Evidence**:
  - Direct Quote: *"GreenPower has made significant investment with our in-house body division..."*
  - Data Points: *"Investment in GP Truck Body"*, *"New product lines"*, *"$500 million in zero-emission school bus initiative"*, *"Partnership with EDC"*
- **Directional Impact**: **UP** with **STRONG** conviction
- **Rationale**: Strategic investments and expansions signal confidence in long-term growth and market leadership.
- **Evolution**: Highlights strategic moves, showing commitment to scaling and innovation.

Decision Point 5: **Risk Factors and Mitigation**
- **Sentences Covered**: 81-95

- **Core SAE Concept Cluster**: **"Regulatory Risks", "Supply Chain Vulnerabilities", "Market Volatility", "Financial Stability"**
- **Secondary Concepts**: **"Inventory Management", "Capital Constraints", "Operational Challenges"**
- **Financial Signal**: **Potential Risks**, **Mitigation Strategies**
- **Key Evidence**:
  - Direct Quote: *"We face challenges in the medium-term, short-term, as far as the delivery on those contracts..."*
  - Data Points: *"Charging infrastructure issues"*, *"Capital access challenges"*, *"Inventory management"*, *"Potential delays in production"*
- **Directional Impact**: **MIXED** with **WEAK** conviction
- **Rationale**: Mixed signals from regulatory and operational risks, but mitigation strategies suggest resilience.
- **Evolution**: Provides a balanced view of opportunities and challenges, indicating cautious optimism.

Trajectory Analysis:

Narrative Arc:
The narrative begins with strong revenue growth and production expansion, followed by margin declines due to inventory write-downs, then positive forward guidance and market expansion. Strategic investments and partnerships are highlighted, but risk factors such as regulatory and operational challenges are acknowledged. The trajectory shows a mix of upward and downward movements, with a focus on long-term growth and strategic positioning.

Consistency Check:
- **Aligned Signals**: Revenue growth, margin improvements, and forward guidance align with positive sentiment.
- **Conflicting Signals**: Margin decline and risk factors create tension, but strategic initiatives offset concerns.
- **Resolution**: Conflicts are resolved through strategic investments and mitigating factors, reinforcing long-term optimism.

Momentum Assessment:
- **Starting Position**: Strong revenue growth and production expansion.
- **Ending Position**: Optimistic outlook with mixed risk factors.
- **Trajectory Shape**: **U-shaped** with upward movement in the middle, reflecting growth and strategic positioning.

Final Prediction:

- **Stock Direction**: **UP**
- **Confidence**: **HIGH**
- **Time Horizon**: **Medium-term (weeks)**
- **Conviction Drivers**:
  1. **Strong Revenue Growth** and **Production Expansion**
  2. **Positive Forward Guidance** and **Market Expansion**
  3. **Strategic Investments** and **Partnerships**
- **Hedge Factors**:
  1. **Potential Regulatory and Operational Risks**
  2. **Inventory Management Challenges**

Conclusion:

```
The earnings call demonstrates robust performance, strategic expansion
    , and positive market outlook, despite some operational and
    regulatory risks. The trajectory suggests a **high-probability
    upward movement** in the medium-term, with strong conviction in
    the company's long-term growth and market leadership.
```

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    Justification: The paper does not involve crowdsourcing nor research with human subjects.

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16. **Declaration of LLM usage**

    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

    Answer: [Yes]

    Justification: LLMs are used in the following key areas:

    - **As the Base Model for Analysis**: The entire SRC framework is built upon extracting concepts from the internal hidden states of a base LLM. The specific model used for this purpose is Qwen3-1.7B-Instruct.
    - **For Generating Feature Descriptions**: After the Sparse Autoencoder (SAE) extracts interpretable features, the paper follows a procedure where an LLM is used to generate a natural language description for each feature, giving it semantic meaning.
    - **To Synthesize the Final Explanation**: In the final stage of the pipeline, a generative LLM is prompted to synthesize the extracted evidence (the most activated sentences) into a coherent, narrative reasoning trajectory.
    - **For Experimental Evaluation**: The paper uses the G-Eval framework to evaluate the **coherence** and **faithfulness** of the generated explanations.

    Guidelines:

    - The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
    - Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.