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HoliStat: An AI-Powered Holistic Model for Financial Trustworthiness

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Introduction

With traditional credit scoring systems being rigid and forcing users to conform to the enterprise's scoring system, there have been significant barriers to estimating an accurate risk profile for users with limited to no credit history. With HoliStat, this systemic problem can be addressed through capturing a person's true so-called responsibility habits without requiring additional information beyond what is already requested. These habits may include responsible driving, consistent employment, and making on-time payments for various bills. Students, immigrants, and recent graduates all benefit from a new way of processing data by consensually sharing data they are comfortable with. For users with a consistent employment history, pursuing higher education, and demonstrating consistent behavioral and financial responsibility, this enhanced credit scoring system enables banks to assess an individual's risk on a personal level accurately.

The proposed system is not intended to replace traditional scores but to enhance them, providing lenders with a richer, more nuanced profile of loan applicants. By leveraging machine learning models, which use statistical principles to make predictions, HoliStat offers a scalable and affordable Infrastructure as a Service (IaaS) solution for financial institutions. The system is optimized for both consumers and lenders. Individuals can choose to share additional data to potentially improve their risk profile, with no penalty for not opting in. This approach empowers consumers and promotes a more transparent and fair lending environment.

With more personalized credit scores, lenders can assess the risk for each individual borrower. Shifting away from generalizations based on financial data, users have the option to provide behavioral data to provide a holistic insight into each borrower's lifestyle. This affordable, scalable IaaS solution enables financial institutions to ingest additional information to forecast individual risk profiles and compare them to other users. Borrowers have complete discretion in using this system; they can choose which information to share with their lender without facing penalties for not participating. For those who opt into the HoliStat system, their current scores are enhanced, not replaced. This approach enables banks to conduct their business with fewer risks and allows users to protect their privacy by giving each user more control over their data.

Deficiencies in Established Credit Systems

Current credit scoring models present significant challenges for young adults, students, and immigrants. These individuals often lack a lengthy financial history. Consequently, financial institutions are apprehensive due to the uncertainty surrounding how each person will behave during repayment. Facing these disadvantages, many individuals struggle to achieve a favorable credit score. This, in turn, affects personal loans, mortgages, and much more. This highlights a systemic issue: many individuals who need credit are often neglected because banks are unsure of their individual creditworthiness. This financial exclusion often delays economic mobility in new graduates and immigrants, which can stifle growth. The purpose of HoliStat is to break this cyclical pattern of discrimination by quantifying indicators of responsible behavior and changing how financial institutions process data.

The HoliStat Solution: Technology and Methodology

Combining "several deep learning methods" used in the Siamese Neural Network architecture, HoliStat uses provided user information to create two different scores derived from their personal and financial history, respectively (Varior et al., 2016). These two scores are combined into one unified score through the two-tower model. This two-tower model is composed of two main pipelines: one to process financial data and one to process behavioral data. These pipelines enable financial institutions to compare users with other users to make informed decisions based on historical data. In other words, the current user being evaluated may have a similar outcome to previous users, allowing banks to make informed business decisions. Two-tower models have become popular, as this architecture is used by YouTube, Netflix, and many other large companies. These companies compare products and media consumption to provide a custom feed for each user, depending on the viewing history. Instead of relying on user characteristics, HoliStat uses financial and behavioral data. By taking in this data and adapting the two-tower architecture, financial institutions can assign numerical values to behavioral traits to better assess a user's risk profile. At a more detailed level, the two towers operate as follows:

- Tower A (The Financial Tower): This tower analyzes a person's historical financial decisions. It processes traditional data such as consistency in paying bills, income stability, and lifestyle habits to build a picture of their financial responsibility.
- Tower B (The Behavioral Tower): This is what makes HoliStat different from traditional credit scoring models. This added tower processes voluntarily shared information that demonstrates responsible behavior but is absent from a standard credit report. This allows banks to view a person's overall responsibility habits to adjust interest rates, the length of lending, and the likelihood of new loans.

The AI learns the connections between these two towers. It might discover, for example, that individuals with a specific professional certification (Tower B) and a history of stable rent payments (Tower B) are highly likely to be responsible borrowers (Tower A), even in the absence of a formal credit history. For a student or a recent graduate, the Financial Tower might be mostly empty. Traditional systems would stop there, but HoliStat uses the rich information in the Behavioral Tower to make a data-driven and AI-based prediction about that person's payment reliability.

The neural network underpinning the solution allows the scoring model to learn from previous data by drawing connections between the two towers. These connections could enable the model to predict that individuals with stable incomes and high-earning positions tend to repay loans more reliably than those with inconsistent employment.

The data categories used to augment the traditional risk profiling are grouped into several key domains:

- Education and Skills: Formal degrees, certifications, internships, trade school qualifications, and bootcamp completions.
- Work and Income Stability: Employment history, industry-specific earning potential, and rental payment history.
- Financial Behavior: This includes budgeting habits, investment activity, and on-time bill payments for utilities and rent.
- Civic and Community Engagement: Metrics such as volunteer history or consistent participation in community organizations, which can be indicative of stability and reliability.

Implementation and Business Viability

For any company to implement the HoliStat IaaS solution, a multiphase process is designed to ensure security, accuracy, and successful market integration. The projected cost ranges from $800,000 - $2.3 million with a timeline of 18 to 36 months.

1. Phase 1: Partnerships and Foundation (6-12 months): Establishing the business framework by forging partnerships with financial institutions and finalizing contracts. These contracts begin with negotiations with Plaid and Parchment to ensure compliance requirements are met and proper authorization is obtained to access personal financial and education records. Plaid is a personalized budgeting app (https://plaid.com/en-eu/) that automatically tracks every dollar received and spent. This would allow HoliStat to gauge if a user is living within their financial means. Parchment is a

platform where students can send verified transcripts to prove that they are responsibly focused in their education (https://www.parchment.com/).

2. Phase 2: AI Development and Security (6-12 months): Training the Siamese neural network on consensual, anonymized partner data and conducting rigorous penetration testing to ensure system security.
3. Phase 3: Final Testing and Launch (6-12 months): Conducting comprehensive real-world testing to ensure the model is accurate, fair, and reliable before launching with partner institutions.

The model is designed to allow banks to accurately forecast the amount of risk before approving loans and credit cards. This improved credit model also ensures a consistent stream of income for the bank by allowing users to consensually share information about, e.g., income and bill payments.

Conclusion

HoliStat offers a robust, innovative solution to the rigid systems of traditional credit scoring models. By using an adapted version of the two-tower infrastructure, HoliStat leverages machine learning to forecast risks based on financial and behavioral patterns. With this information, financial institutions can view a comprehensive picture of an individual's lifestyle and make informed business decisions accordingly. In addition to securing a reliable stream of revenue for the banks, HoliStat aims to improve the quality of life for those who exercise responsibility in their lives and remove the risk when lending individuals with minimal or no financial history. Through the strategic implementation plan, Holistat's goal is to innovate credit scoring and improve the lending landscape for both consumers and lenders.

More Information

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Declaration of AI Statement

Google Gemini was used to convey thoughts more fluidly after being provided the structure of the paper. Grammarly was then used to improve subsequent drafts to eliminate grammatical errors.

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