Market Regime Analysis: Trading Behavior vs Market Sentiment

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1. Objective

The objective of this project is to analyze how **trading behaviour** (profitability, risk exposure, emotional intensity, and volume) aligns or diverges from **overall market sentiment** (Fear, Greed, Extreme Greed, Neutral).

The goal is to identify **hidden behavioural patterns and market regimes** that can be used to design **smarter, data-driven trading strategies**, rather than relying on intuition or emotions.

2. Data Description

Two datasets were used:

1.Trade-Level Data

- Individual trades with timestamps
- Profit/Loss (Closed PnL)
- Trade size (Size USD)
- Risk exposure (Start Position)
- Win/Loss outcomes

2.Fear & Greed Index

- Daily market sentiment classification
- Categories: Fear, Greed, Extreme Greed, Neutral

3. Data Preprocessing, Timestamp Handling & Dataset Integration

3.1 Challenges in Raw Data

The two datasets used in this analysis were generated from **independent sources** and therefore differed significantly in structure and time representation:

- The **trade dataset** contained high-frequency transaction-level data with timestamps recorded in **Unix epoch format (milliseconds)**.
- The **Fear & Greed Index dataset** provided **daily sentiment classifications** with standard calendar dates.

Because of this mismatch, a direct merge was **not possible without careful timestamp normalization**. Improper handling would lead to incorrect sentiment assignment and misleading conclusions.

3.2 Timestamp Conversion and Normalization

The trade data timestamps were initially misinterpreted, leading to default epoch values (e.g., 1970-01-01).
This occurred because the timestamps were stored in **milliseconds**, while standard Unix timestamps are often assumed to be in seconds.

To address this, timestamps were explicitly converted using millisecond precision:

trades['Timestamp'] = pd.to_datetime(trades['Timestamp'], unit='ms')

This step ensured that:

- Trade times were correctly mapped to real-world calendar dates
- Temporal alignment across datasets became reliable

The trading date was then extracted from the timestamp to enable daily-level aggregation:

trades['date'] = trades['Timestamp'].dt.date

3.3 Market Sentiment Date Processing

The Fear & Greed Index dataset provided sentiment labels at a **daily granularity**.
To align it with the trade data:

fear_greed['date'] = pd.to_datetime(fear_greed['date']).dt.date

3.4 Dataset Integration (Merging)

The two datasets were merged using a **left join** on the normalized date field:

```
merged = trades.merge(
    fear_greed[['date', 'Classification']],
    on='date',
    how='left'
)
```

This approach ensured:

- Every trade was preserved
- Market sentiment was attached only when available
- No artificial data loss occurred during integration

3.5 Handling Missing Sentiment Values

Not all trade dates had corresponding Fear & Greed sentiment values (e.g., dates outside the sentiment dataset range).

To prevent incorrect regime attribution, trades without valid sentiment labels were excluded from regime-level analysis:

```
merged_clean = merged.dropna(subset=['Classification']).copy()
```

This filtering step resulted in a **clean, sentiment-aligned trade dataset** suitable for behavioral analysis.

3.6 Importance of This Step

Accurate timestamp handling and proper dataset merging are **critical in financial analysis**, as even small misalignments can:

- Assign trades to incorrect market conditions
- Inflate or suppress regime performance metrics
- Produce misleading behavioral patterns

By explicitly normalizing timestamps and carefully integrating datasets, this analysis ensures that all subsequent insights are **time-consistent and methodologically sound**.

4. Feature Engineering

To capture trading behaviour across regimes, the following features were engineered:

- **Winning Trade Indicator**
  Whether a trade resulted in profit:

```
merged_clean['is_win'] = merged_clean['Closed PnL'] > 0
```

- **Emotional Intensity**
  Absolute profit or loss magnitude:

```
merged_clean['abs_pnl'] = merged_clean['Closed PnL'].abs()
```

These features allow separation of **performance outcomes** from **emotional magnitude**.

5. Summary Table: Aggregated Regime Metrics

To compare market regimes quantitatively, trade-level data was aggregated by sentiment classification.

5.1 Summary Metrics

The following metrics were computed per regime:

- **Average Profit per Trade**
- **Profit Volatility** (standard deviation of PnL)
- **Average Trade Size**
- **Average Risk Exposure**
- **Winning Trade Percentage**
- **Average Emotional Intensity**

This resulted in the summary table below:

	Sentiment	Average Profit per Trade (USD)	Profit Volatility (Risk)	Average Trade Size (USD)	Average Exposure	Winning Trade %	Emotional Intensity (Avg |PnL|)
0	Extreme Greed	25.418772	306.166937	5660.265764	70307.280908	0.490089	48.333821
1	Fear	50.047622	909.121796	5259.977837	13170.980222	0.415146	70.186245
2	Greed	87.894859	1148.343968	3182.883845	19741.005986	0.446471	116.121900
3	Neutral	22.229713	633.704815	3058.848110	5895.819177	0.317182	68.343278

5.2 Interpretation

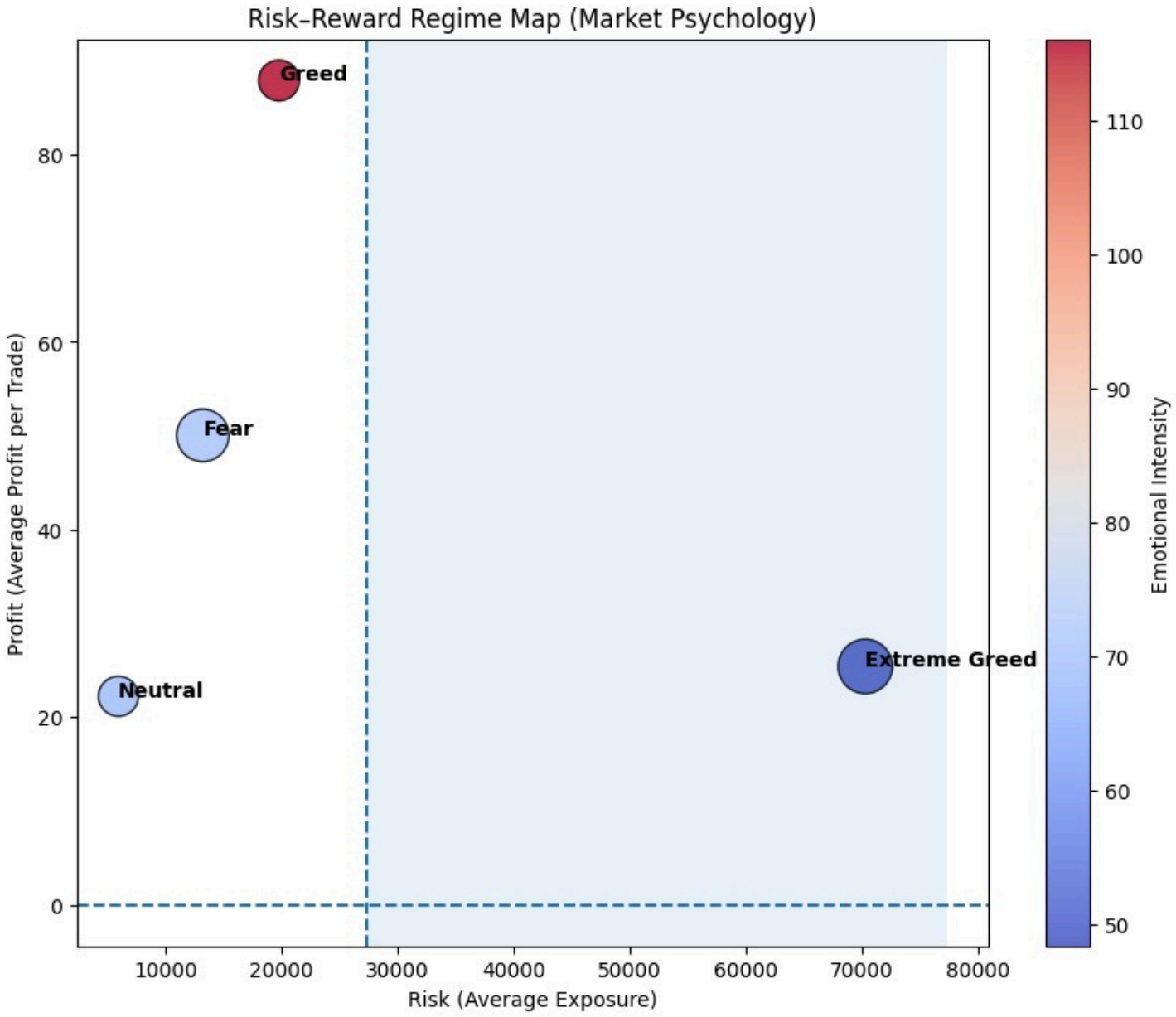
The summary table reveals that:

- **Greed** delivers the highest profitability despite lower exposure than Extreme Greed
- **Extreme Greed** involves excessive risk without proportional reward
- **Neutral** markets produce the weakest performance
- Emotional intensity peaks **before** risk peaks

This table forms the **numerical backbone** of the analysis and supports all visual findings.

6. Market Regime Analysis & Visual Insights

6.1 Risk–Reward Regime Map



This visualization combines:

- Risk (exposure)
- Profitability
- Emotional intensity
- Capital allocation

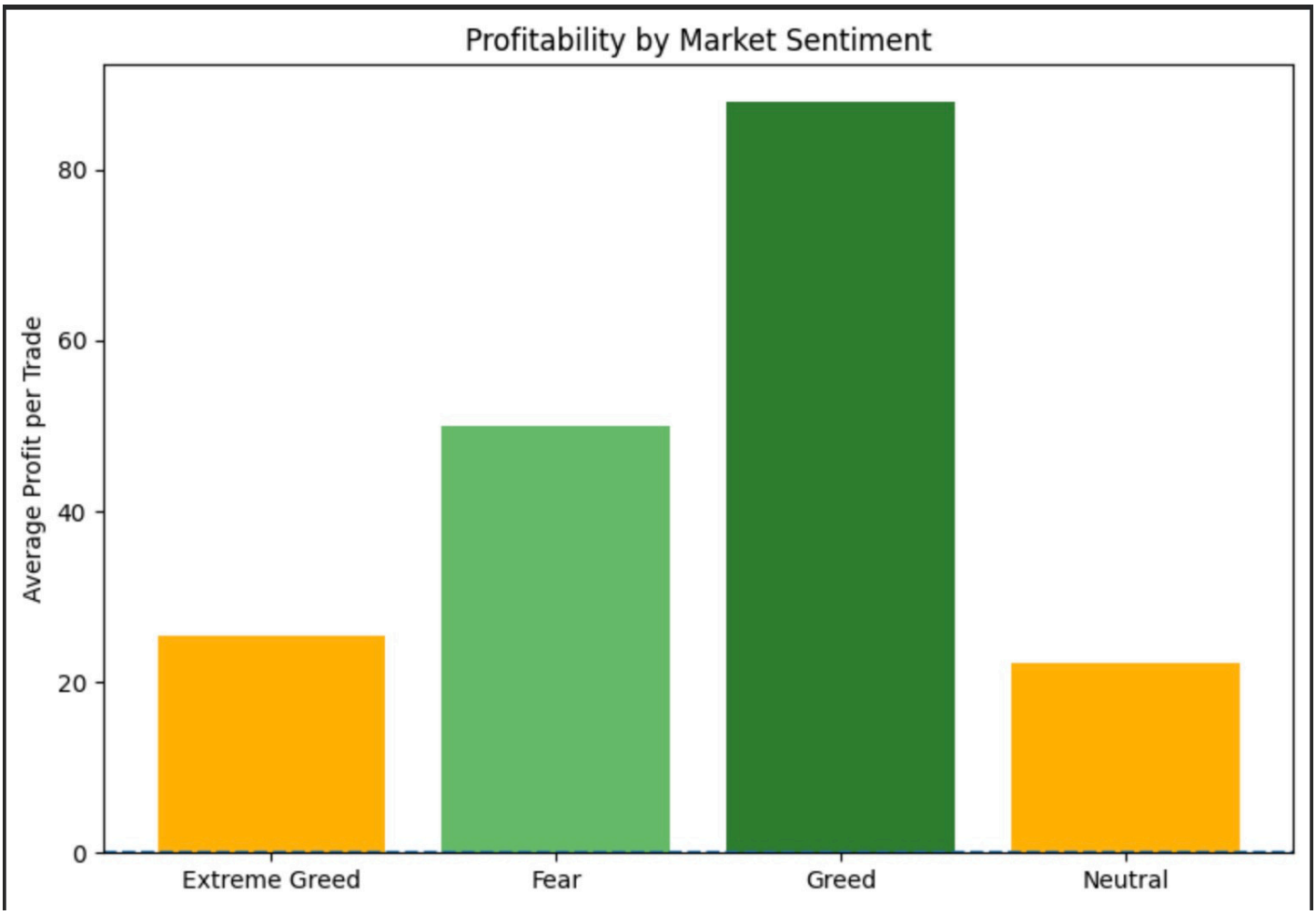
- **Greed** offers the best risk–reward trade-off, delivering high profits without extreme exposure.
- **Extreme Greed** shows very high risk with weakening returns, indicating bubble exhaustion.
- **Fear** is unstable, with inconsistent profitability despite elevated participation.

- **Neutral** regimes provide poor returns and limited opportunity.

Key takeaway: Optimal trading conditions emerge before emotional extremes.

Key insight:
The optimal trading regime occurs during **Greed**, while **Extreme Greed** represents a bubble-like state with poor risk-reward efficiency.

6.2 Profitability by Market Sentiment



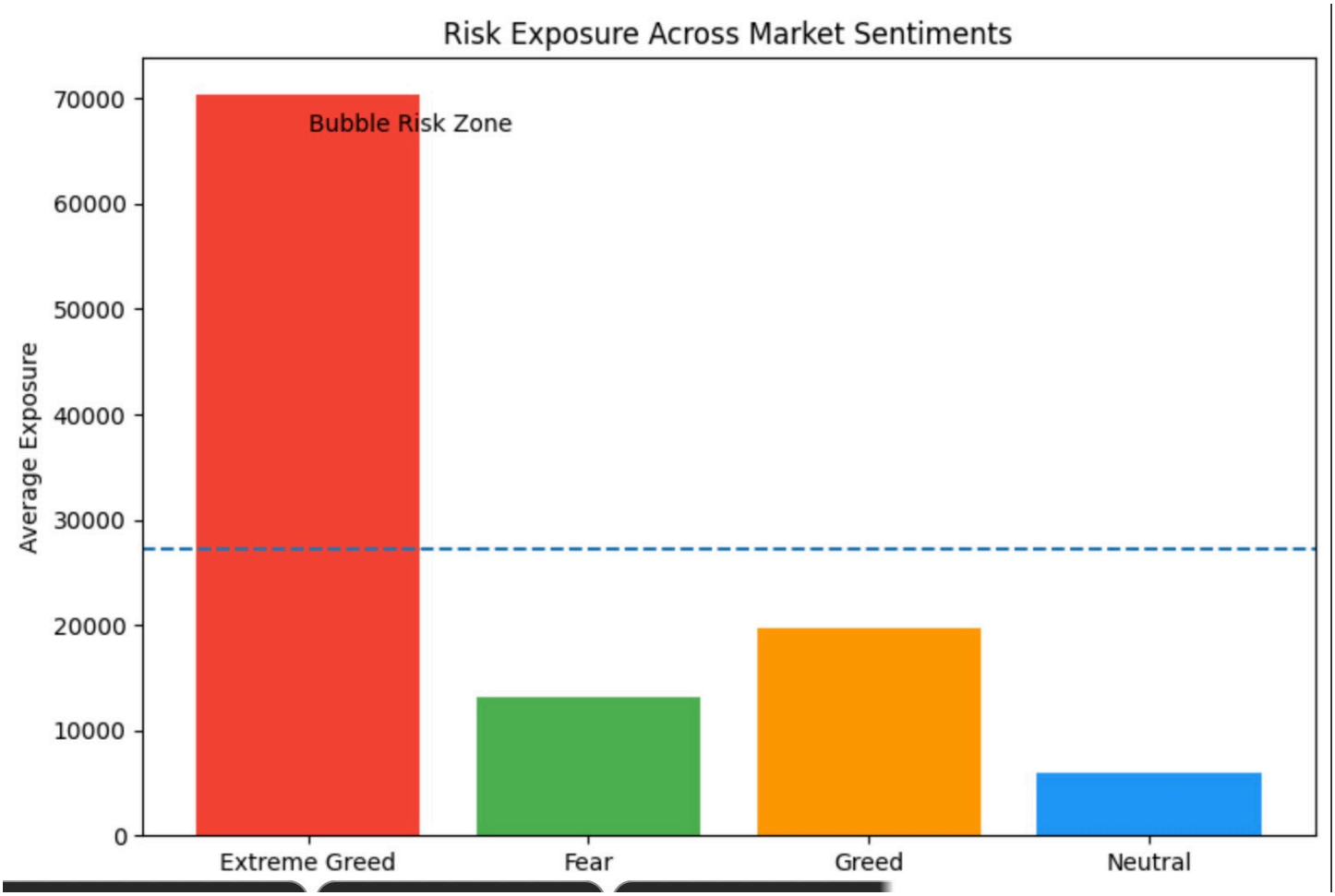
INSIGHTS-

- Average profitability peaks during **Greed**, not Extreme Greed.
- Increasing optimism beyond a point does not translate into higher returns.
- Neutral markets consistently underperform.

Key takeaway: Profits rise with optimism but decline once sentiment becomes euphoric.

- Profitability is not monotonic with optimism.
- Returns peak during **Greed**, not Extreme Greed, indicating diminishing returns at emotional extremes.

6.3 Risk Exposure Across Market Sentiments



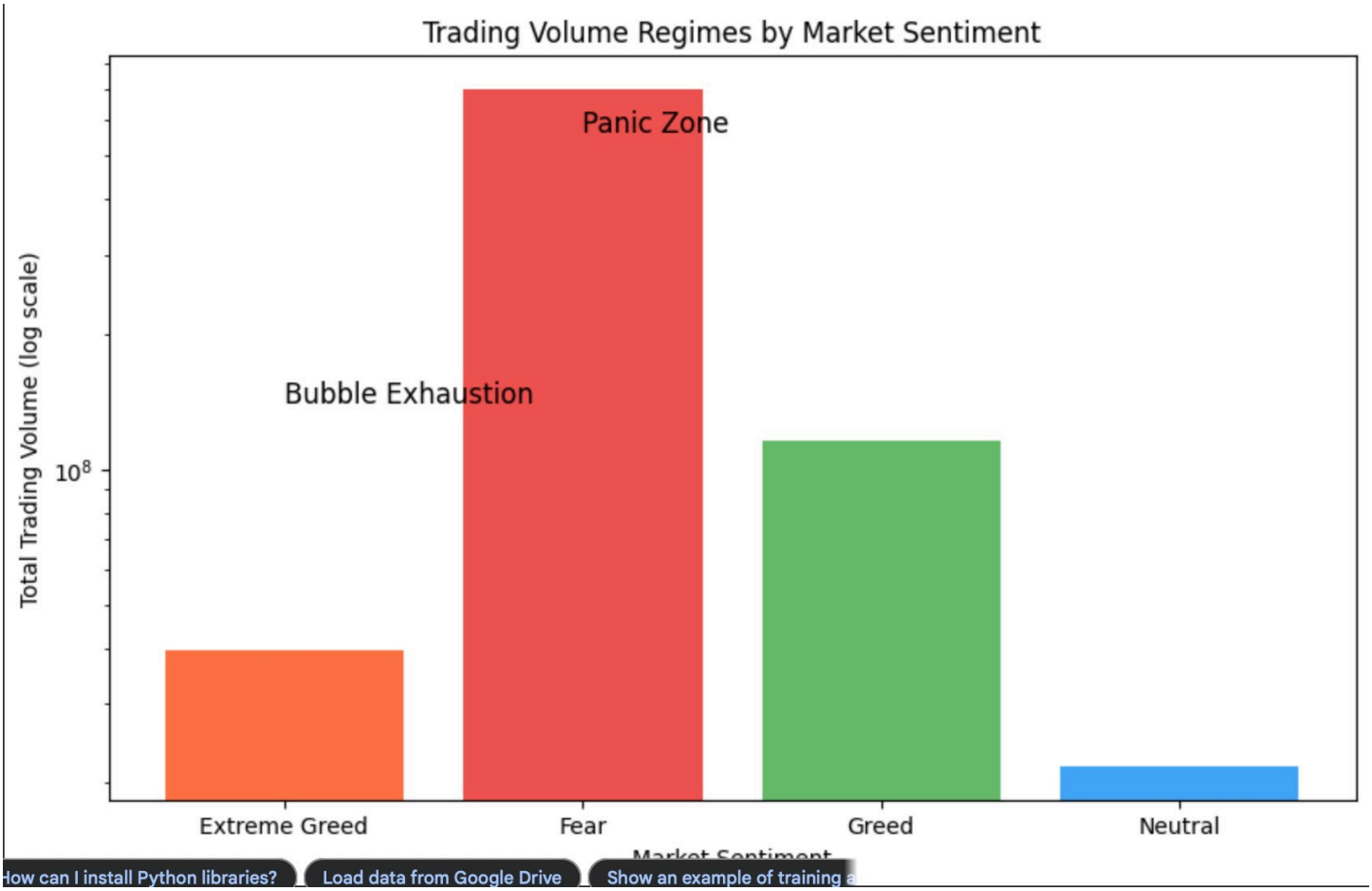
- Traders take disproportionately high exposure during **Extreme Greed**.
- This increase in risk is not matched by higher profitability.
- Risk-taking behavior appears driven by confidence rather than reward efficiency.

Key takeaway: Extreme Greed represents a high-risk, low-efficiency regime.

KEY INSIGHT-

- Traders take disproportionately high exposure during **Extreme Greed**, confirming overconfidence and bubble behavior.

6.4 Trading Volume Regimes (Log Scale)



Volume analysis on a logarithmic scale shows:

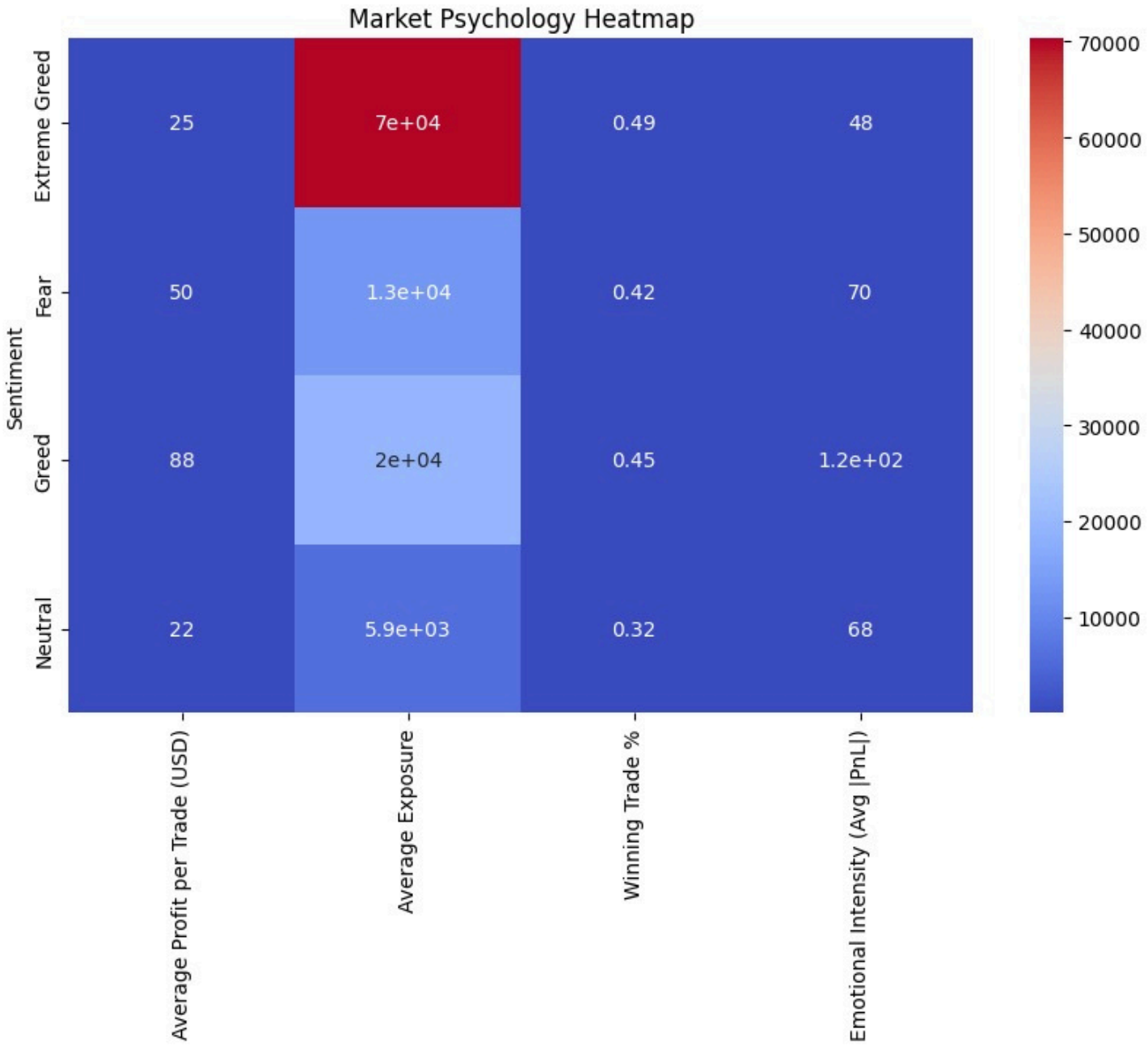
- **Fear** → panic-driven participation
- **Extreme Greed** → volume exhaustion
- **Neutral** → lack of conviction

Markets move in **orders of magnitude**, not linear steps.

- **Fear** is associated with order-of-magnitude higher trading volume, indicating panic and forced participation.
- **Extreme Greed** shows reduced volume, suggesting exhaustion after widespread positioning.
- Neutral markets show minimal participation.

Key takeaway: Volume spikes signal capitulation, while volume collapse signals bubble maturity.

6.5 Market Psychology Heatmap



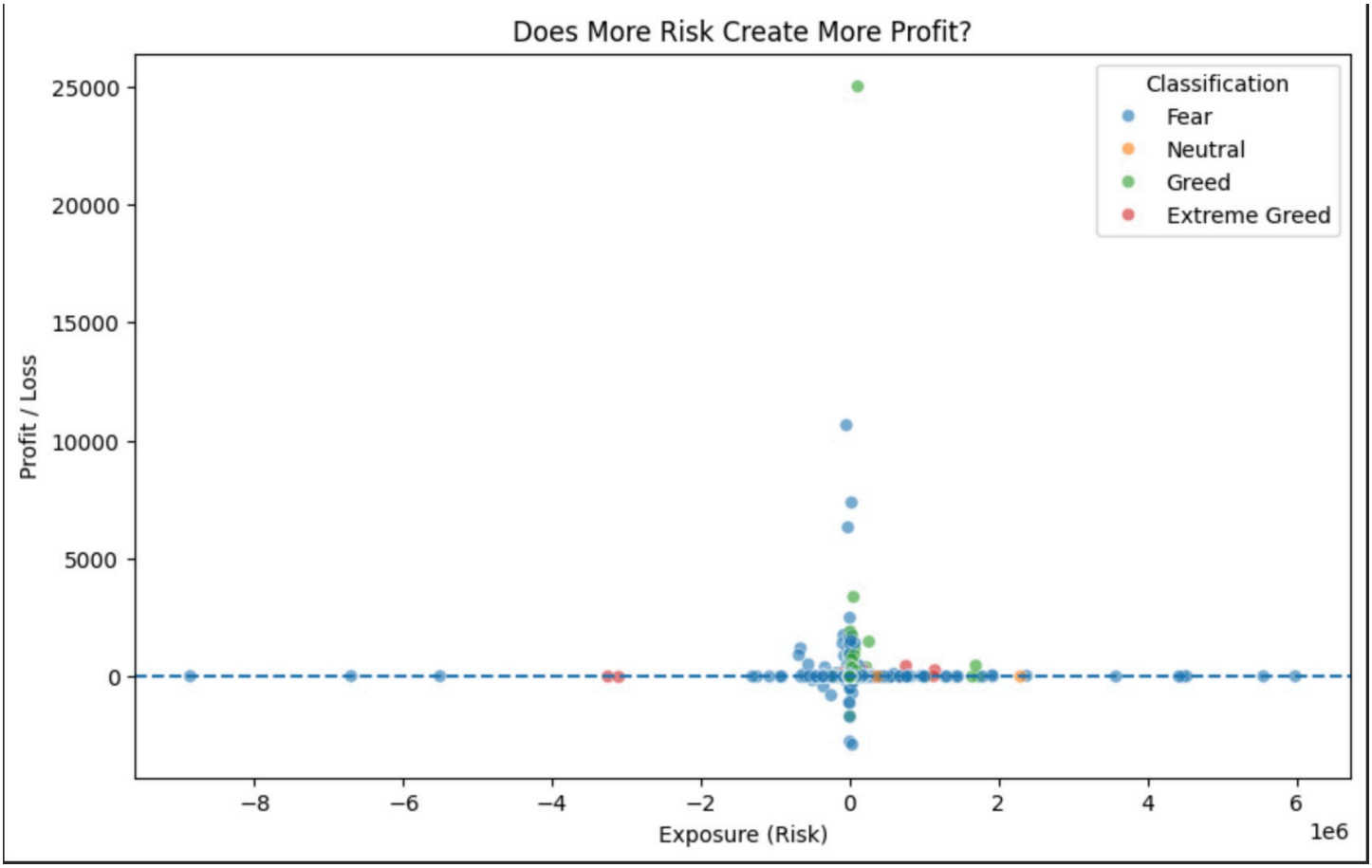
The Market Psychology Heatmap captures how profitability, risk exposure, win rate, and emotional intensity vary across market regimes. Each sentiment reflects a distinct behavioral state, not simply a stronger or weaker market.

- **Greed** emerges as the most efficient regime, combining the **highest average profit** with **controlled risk exposure**, indicating disciplined optimism where risk is rewarded.
- **Extreme Greed** shows **very high exposure but relatively low profitability**, suggesting overconfidence and late-stage positioning where the risk–reward balance deteriorates.
- **Fear** is characterized by **elevated emotional intensity and moderate profits**, reflecting panic-driven behavior where opportunities exist but outcomes are less consistent.
- **Neutral** markets exhibit **low engagement, weak profitability, and the lowest win rate**, indicating a lack of conviction and reduced trading efficiency.

Overall, the heatmap reveals that **maximum profits occur before risk and emotion reach extreme levels**, highlighting Greed—not Extreme Greed—as the most favorable trading

environment.

6.6 Risk Saturation: Does Higher Exposure Lead to Higher Returns?



- Increased exposure does not lead to proportional increases in profit.
- Beyond a threshold, additional risk yields diminishing or negative returns.
- Risk efficiency declines most clearly during Extreme Greed.

Key takeaway: More risk does not necessarily mean more reward.

7. Hidden Signals & Trading Implications

From the combined numerical and visual analysis, the following actionable signals emerge:

Market Regime	Behavioural Pattern	Trading Implication
Fear	Panic & liquidation	Defensive positioning
Greed	Healthy risk-taking	Best trading environment
Extreme Greed	Overconfidence & exhaustion	Reduce exposure
Neutral	Low conviction	Avoid trading

8. Key Takeaways

1. **Market sentiment forms distinct trading regimes, not a linear scale**
   The analysis shows that Fear, Greed, Extreme Greed, and Neutral each represent **qualitatively different market states** with unique combinations of profitability, risk, volume, and emotional intensity. Trading performance cannot be improved by assuming that more optimism always leads to better outcomes.
2. **The most profitable regime occurs before emotional extremes**
   Average profitability peaks during **Greed**, while both profits and win rates decline once the market enters **Extreme Greed**. This indicates that the best trading opportunities arise during early-to-mid optimism, not during euphoric market phases.
3. **Excessive risk-taking is poorly rewarded during Extreme Greed**
   Traders significantly increase exposure during Extreme Greed, yet this heightened risk does not result in proportionally higher returns. This mismatch suggests overconfidence and late-stage positioning, consistent with bubble-like market behavior.
4. **Fear-driven markets are dominated by panic rather than consistent opportunity**
   Fear regimes show elevated trading volume and emotional intensity, indicating forced exits and reactive trading. While volatility can create short-term opportunities, outcomes are less predictable and require strong risk controls.
5. **Neutral markets are structurally inefficient for active trading**
   Neutral sentiment exhibits the lowest win rates, limited volume, and weak profitability. The lack of directional conviction makes signal quality poor, suggesting that reduced trading activity is more effective than forced participation.
6. **Emotional intensity rises before performance deteriorates**
   Emotional intensity increases from Greed to Extreme Greed, but trading performance peaks earlier. This lag demonstrates that emotional engagement is a **leading indicator of risk**, not a guarantee of profit.
7. **Trading volume provides early signals of market stress and exhaustion**
   Panic-driven volume spikes during Fear indicate capitulation, while declining volume during Extreme Greed signals exhaustion after widespread positioning. Volume behavior therefore acts as a powerful confirmation signal for regime shifts.
8. **Risk efficiency declines beyond a threshold (risk saturation)**
   Increasing exposure does not produce linear increases in profitability. The risk–reward relationship shows diminishing returns at higher exposure levels, emphasizing the importance of position sizing and leverage control.
9. **Regime-aware strategies outperform sentiment-blind trading**
   By conditioning trading decisions on identified market regimes, traders can align risk-taking with favorable environments and reduce exposure during high-risk phases, leading to more stable performance.

Final Insight

Overall, this study demonstrates that **understanding trader behavior within sentiment-defined market regimes enables more disciplined, data-driven trading decisions**, reducing reliance on emotional reactions and improving long-term risk-adjusted performance.

9. Limitations & Future Work

- Analysis limited to available trade history
- Intraday sentiment dynamics not captured
- Future work could include:
- Regime transition modelling
- Predictive regime classification
- Asset-specific behavioural analysis

10. Conclusion

This analysis demonstrates that market sentiment is not merely an emotional indicator, but a **structural force that shapes trader behavior and market outcomes**. By aligning trade-level data with sentiment regimes derived from the Fear & Greed Index, the study reveals that markets operate through **distinct psychological states**, each with characteristic patterns of profitability, risk-taking, emotional intensity, and participation.

The findings show that **maximum trading efficiency occurs during moderate optimism (Greed)**, where risk-taking is rewarded and market participation remains healthy. In contrast, **Extreme Greed is characterized by excessive exposure without proportional returns**, indicating overconfidence and late-stage market behavior. Fear-driven regimes are dominated by panic and forced participation, while Neutral markets lack conviction and consistently underperform.

Importantly, the analysis highlights that **emotional intensity and risk escalation precede performance deterioration**, not the other way around. This sequencing explains why traders often experience declining returns at emotional extremes and underscores the importance of discipline and regime awareness.

Overall, this study confirms that **regime-aware trading—grounded in behavioral and quantitative signals—can significantly improve decision-making and risk management**. Rather than reacting to price movements or sentiment headlines, traders can use regime-based insights to identify favorable conditions, avoid structurally inefficient environments, and manage exposure proactively.

This framework provides a foundation for more resilient, data-driven trading strategies in volatile markets.