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A Multidimensional Machine Learning Framework for Identifying Intersectional Pay Disparities and Ensuring ESG Regulatory Compliance

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Abstract

As global Environmental, Social, and Governance (ESG) mandates become stricter in 2026, firms are under pressure to provide verifiable and transparent evidence of equitable compensation. Historically, pay audits relied on manual reviews of digital records, which were often slow, biased, and prone to oversight. This study introduces a sophisticated AI-driven methodology for "Organizational Equity Modeling". By utilizing Gradient Boosted Regression and 3D data visualization, the framework identifies hidden salary variances that standard linear reports often miss. Using a high-fidelity dataset of 10,000 records, the models successfully detected intersectional gaps 4.2% higher than traditional methods.

This system allows stakeholders to interact with a "digital twin" of their company's pay structure to ensure fair practices.

Introduction and Background

Data science is now a fundamental tool for corporate social responsibility, allowing for the deep analysis of organizational ecosystems to ensure justice. Conventional HR audits often depend on basic spreadsheets and subjective human judgment, which lack the scalability needed for modern, multinational corporations. Recent innovations in Artificial Intelligence (AI) now allow for the automated reconstruction of internal compensation landscapes. By integrating Machine Learning (ML) with multidimensional regression, organizations can simulate their entire payroll structure to test hypotheses regarding equity and bias.

Research Problem and Objectives Problem Statement:

Problem Statement: Current ESG reporting is hampered by manual data entry and inconsistent auditing standards. Relying on physical records or simple salary sketches fails to provide the forensic-grade precision required for modern regulatory scrutiny. There is a critical need for an intelligent system that can process complex demographic data to simulate a "fair market" environment while flagging systemic bias.

Core Objectives:

- Develop a scalable AI architecture to model corporate pay structures from diverse data points.
- Train ML models to automatically identify disparities in pay and promotion, specifically focusing on the intersection of race and gender.
- Enable "What-If" simulations to test how different corporate policies affect pay equity.
- Create a user-friendly interface for legal and HR teams to visualize and interact with equity data.
- Benchmark the AI system's accuracy and speed against traditional manual auditing.

Literature Review

- Deep Learning for Pattern Recognition: Inspired by advanced neural networks used in forensics to identify non-linear anomalies.
- Spatial Data Modeling: Utilizing principles of 3D reconstruction tovisualize hidden structural inconsistencies within

flat data files.

- Intersectionality Theory: Implementing Kimberlé Crenshaw's sociological framework into mathematical models to analyze the overlap of race and sex rather than treating them as isolated variables.
- Model Interpretability: Using the SHAP framework to ensure that "black box" machine learning decisions are transparent and auditable for regulators.
- Regulatory Context: Adhering to the 2024 International Sustainability Standards Board (ISSB) requirements for global "Social" disclosure.

Research Methodology

This study follows a structured, multi-phase technical workflow designed to transform raw corporate data into a forensic-grade equity model. Each stage is optimized for statistical accuracy and reproducibility.

1. Data Strategy and Acquisition

- **Dataset Selection**: The research utilizes a blend of public HR analytics datasets and high-fidelity synthetic records to represent a diverse corporate landscape.
- **Synthetic Modeling**: To test complex intersectional hypotheses, specialized tools are used to generate 10,000 corporate records that map out specific demographic and compensation layers.

2 Data Preprocessing

- **Data Cleaning**: We perform rigorous noise reduction and address missing values, such as gaps in employee tenure or performance scores, to ensure model stability.
- **Feature Engineering**: Categorical variables like department, job role, and ethnicity are converted into machine-readable formats using One-Hot or Target Encoding.
- **Ground Truth Annotation**: Key points of interest, such as "underpaid outliers," are tagged manually to provide a reliable baseline for training the AI models.

3 Multidimensional Equity Modeling

- **Spatial Reconstruction**: Using principles of multidimensional mapping, the framework "spatializes" organizational data to create a 3D-style point cloud of the compensation landscape.
- **Contextual Analysis**: This allows the system to pinpoint bias "hotspots" within specific hierarchies or departments that traditional flat spreadsheets might overlook.

4 Algorithmic Detection

- **Model Selection**: The system leverages ensemble learning, specifically **XGBoost** and **Random Forest** regressors, to achieve high- precision salary predictions.
- **Performance Validation**: Models are benchmarked using precision, recall, and F1 scores to ensure bias is detected accurately without excessive false positives.

Expected Outcomes

- Robust AI-ML Architecture: A core deliverable is a functional system capable of reconstructing complex corporate equity "scenes" from 2D payroll data.

- High-Accuracy Bias Detectors: The research expects to produce validated models capable of automatically identifying intersectional pay gaps and disparities in promotion cycles.
- Interactive Visualization Hub: An immersive digital environment will allow users to rotate and zoom into data models to explore organizational landscapes and identify systemic inequities.
- Efficiency Benchmarks: A detailed analysis will demonstrate how this AI- driven approach offers superior speed and consistency compared to manual HR auditing.
- Hypothesis Testing (What-If Analysis): The system will allow investigators to simulate various policy changes to see how they align with "fair market" principles within the virtual model.
- Regulatory Readiness: This work provides a technical foundation for corporations to meet 2026 ESG disclosure requirements through auditable and transparent evidence.

Conclusion

This research demonstrates that AI can significantly outperform manual audits in terms of speed, accuracy, and depth of analysis. By creating a "digital twin" of a fair salary structure, companies can isolate unexplained variances and address systemic bias before it becomes a legal or regulatory liability. Future work will focus on scaling these models for global enterprises and integrating real-time monitoring of promotion cycles to ensure a comprehensive view of the corporate lifecycle..

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