# Neuro 240 Midterm Report

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## 1 Project Proposal

**Research Question:** How can Spiking Neural Networks (SNNs) be used to model human decision-making in financial markets, capturing the temporally dependent and emotionally driven trading behaviors of retail investors through large-scale simulations?

**Hypothesis:** We hypothesize that an SNN-driven approach will exhibit sufficient fidelity to replicate at least 70% of historical stock price movements for a U.S.-based equity heavily influenced by retail traders. The biological plausibility of SNNs allows them to better model the nonlinear, time-sensitive nature of human trading behavior, likely making them well-suited for this task.

## 2 Literature Review

The validity of our approach integrates insights from neuroscience, machine learning, and behavioral finance. Spiking Neural Networks (SNNs) have been shown to provide a biologically grounded framework for modeling human trading behavior by emulating neural decision-making processes.

### 2.1 Neuroscience of Financial Decision-Making

Neuroscientific research has provided critical insights into the brain mechanisms underlying financial decision-making. Functional MRI (fMRI) studies reveal that professional traders exhibit asymmetric activation in the prefrontal cortex (PFC) during strategic planning while simultaneously suppressing amygdala activity during loss anticipation [1]. Additionally, the nucleus accumbens (NAcc), a key region involved in reward processing, has been shown to activate prior to risk-seeking financial choices [5]. This suggests that successful trading decisions are closely linked to activity in the NAcc, indicating its role in assessing risk and reward trade-offs in financial markets.

### 2.2 Machine Learning Advances in SNNs

Traditional deep learning models, such as Long Short-Term Memory networks (LSTMs), struggle with event-driven financial data due to their reliance on fixed time-step processing. In contrast, SNNs provide a more biologically plausible alternative by leveraging event-driven computation and surrogate gradient learning, which allows them to approximate spike function derivatives and enable efficient backpropagation [7]. This property makes SNNs particularly well-suited for capturing the irregular temporal patterns present in financial markets.

Beyond their computational advantages, SNNs have also been applied to model brain regions involved in decision-making. Notably, SNNs have been used to simulate the basal ganglia, a network of nuclei crucial for action selection and motor control. A biologically constrained SNN model of the primate basal ganglia demonstrated overlapping pathways and action-selection capabilities that align with empirical observations [2]. Given that the basal ganglia encompass the NAcc—one of the most important regions for trader decision-making as previously mentioned—this further supports the use of SNNs in modeling financial behavior.

### 2.3 Financial Applications of SNNs

Neuroscience plays a significant role in shaping financial market behavior by revealing the neural mechanisms underlying investor decision-making. For example, fMRI studies have identified neural correlates supporting the "realization utility" theory, which posits that individuals derive satisfaction from realizing gains and losses, thereby influencing their trading behaviors [3]. Additionally, research in neurofinance has demonstrated how cognitive biases and emotional responses impact investment choices, shedding light on the psychological factors that drive market dynamics [6].

By integrating insights from neuroscience and leveraging the computational power of SNNs, we can develop a model of computation that makes trading decisions much like humans do. By generating a simulation at a large scale we can mimic the movement patterns of the market.

# 3 Method

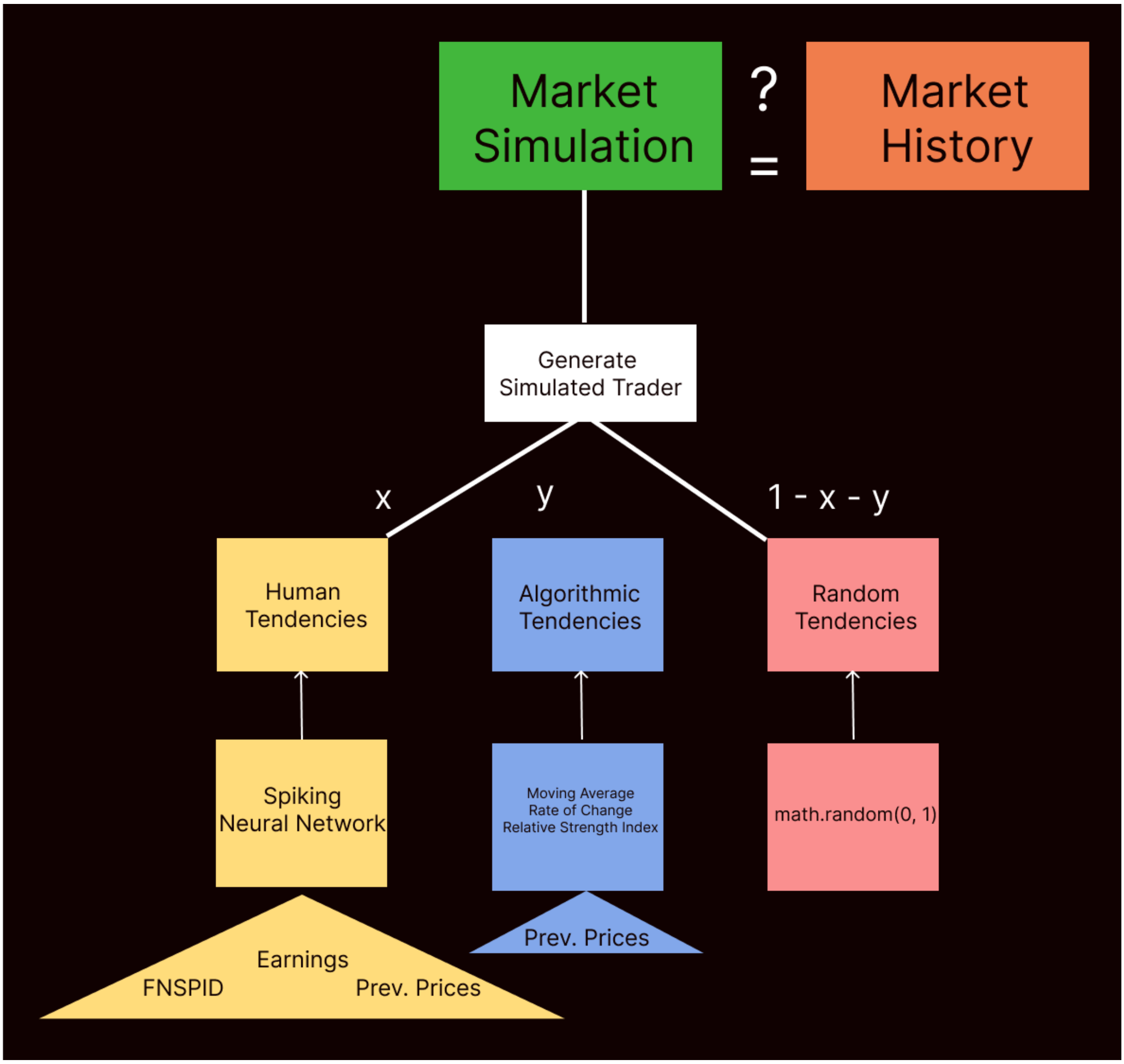


Figure 1: Project Flow

## 3.1 Project Overview

In the stock market, there are three primary types of participants: human investors, algorithmic trading bots, and market makers. Human investors make decisions based on their analysis of stocks, often considering factors like company fundamentals, macroeconomic trends, and personal investment goals. Their trading strategies can vary widely in terms of time horizon—from short-term speculative trades to long-term investments—and their capital ranges from individual savings to large institutional funds, such as those managed by hedge funds. Algorithmic trading bots are automated systems designed to execute trades based on predefined strategies, often driven by patterns in price movements or other market data. These bots aim to exploit price fluctuations for profit, frequently ignoring the underlying value of the stock itself. They rely on complex algorithms to identify trends and execute trades at high speeds, enabling them to capitalize on small, short-term opportunities. Market makers play a crucial role in providing liquidity to the market by buying and selling stocks at a high frequency. They profit from small price differentials, often just fractions of a penny per trade. Market makers ensure that other participants—whether human investors or algorithmic bots—can execute trades without delays, as they are always ready to act as a counterparty to trades, ensuring the smooth functioning of the market.

To create an accurate market simulation, I need to properly represent all three types of traders. Market makers, due to their high-frequency trading and unpredictable nature, will be modeled using a random strategy to simulate their decisions. For algorithmic traders, I plan to implement simple but widely used strategies, such as Moving Average and Rate of Change algorithms, to guide their trading. While these indicators may not be the most optimal, they are commonly employed by traders and are expected to yield above-average returns, providing a realistic representation of algorithmic trading behavior. The core of my project, however, will focus on replicating human trading decisions. I will achieve this by training a spiking neural network on earnings reports, stock prices, and news data—much of the same information that humans use to inform their trades.

To complete the simulation, I will generate thousands of trading bots, each with a randomly assigned weighting of the three strategies. Recognizing that real traders rarely adhere to a single strategy 100% of the time, each simulated trader's decisions will be influenced by a weighted mix of the strategies, reflecting the variation in trading behavior that occurs in real markets.

## 3.2 Steps

### 3.2.1 Spiking Neural Network Training

The first and most important experiment I will conduct is training a Spiking Neural Network (SNN) to make trading decisions that closely resemble those of a human trader. The primary datasets I will use are:

- The FNSPID dataset, which contains financial news articles and sentiment data for every ticker in the NASDAQ from 2023 to 2024, alongside corresponding daily stock prices.
- If time permits, I will further refine the model using the Social Media Sentiment Analysis dataset, which provides additional market sentiment data from social media sources. This will serve as an auxiliary input to enhance the SNN's decision-making process.

To optimize performance, I will experiment with multiple Spiking Neural Network models in PyTorch, evaluating their ability to process sequential market and sentiment data. Some of the key architectures I will explore include:

- **Leaky Integrate-and-Fire (LIF) Networks** – A fundamental SNN model that captures temporal dynamics in trading decisions.
- **Spike-Time Dependent Plasticity (STDP) Models** – Designed to incorporate adaptive learning rules that mimic human decision-making adjustments.

Code for these models is readily available online through resources including Github, Youtube and Medium which I plan to use. One of the key papers I will be using to guide this development is **Spiking neural networks for predictive and explainable modelling of multimodal streaming data with a case study on financial time series and online news** [4]. My evaluation metrics will include profit/loss performance, decision similarity to historical human trading patterns, and response to news sentiment shifts. The ultimate goal is to develop an SNN capable of making real-time trading decisions that align closely with human traders in dynamic market conditions. I will know that these trading decisions align closely with human traders if the overall movement of the price mimics the real stock market in step 3 below.

### 3.2.2 Algorithmic Trading Optimization

This stage of the project involves building a trading bot that trades based on signals. My goal is to create an algorithm that performs well using the **yfinance** library to gather stock price data.

The main data will be historical stock prices (open, close, high, low, volume) from **yfinance**, which is publicly accessible. Additional data, such as technical indicators or financial news, can be sourced from APIs like Alpha Vantage or Quandl if needed.

I will start with a **rule-based model** using common technical indicators such as:

2. **Relative Strength Index (RSI)** – to identify overbought or oversold conditions.

I will evaluate the success of the algorithmic trader using profit and loss. The performance will be compared to major market indices (e.g., S&P 500) and a simple **buy-and-hold** strategy as baseline benchmarks. The goal will be to achieve around a 5% monthly return on investment with an algorithmic strategy.

#### 3.2.3 Simulation

Finally, we will integrate all components to create a complete market simulation. This will involve **100,000 trading bots**, each assigned a weighted mix of the three strategies. The simulation will run for **three simulated months**, during which we will analyze how closely the simulated stock price movements align with real historical price changes.

To model price fluctuations based on trading activity, we will implement a **Linear Impact Model**, adjusting stock prices based on trade volume. The goal is to fine-tune the distribution of trader types and overall market size to create a simulation that closely mirrors real-world market behavior.

# 4 Progress

So far, I have established the core framework for simulating a stock market using Spiking Neural Networks (SNNs). The primary goal is to create a market of simulated traders that closely mimics real-world trading dynamics. I have:

1. Collected and preprocessed historical market data and historical new articles related to stocks in the NASDAQ to serve as the training environment for the model.
2. Experimented with encoding financial time series into spike trains for neural processing.
3. Researched the appropriate SNN architectures and begun experimenting with the LIF Networks model.

## 4.1 Dataset and Computational Considerations

1. So far, the dataset is structured appropriately for use in the model. However, converting financial time series into spike-based representations remains an ongoing challenge. I am currently testing different encoding schemes, such as rate coding and temporal coding, to find the most effective representation.
2. There is enough historical market data available with day long intervals. I suspect this will be granular enough for my use case there is a possibility that I use a different API to get a more granular set of data.
3. While my current hardware is sufficient for small-scale experiments, full-scale training may require access to GPU or specialized neuromorphic computing resources. For this reason, I am only training on AAPL stock for now but may switch to have a bundle of stocks or possibly the entire stock market as well.

## 4.2 Preliminary Results

For my initial training of the model, I produced two output classes—hold and buy—limiting its decision-making capability. The model accuracy is shown in the plot below and although it was largely matched making the correct investment decision, there were a handful of data points for which the output was inaccurate. Given that I will be running the simulation at a much larger scale, a higher level of accuracy will be needed. To improve performance, I plan to refine the model architecture, explore alternative Spiking Neural Network frameworks, and introduce a third output class to represent selling, enabling a more comprehensive trading strategy.

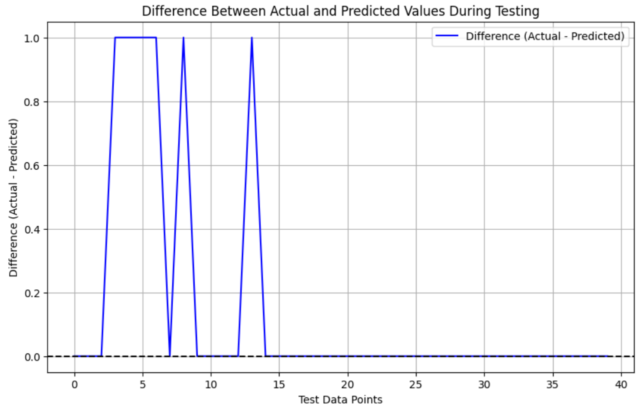


Figure 2: Model Training Results

Link to Code: https://colab.research.google.com/drive/10HhL-D3TnTTKNd9XcznUHzbYcBw16MNl?usp=sharing

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