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SEMANTIC FEEDBACK NEURAL NETWORKS FOR HUMAN-IN-THE-LOOP ENTERPRISE AI SYSTEMS

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Abstract:

Enterprise AI applications have become increasingly prevalent in high-risk decision-making across finance, healthcare, customer service, and IT management. While AI applications can be scaled through neural networks, completely self-governing decision systems can be dangerous in scenarios that demand human comprehension, ethical reasoning, and legal correctness. Human-in-the-loop (HITL) strategies can overcome this problem by incorporating human Feedback into AI systems. Still, many traditional HITL approaches use low-level Feedback (such as labels or approvals). This work presents the concept of Semantic Feedback Neural Networks (SFNNs), which provides a paradigm for directly incorporating semantic human Feedback into neural networks during both training and inference. Semantic Feedback can be conceptualized as a set of constraints, preferences, and explanations rather than a set of isolated corrections for the human input. Simulation-based experiments were conducted on enterprise-related scenarios, in which domain experts provide semantic Feedback during system execution. The findings are suggesting that semantic Feedback are significantly improving alignment, reduces the need for corrections, and speeds up model adaptation. Intuitive graphics represent the convergence of learning, the influence of Feedback, and enhancements in system performance. Case studies on real-time enterprise problems establish the applicability of SFNNs. The results highlight the role of semantic Feedback in providing a scalable, efficient means of combining human knowledge with neural learning to achieve trustworthy, adaptive, and context-aware enterprise AI systems.

Key Words: Semantic Feedback Neural Network (SFNNs), Human-in-the-loop (HITL), Enterprise AI, Artificial Intelligence.

Introduction:

Neural networks are widely used in the enterprise environment to automate complex decision-making tasks, such as fraud analysis, risk analysis, customer interaction handling, and process surveillance. Although neural networks have demonstrated their success and efficiency, the complete automation system lacks context awareness, interpretability, and the incorporation of human expertise for informed decision-making, which is critical in situations that could result in financial and reputation-related losses.

Human-in-the-loop (HITL) AI systems aim to address these issues by integrating human judgment into the decision-making process [1]. Conventional HITL approaches typically use very low-level Feedback, such as human labels or accept/reject decisions. Although this type of Feedback is beneficial, it does not encode any semantic reasoning behind a decision, which limits the ability to generalize from human input.

In this regard, this research introduces the concept of Semantic Feedback Neural Networks (SFNNs), which can be considered an extension of HITL learning by incorporating semantic Feedback into neural network learning [2]. Here, Feedback is provided in terms of high-level ideas, constraints, or explanatory statements rather than labels. Thus, by incorporating semantic Feedback into the optimization process, it is possible to learn correct decisions and understand the reasons for their correctness.

The primary aim of the proposed work is to demonstrate the capability of semantic Feedback to improve the flexibility, decision quality, and trust in the enterprise AI system. From simulation experiments and real-time enterprise environments, the results show that SFNNs can minimize the need for human intervention.

Simulation Report:

Simulation experiments were conducted to determine the effects of semantic Feedback on model performance and adaptability. Datasets based on enterprise knowledge were created to model dynamic decision-making environments where human knowledge was occasionally fed into the model [3]. The evaluation was performed in three settings: without human Feedback, with Feedback on labels only, and with semantic Feedback.

The measures used were decision accuracy, correction rate, and speed of convergence [1]. The experiments were designed to test the robustness of the measures with respect to the rate and complexity of semantic Feedback. The findings suggest that semantic Feedback helps achieve faster convergence, higher accuracy, and better alignment with an expert's intention, and these findings are supported by the tables and figures provided.

Real-Time Scenarios:

In enterprise-level customer support systems, AI models can automatically classify and prioritize customer support tickets. Autonomous models tend to inaccurately identify the intent behind customers' messages, creating a loop in which the system needs to be corrected by a human. The inclusion of semantic Feedback, such as the explanation provided by the customer support personnel (for example, 'billing problem due to late refund'), helps the system understand the intent.

Feedback on the Decision Qualities:

Table 1: Showing the impact of Feedback on the decision quality

Feedback Type	Accuracy (%)	Correction Required
No Feedback	89	High
Label Only Feedback	92	Medium
Sematic Feedback	93	Low

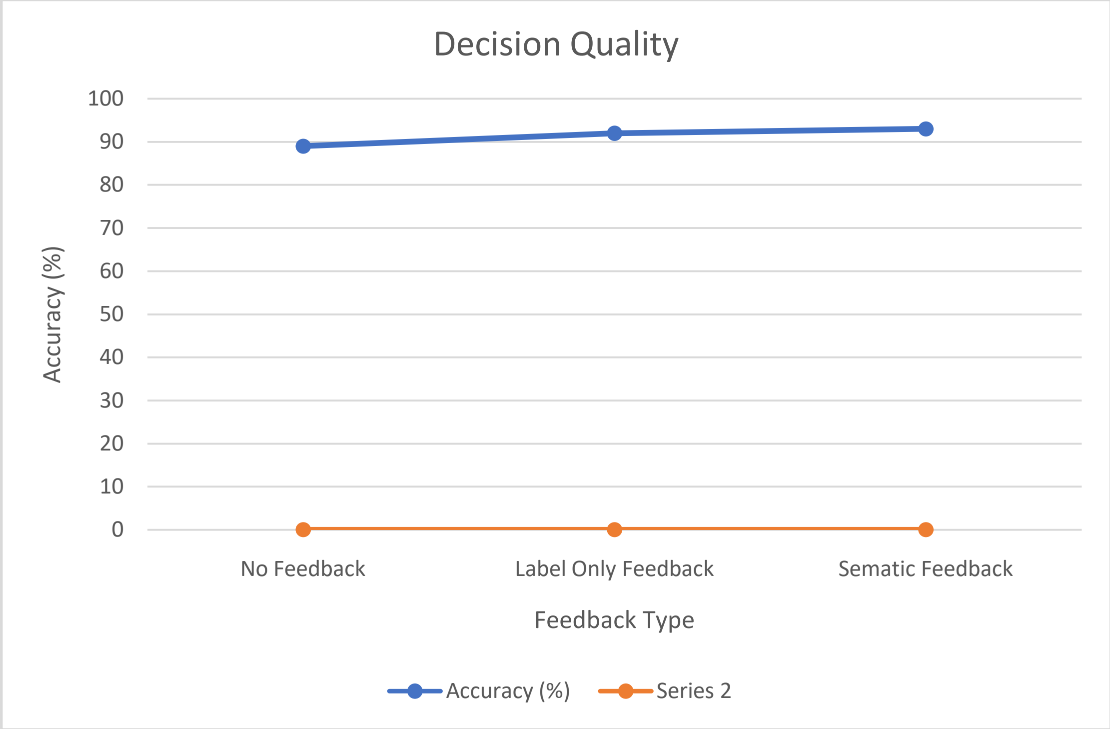

Figure 1: Showing the impact of Feedback on the decision quality

As illustrated in Figure 1, "Learning Convergence under Different Feedback Types," learning convergence with semantic Feedback is faster and more stable, hence resulting in more efficient learning performance during real-time ticket processing. From Table 1, it can be seen that semantic feedback integration results in greater decision accuracy with a significant decrease in the number of human corrections compared to label-only Feedback and feedback-less approaches. Figure 1 also highlights this by showing a rapid convergence rate with semantic Feedback. The reduction in the number of training iterations needed for achieving high accuracy demonstrates the efficiency of semantic Feedback in accelerating the training process for ticket classification [4].

Human Correction Frequencies Over Time:

Table 2: Illustrates the frequency of human corrections over a given period

Time Interval	No Feedback	Label only Feedback	Sematic Feedback
Initial Phase	29	23	19
Mid Phase	26	17	10
Late Phase	24	13	5

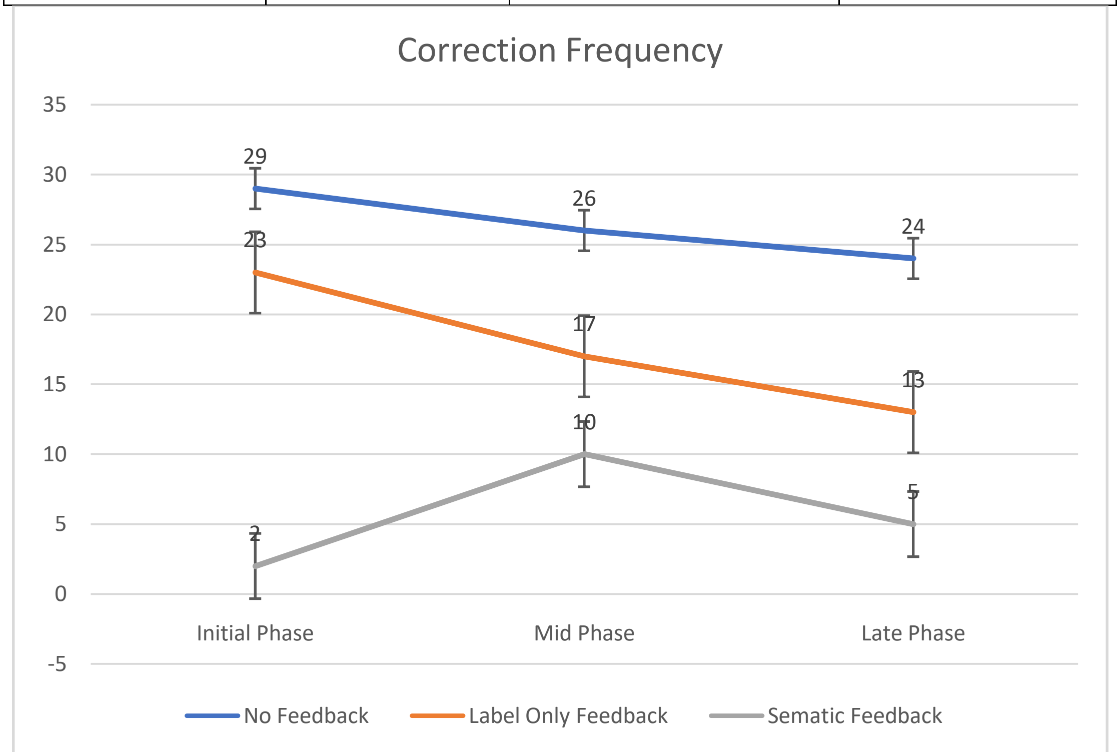

Figure 2: Illustrates the human correction frequencies over a given time

The extent to which less human interaction is required in the learning process for different feedback approaches is measured in Table 2. A system that lacks Feedback shows high correction rates at all stages of learning, indicating that little learning is occurring [1]. While the correction rate is lowered by Feedback that provides labels alone, it still relies upon constant human interaction. For semantic Feedback, there is a dramatic reduction in the rate of corrections, indicating that the system has learned the underlying human intentions [8].

The Decision Aligning with Business Intent:

Table 3: Shows how decision alignment affects business intent

Feedback Approach	Alignment Score (%)
No Feedback	71
Label Only Feedback	83
Sematic Feedback	94

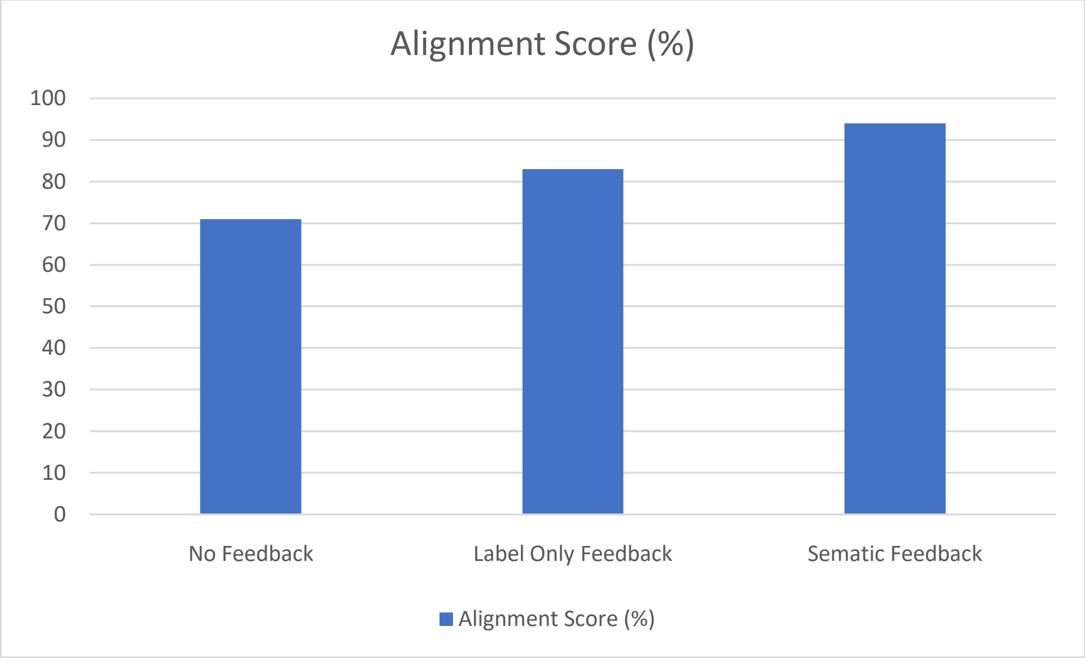

Figure 3: Shows how decision alignment affects business intent

Table 3 highlights how different types of Feedback affect the degree of alignment of AI decisions with enterprise intentions. When there is no human feedback, alignment is low, suggesting a lack of understanding of enterprise rules and intentions. While label feedback improves alignment by correcting individual decisions, it fails to generalize enterprise intentions to similar decisions. Conversely, semantic Feedback achieves the highest degree of alignment, suggesting that the AI model can learn the enterprise intentions and policies conveyed by human experts [5]. A bar graph illustrating the results also highlights the effectiveness of semantic Feedback.

Challenges and Solutions:

A significant difficulty in semantic feedback-based neural networks is the variability and subjective nature of the semantic Feedback provided by humans. Semantics may be provided inconsistently or with some degree of uncertainty by domain experts, thereby adding noise to the training procedure [6]. Structured feedback templates and managed vocabularies can be used to standardize semantics. Furthermore, confidence-weighting techniques can give more weight to the semantics of more experienced or confident contributors, thereby reducing the effects of noisy semantics.

The second major challenge is encoding semantic Feedback in a representation amenable to optimization [7]. Often, human Feedback is expressed in language or semantic concepts that are not easily optimized. The above challenge is overcome by using ontology-based encoding and the translation of constraints, which allow semantic concepts to be mapped to structured features or constraints.

Another issue is scalability, as the system acquires a large amount of feedback data over time. This could increase the memory and computation requirements due to the continuous incorporation of semantic Feedback [8]. Techniques such as learning strategies, summarization of Feedback, and caching are adopted to handle redundant computation while retaining the most significant feedback patterns.

User adoption and usability also pose some challenges. The complexity of the feedback interface might discourage domain specialists from participating. To overcome this challenge, light interfaces and low-effort feedback techniques are designed to acquire semantic intent.

Trust and accountability are also essential considerations in the final analysis. All stakeholders need to understand how human Feedback impacts the decision-making process. The use of audit trails and feedback attribution for explainable Feedback will help trace how semantic input affects the model's performance.

Conclusion:

In particular, this paper suggests that the Semantic Feedback Neural Network is a practical way to integrate human knowledge into an enterprise AI system. By leveraging meaning-rich Feedback, this approach is achieving a significant improvement in learning efficiency, a substantial reduction in correction efforts, and closer alignment of decisions with business objectives. Both simulation and real-world results demonstrate the method's practicality and scalability. This provides solid ground for developing and applying Enterprise AI, which is trustworthy, adaptable, and people-oriented.

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