# Quantum-Inspired Observational–Expected Distribution Algorithm

This document presents a description of a quantum-inspired algorithm for managing and predicting outcomes with separate "observed" and "expected" amplitude distributions. The method is designed to capture and adapt to loose or cyclical patterns in a (near-)random process, especially one separated into two categories (`pb` and `mb`) that occur on different days of the week.

## 1 Overview

- **Major Sets**
  - `pb`: Occurs on Monday, Wednesday, and Saturday.
    - State space $\Omega_{pb}$ consists of combinations (5 from 1–69, 1 from 1–26).
  - `mb`: Occurs on Tuesday and Friday.
    - State space $\Omega_{mb}$ consists of combinations (5 from 1–70, 1 from 1–25).
- **Amplitude Distributions**

  Each major set has two separate amplitude distributions:

  1. **Observed Distribution** $\alpha^{(\mathrm{obs})}$ – tracks empirical data in near-real time.
  2. **Expected Distribution** $\alpha^{(\mathrm{exp})}$ – represents a stable forecast or model of future outcomes.

## 2 State Spaces

### 2.1 Define $\Omega_{pb}$

$$\Omega_{pb} = \{s \mid s \text{ is a 6-value outcome for pb}\}, \quad |\Omega_{pb}| = \binom{69}{5} \times 26.$$

### 2.2 Define $\Omega_{mb}$

$$\Omega_{mb} = \{s \mid s \text{ is a 6-value outcome for mb}\}, \quad |\Omega_{mb}| = \binom{70}{5} \times 25.$$

### 2.3 Initialize Distributions

For each set $\Omega_{pb}$ and $\Omega_{mb}$, initialize two vectors of amplitudes:

$$\alpha_s^{(\text{obs})} \quad \text{and} \quad \alpha_s^{(\text{exp})},$$

where $s \in \Omega_{pb}$ or $s \in \Omega_{mb}$. Each vector is normalized so that

$$\sum_{s \in \Omega_{pb}} \left|\alpha_s^{(\text{obs})}\right|^2 = 1, \quad \sum_{s \in \Omega_{pb}} \left|\alpha_s^{(\text{exp})}\right|^2 = 1,$$

and similarly for $\Omega_{mb}$.

## 3 Observational Updates

### 3.1 Observed Distribution Update

**Purpose** Reflects the direct frequency of outcomes in the data, potentially with a smoothing or decay factor to emphasize recent observations.

**Example Rule** When a new outcome $s_{\text{obs}}$ in $\Omega_{pb}$ or $\Omega_{mb}$ is recorded, update the corresponding observed distribution as follows:

1. Apply an exponential decay to all amplitudes:

   $$\alpha_s^{(\text{obs})} \leftarrow \gamma \cdot \alpha_s^{(\text{obs})},$$

   for each $s \in \Omega$, where $\gamma \in [0, 1)$ is a decay parameter.

2. Boost the observed amplitude for the actually drawn state:

   $$\alpha_{s_{\text{obs}}}^{(\text{obs})} \leftarrow \alpha_{s_{\text{obs}}}^{(\text{obs})} + (1 - \gamma).$$

3. Normalize to ensure:

   $$\sum_{s \in \Omega} \left|\alpha_s^{(\text{obs})}\right|^2 = 1.$$

### 3.2 Expected Distribution Update

**Purpose** Maintains a stable prediction model that does not overreact to individual observations.

**Example Rule** After updating the observed distribution, adjust the expected distribution with a small learning rate $\eta$:

$$\alpha_s^{(\text{exp})} \leftarrow \alpha_s^{(\text{exp})} + \eta\Big(\alpha_s^{(\text{obs})} - \alpha_s^{(\text{exp})}\Big).$$

Then normalize:

$$\sum_{s \in \Omega} \left|\alpha_s^{(\text{exp})}\right|^2 = 1.$$

## 4 Daily Procedure

The following procedure outlines how the algorithm is executed each day of the week, respecting the schedules for `pb` and `mb`:

**Algorithm QuantumInspiredObservationalExpectedModel:**

1. For each day $D$ in the repeating weekly cycle:
   (a) If $D$ is one of $\{$*Monday, Wednesday, Saturday*$\}$:
      i. Obtain the real-world outcome $s_{\text{obs}}$ in $\Omega_{pb}$.
      ii. Update Observed Distribution $\alpha^{(\text{obs, pb})}$:
         - Apply exponential decay: $\alpha_s^{(\text{obs, pb})} \leftarrow \gamma \cdot \alpha_s^{(\text{obs, pb})}$.
         - Increment $\alpha_{s_{\text{obs}}}^{(\text{obs, pb})}$ by $(1-\gamma)$.
         - Normalize $\alpha^{(\text{obs, pb})}$.
      iii. Update Expected Distribution $\alpha^{(\text{exp, pb})}$:
         - For each $s \in \Omega_{pb}$:

$$\alpha_s^{(\text{exp, pb})} \;\leftarrow\; \alpha_s^{(\text{exp, pb})} + \eta\Big(\alpha_s^{(\text{obs, pb})} - \alpha_s^{(\text{exp, pb})}\Big).$$

         - Normalize $\alpha^{(\text{exp, pb})}$.
   (b) Else if $D$ is one of $\{$*Tuesday, Friday*$\}$:
      i. Obtain the real-world outcome $s_{\text{obs}}$ in $\Omega_{mb}$.
      ii. Update Observed Distribution $\alpha^{(\text{obs, mb})}$:
         - Apply exponential decay: $\alpha_s^{(\text{obs, mb})} \leftarrow \gamma \cdot \alpha_s^{(\text{obs, mb})}$.
         - Increment $\alpha_{s_{\text{obs}}}^{(\text{obs, mb})}$ by $(1-\gamma)$.
         - Normalize $\alpha^{(\text{obs, mb})}$.
      iii. Update Expected Distribution $\alpha^{(\text{exp, mb})}$:
         - For each $s \in \Omega_{mb}$:

$$\alpha_s^{(\text{exp, mb})} \;\leftarrow\; \alpha_s^{(\text{exp, mb})} + \eta\Big(\alpha_s^{(\text{obs, mb})} - \alpha_s^{(\text{exp, mb})}\Big).$$

         - Normalize $\alpha^{(\text{exp, mb})}$.
2. End For

## 5 Optional Quantum Interference Extension

In a strictly real-valued approach, amplitudes $\alpha_s$ are non-negative. A quantum-inspired algorithm can allow **complex amplitudes** with phases, enabling interference effects:

1. **Complex Representation**:

$$\alpha_s = r_s \, e^{i\,\theta_s},$$

   where $r_s \geq 0$ and $\theta_s \in [0, 2\pi)$.

2. **Phase Updates**: Observed outcomes or suspected cyclical patterns can trigger phase shifts. For instance:

$$\theta_s \;\leftarrow\; \theta_s + \Delta\theta \quad \text{(constructive shift if } s \text{ aligns with observation)},$$

or

$$\theta_s \;\leftarrow\; \theta_s - \Delta\theta \quad \text{(destructive shift if } s \text{ conflicts with observation)}.$$

Magnitudes are also updated to reflect empirical frequency. This method can highlight or suppress overlapping patterns via interference.

3. **Normalization**:

$$\sum_s |\alpha_s|^2 = 1$$

remains a strict requirement after each update step.

# 6 Use Cases and Benefits

- **Adaptive Forecasting**: The expected distribution adjusts gently over time, guided by the observed distribution, which tracks new data more directly.
- **Noise vs. Pattern Detection**: Persistent increases in observed amplitude for certain outcomes indicate recurring patterns, while sporadic occurrences fade due to exponential decay.
- **Quantum-Inspired Explorations**: Introducing phases allows the system to represent and potentially amplify loose or cyclic patterns that might not be captured well by purely real-valued probability models.

# 7 Conclusion

The described *Quantum-Inspired Observational–Expected Distribution Algorithm* maintains two amplitude distributions for each major set (`pb` or `mb`), reflecting both empirical outcomes and stable predictive expectations. The daily update cycle ensures alignment with real-world data while avoiding overfitting to single observations. Extensions with complex phases permit interference, a core quantum phenomenon that can further expose or harness subtle recurring structures in near-random processes.