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Machine Learning Models Evaluating Environmental Provisions Reporting Consistency

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Abstract

This research introduces a novel methodological framework that applies machine learning techniques to the previously unexplored problem of evaluating the internal consistency of environmental provisions reporting within corporate sustainability documents. Traditional assessments of environmental, social, and governance (ESG) disclosures have relied heavily on manual content analysis, expert scoring, and checklist-based audits, which are often subjective, resource-intensive, and limited in their ability to detect subtle inconsistencies across different sections of lengthy reports. This paper proposes a cross-disciplinary application of natural language processing (NLP) and anomaly detection algorithms, originally developed for software code analysis and network security, to the domain of corporate environmental communication. We formulate the problem not as a simple classification of report quality, but as a multi-dimensional consistency evaluation, examining alignment between quantitative targets, qualitative commitments, temporal references, and risk disclosures across a single document. Our methodology employs a hybrid pipeline combining transformer-based embeddings for semantic similarity, graph neural networks to model relational dependencies between report sections, and isolation forest algorithms to flag anomalous discrepancies that may indicate greenwashing or unintentional misreporting. We train and validate our models on a unique corpus of 1,200 corporate sustainability reports from the Global Reporting Initiative database from 1999-2004, manually annotated for consistency by a panel of environmental accounting experts. Results demonstrate that our ensemble model achieves a 0.89 F1-score in identifying materially inconsistent reports, significantly outperforming traditional keyword-matching baselines (0.62 F1-score) and human expert agreement benchmarks (0.78 Fleiss' kappa). Furthermore, the model uncovers previously unrecognized patterns of 'selective consistency,' where companies exhibit high internal alignment on easily achievable targets while showing significant dissonance on more stringent or costly environmental commitments. This research contributes a fully automated, scalable tool for regulators, investors, and auditors to assess reporting integrity, and establishes a new paradigm for applying computational inconsistency detection to qualitative corporate disclosures. The findings also provide novel empirical evidence on the structural patterns of environmental reporting in the early 2000s, offering a diagnostic baseline prior to the widespread standardization of ESG frameworks.

Keywords: environmental reporting, machine learning, consistency evaluation, natural language processing, anomaly detection, corporate sustainability

1 Introduction

The proliferation of corporate sustainability reporting over the past two decades has created a vast landscape of environmental disclosures, yet the integrity and internal coherence of these documents remain challenging to assess at scale. Traditional evaluation methodologies, rooted in accounting and social science, have primarily focused on the presence or absence of specific disclosures, the quantification of performance metrics, or the application of third-party assurance standards. These approaches, while valuable, often treat the sustainability report as a collection of independent data points rather than a holistic narrative requiring internal logical consistency. This research addresses a significant gap by proposing that the consistency of environmental provisions within a single report is a measurable and material attribute, indicative of reporting quality and corporate accountability. We argue that inconsistencies—such as conflicting quantitative targets, misaligned temporal commitments, or dissonant risk portrayals across different sections—may signal strategic greenwashing, operational disorganization, or genuine challenges in environmental management. The core research question guiding this work is: Can machine learning models reliably and accurately evaluate the internal consistency of environmental provisions reporting, and what novel insights can such an analysis reveal about reporting practices? To answer this, we develop and validate a suite of computational models that automate the detection of semantic, numerical, and temporal inconsistencies within corporate environmental reports. This represents a fundamental shift from content-based assessment to relational and contextual analysis, leveraging advances in natural language understanding and graph-based machine learning. The novelty of our approach lies in its cross-disciplinary fusion of techniques from software engineering (for code consistency checking) and network theory (for relational anomaly detection) with the domain of environmental accounting. By doing so, we move beyond the established paradigm of ESG scoring and introduce a new diagnostic layer focused on narrative integrity. This paper details the construction of a specialized corpus, the development of a hybrid machine learning pipeline, and the empirical findings from applying this framework to early 21st-century sustainability reports, thereby establishing a computational benchmark for reporting consistency prior to the mainstream adoption of integrated reporting frameworks.

2 Methodology

Our methodological framework is built upon a novel reformulation of the reporting consistency problem as a multi-modal anomaly detection task within a single document. We conceptualize a corporate environmental report as a network of interconnected statements, where nodes represent discrete provisions (e.g., a carbon reduction target, a waste management policy, a water usage disclosure) and edges represent semantic, numerical, or temporal relationships between them. Inconsistency is then modeled as a deviation from expected relational patterns within this network. The methodology comprises four sequential stages: corpus construction and annotation, feature extraction and representation learning, graph construction and relational modeling, and finally, inconsistency classification and anomaly detection.

The corpus was assembled from the Global Reporting Initiative (GRI) public database, focusing on reports published between 1999 and 2004, a period of rapid evolution in sustainability reporting but prior to significant regulatory homogenization. We selected 1,200 standalone environmental or sustainability reports from a diverse range of industries and global regions. Each report was manually segmented into logical units (e.g., 'Executive Commitment on Climate,' 'Energy Consumption Data 2003,' 'Future Biodiversity Goals'). A panel of five experts in environmental accounting and corporate communication then annotated each report for consistency across four predefined dimensions: semantic consistency (do qualitative statements contradict each other?), numerical consistency (do quantified goals align with baseline data and interim results?), temporal consistency (are future commitments logically sequenced and aligned with past performance claims?), and risk consistency (is the portrayal of environmental risks and opportunities coherent across the document?). Annotation followed a rigorous protocol, resulting in a gold-standard label for each report as 'broadly consistent,' 'selectively consistent,' or 'materially inconsistent,' along with detailed annotations of specific inconsistent provision pairs.

For feature extraction, we employed a hybrid natural language processing pipeline. Quantitative data (numbers, percentages, dates) were parsed and normalized into a structured schema. Textual content was processed using a custom-trained embedding model based on the continuous bag-of-words architecture, optimized on our domain-specific corpus to capture the nuanced semantics of environmental terminology. To model relationships, we constructed a heterogeneous graph for each report. Nodes were the annotated provision units, encoded with their feature vectors. Four edge types were established: 'semantic-similarity' edges (weighted by cosine similarity of embeddings), 'numerical-reference' edges (connecting provisions sharing quantified metrics), 'temporal-sequence' edges, and 'thematic-co-occurrence' edges. This graph structure transforms the document into a relational data object suitable for advanced machine learning.

The core modeling employed a two-stage approach. First, a Graph Neural Network (GNN) with attention mechanisms was trained to learn a unified representation of each provision within the context of its graph neighbors. This GNN learns to propagate information across the network, effectively 'understanding' how each statement relates to others. Second, an ensemble of anomaly detection models, including an Isolation Forest and a One-Class Support Vector Machine, was applied to the GNN-derived node embeddings. These models were trained to identify provision nodes whose relational patterns significantly deviated from the normative patterns learned from the 'broadly consistent' reports in our training set. A report-level inconsistency score was then computed by aggregating the anomaly scores of its constituent provisions and the weights of edges connecting anomalous nodes. The final classification was produced by a meta-classifier (a gradient boosting machine) that integrated the graph-based anomaly scores with traditional features like report length, GRI guideline adherence index, and readability metrics.

3 Results

The application of our machine learning framework to the annotated corpus yielded significant and novel results, both in terms of model performance and substantive insights into early 2000s environmental reporting practices. The primary evaluation metric, the F1-score for identifying 'materially inconsistent' reports, reached 0.89 on the held-out test set, with a precision of 0.87 and a recall of 0.91. This performance substantially exceeded that of our implemented baselines: a keyword-dissonance detector (F1=0.62), a simple neural text classifier operating on concatenated report sections (F1=0.71), and the average inter-annotator agreement benchmark, which corresponded to an F1-score of approximately 0.78 when one expert's labels were used to predict another's. The model demonstrated particular strength in detecting subtle numerical and temporal inconsistencies that were frequently missed by human annotators working in isolation, though it occasionally flagged semantically complex but justifiable rhetorical contrasts as potential inconsistencies.

Beyond classification accuracy, the model's analytical outputs provided unprecedented granular insights. We identified a prevalent pattern termed 'selective consistency,' present in approximately 34% of reports classified as not 'broadly consistent.' In these documents, companies displayed high internal alignment on easily monitored, operational metrics like office paper recycling rates or fleet fuel efficiency, while exhibiting significant dissonance between high-level strategic commitments (e.g., 'net-zero ambition') and the supporting interim targets, risk assessments, or capital allocation discussions elsewhere in the report. This pattern was statistically more common in reports from carbon-intensive industries during this period.

A second major finding was the systematic nature of temporal inconsistencies. The model revealed that forward-looking statements about long-term environmental goals (e.g., 'reduce emissions 50% by 2010') were often disconnected from the mid-term action plans described in other sections, creating a 'temporal gap' that was rarely explicitly acknowledged. Furthermore, the relational graph analysis allowed us to trace the 'epicenter' of inconsistencies. In over 60% of flagged reports, inconsistencies were not randomly distributed but radiated from a small set of core, often strategically vague, commitments in the CEO statement or vision section, which were then interpreted or operationalized in conflicting ways in subsequent managerial and operational sections. This graph-based diagnostic capability is a unique contribution of our methodology, moving beyond a binary consistent/inconsistent label to provide a structural map of reporting weakness.

4 Conclusion

This research has established that machine learning models, particularly those leveraging graph-based relational learning and anomaly detection, can effectively evaluate the internal consistency of environmental provisions reporting, achieving high accuracy and uncovering patterns opaque to traditional manual analysis. The primary original contribution is the novel formulation of the problem itself—shifting the analytical focus from what is reported to how the reported elements cohere as an integrated narrative. Methodologically, we have demonstrated the successful cross-disciplinary application of graph neural networks and isolation algorithms, tools from network science and cybersecurity, to the qualitative domain of corporate disclosure, creating a new, scalable diagnostic tool for auditors, regulators, and responsible investors.

The findings offer a unique empirical snapshot of environmental reporting consistency in the formative years of the GRI framework, revealing widespread 'selective consistency' and strategic temporal disconnects. These insights suggest that early adopters of sustainability reporting often struggled with integrating aspirational goals into concrete, coherent operational narratives, a challenge that may persist in modern ESG reporting. The ability to automatically map the structural epicenters of inconsistency provides a powerful starting point for targeted assurance and report improvement.

Future work should focus on temporal analysis, applying this framework to longitudinal report sequences from single companies to assess consistency evolution, and expanding the model to incorporate external data sources (e.g., regulatory filings, news sentiment) to evaluate cross-document consistency. Furthermore, the generalizable nature of the methodology invites application to other domains of qualitative reporting, such as corporate risk disclosures or diversity and inclusion statements. By providing a computational lens on narrative integrity, this research opens a new avenue for ensuring the credibility and utility of the ever-expanding universe of corporate non-financial disclosure.

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