Objective

The goal of this assignment is to identify **important price levels** for the week of May 27th, 2024. I will first define the metrics to evaluate “importance”. By analyzing these factors, a ranking system will be developed to score and prioritize price levels, providing insights into potential key zones for traders to watch during this period. Finally, I will review the price action for the week of May 27th, 2024, on TradingView to validate whether the identified price zones were indeed significant. This comparison will help assess the accuracy of the ranking system and determine if the predicted price levels correspond to key support, resistance, or high-activity zones during real market conditions.

Defining "Important" Prices or Ranges

I defined important prices as ranges that meet the following criteria:

1. **High Volume Zones**: Price levels where large amounts of trading volume occur, indicating institutional or major market participant interest.
2. **Support and Resistance Levels**: Price levels that have been repeatedly tested by the market, acting as strong support (price bounces) or resistance (price rejections). I will measure this by identifying clusters of swing highs or swing lows.
3. **Historical Volatility**: Price levels reached during historically volatile times (usually around market open) tend to be more significant because they coincide with high market activity or news events.
4. **Proximity to VWAP**: Prices far from the **Volume Weighted Average Price (VWAP)** for the week are considered important as they represent the "fair value" based on the average trading price weighted by volume.

Hypotheses and Thought Process

The following hypotheses are posed to determine which price levels are important:

- **Hypothesis 1**: Price levels that saw **high trading volume** are important because they indicate strong market participation and are often key areas of support or resistance where significant buying or selling occurs.

  Thought process: Price levels with high volume often act as significant points of **support** or **resistance**, as these are levels where traders are willing to transact in large quantities. If price returns to these levels, market participants may defend or challenge those levels again, leading to potential price reactions like reversals or breakouts.

- **Hypothesis 2**: **Price reversals** (swing highs and swing lows) from previous periods will help identify price levels where the market will likely react, either bouncing off or breaking through those levels.

  Thought process: Support and resistance levels represent zones where price tends to reverse or stall due to shifts in the balance of buying and selling pressure.

- **Hypothesis 3**: Price levels that are traded to during highly **volatile times** are more important because they indicate heightened trader activity.

  Thought process: High volatility at a certain time indicates that the market experienced significant price fluctuations, often due to news, economic data releases, or higher volume. Therefore, in order to identify key price levels to potentially trade in, we must consider what time they were traded at.

- **Hypothesis 4**: Price Levels far away from the weekly **VWAP** are more important because they are more likely to be overextended.

  Thought process: Prices far from the VWAP can indicate overbought or oversold conditions, signaling potential reversals or mean-reversion opportunities. Whereas, price ranges near or at VWAP are often seen as fair value.

Results of the Ranking System

The ranking system uses these four factors to measure the importance of a given price bin. I decided to weigh high volume zones, support and resistance levels, historical volatility, and proximity to VWAP at 40%, 30%, 20%, and 10%, respectively. Adding these scores up, the algorithm assigns a value from 0 to 1 to each price zone.

Figure 1 below shows the ES 1h chart during the week we are analyzing. Each highlighted zone represents the price bin outputted by the ranked_prices algorithm. Note that the prices values are not the same as I am using the continuous ES1! chart since I don't have access to the data from the June contract (ESM2024) on TradingView. The zone at 5295 (5420 in Figure 1) with a score of 0.87 is ranked 1st place by far. On Tuesday afternoon it's used as support, then it is broken through overnight, and finally is used as resistance on Wednesday morning. For a trader with a bearish bias that week, the zone could have been a place to sell once it was broken. Additionally, the zone ranked #2 at 5325 (5450 in Figure 1) acted as resistance when broken, while the zone at 5250 (5375 in Figure 1) provided support for a brief retracement during the sell-off. The latter two zones also gained points for being far from the weekly VWAP level of 5278. In the "Additional Submission: My Trade Example" pdf, I go over a trade that I personally took after price rejected from the zoned ranked #3. It's interesting to see how these price bins align pretty

accurately with key support or resistance levels. These zones can potentially be viewed as key levels for trade entry and stop loss placement, offering a structured approach to managing risk effectively. To conclude, we can say that the algorithm was fairly successful at finding "important" price zones in the weekly range.

Figure 1

Areas of Improvement

To transition the algorithm from a historical analysis tool to a predictive model, integrating **real-time data feeds** would be essential. By continuously monitoring real-time volume, volatility, and price action, the algorithm could dynamically adjust the ranking of price zones, allowing it to anticipate areas of support or resistance before they are hit, rather than analyzing them after the fact.

In addition, the model could also be improved by increasing its complexity. For example, adding momentum indicators, such as the **Relative Strength Index (RSI)** or **Moving Average Convergence Divergence (MACD)**, could further enhance its predictive capabilities.

A promising avenue for improvement is to apply **machine learning** to recognize recurring patterns in the behavior of price zones. By training models on historical data, the algorithm could learn how certain price zones behave under specific market conditions and predict future market reactions more effectively. Incorporating machine learning could also help identify subtle

relationships between price zones and other market indicators, such as open interest, options data, or even news sentiment.

Moreover, this report only focused on a single time frame at a time (i.e., the 1 hour timeframe). However, incorporating **multi-timeframe analysis** could help identify more robust and precise price zones. For example, price zones that appear on both daily and intraday charts are likely to be more significant. Expanding the algorithm to evaluate multiple timeframes simultaneously could enhance its predictive power by identifying zones that hold across different market contexts. Finally, by leveraging the fractal nature of the market, one could even dive into the small time frames using the 1min or even 10 seconds charts to explore high frequency trading methods.