Exploration vs. Exploitation Challenge Framework

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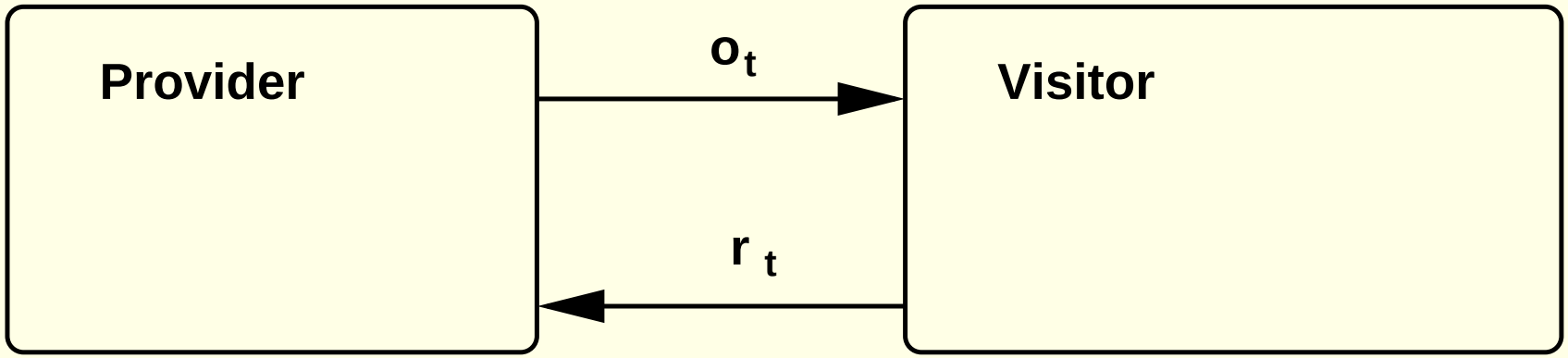
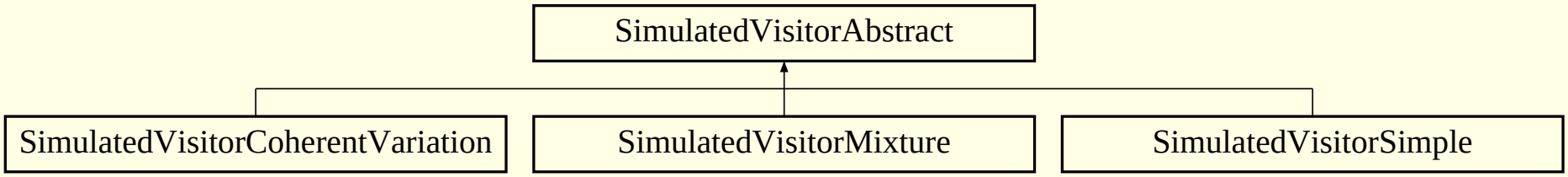
Overview



- A visitor represents a bandit problem.
- A provider realizes a bandit algorithm.
- An option o presented by the provider to the visitor represents an arm of the bandit problem.
- In contrast to the bandit problem, the success probability of an option varies over time: $\mathbf{P}\{r_t = \texttt{true} | o_t\} = p_t(o_t)$.

Simulated Visitors



- Main public method:

  `boolean selectOption( int optionNo )`

- The number `optionNo` of the selected option is passed to the visitor, and the visitor returns success (`true`) or failure (`false`), based on the current success probability of the option and the private coin toss of the visitor.

Simulated Visitors

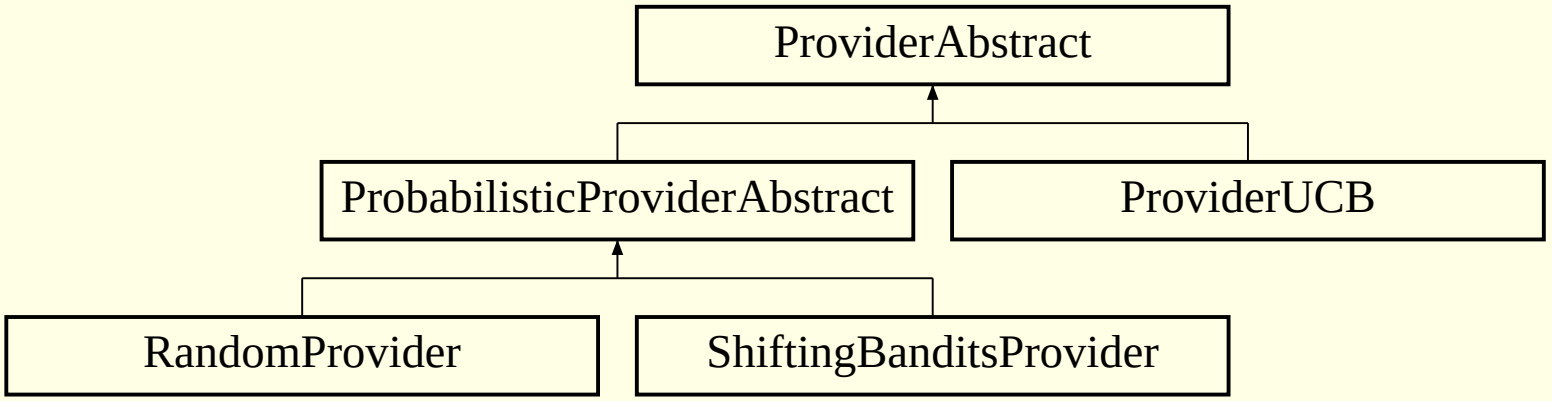
- Additional public methods:
  - `int getNumOptions()`

    Returns the number of available options, $\{0, \ldots,$ `getNumOptions()` $- 1\}$.
  - `float getRegret()`

    Actual regret as compared to the sum of success probabilities of the best option in each trial:

$$\sum_t \max_o p_t(o) - \#\{t : r_t = \texttt{true}\}.$$

Baseline Solutions



- A provider presents options to a visitor.
- The base classes and exemplary learners have been implemented.
- Public constructor:

```
ProviderAbstract(
    SimulatedVisitorAbstract visitor)
```

ProviderAbstract Interface

- `void satisfy()`

  Asks the provider to present an option `o=getCurrentChoice()` to the visitor.

  The response `r` of the visitor is received and the state of the provider is updated by `updateState(o,r)`.

- `abstract int getCurrentChoice()`

  `abstract void updateState( int o, boolean r )`

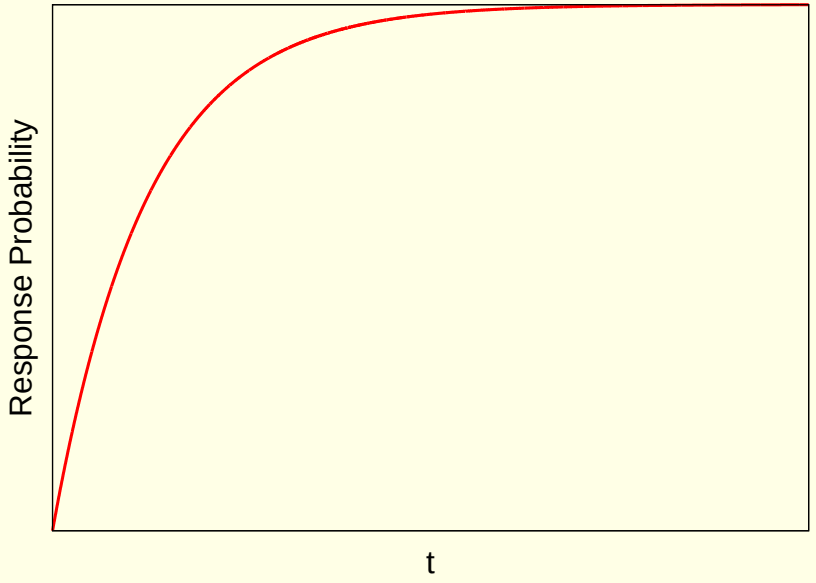
  have to be implemented by the derived classes.

Derived Provider classes

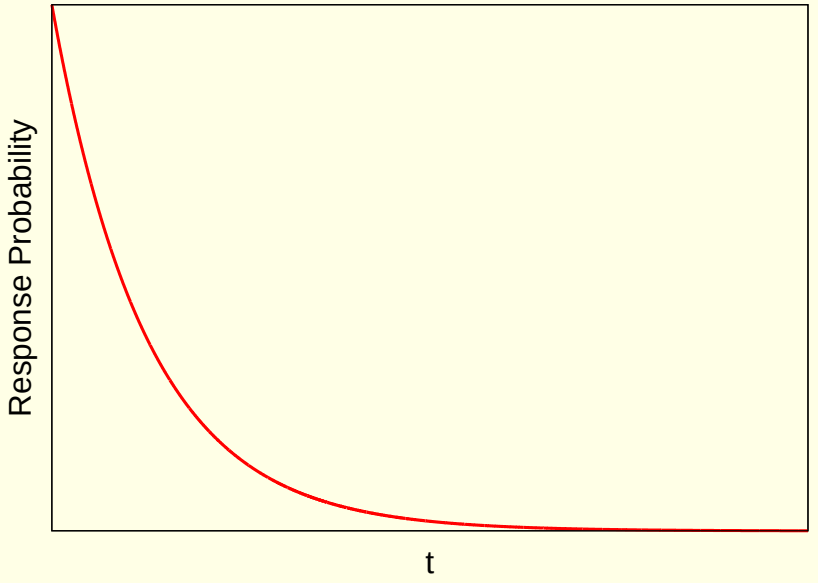
- `ProviderUCB`:
  Deterministic algorithm for random bandit problems.
- `ProbabilisticProviderAbstract`:
  Base class for learners which provide a probability distribution over the options.
  It implements `getCurrentChoice()` by choosing according to this probability distribution.
  Derived classes have to generate this probability distribution in `updateState()`.
- `RandomProvider`:
  Chooses uniformly among the options.
- `ShiftingBanditsProvider`:
  Calculates the probability distribution according to the worst case bandit algorithm with shifting bandits.

Currently implemented options

AsymptoticGrowthOption



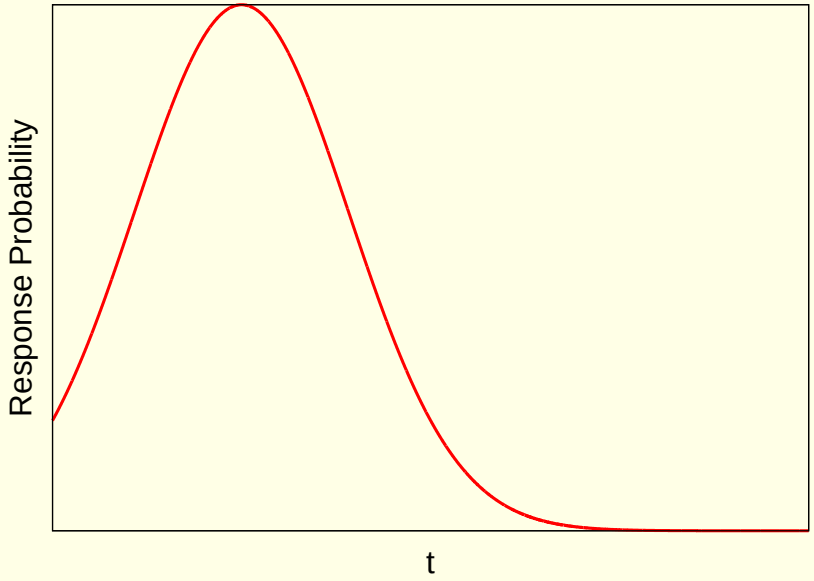
ExponentialDecayOption



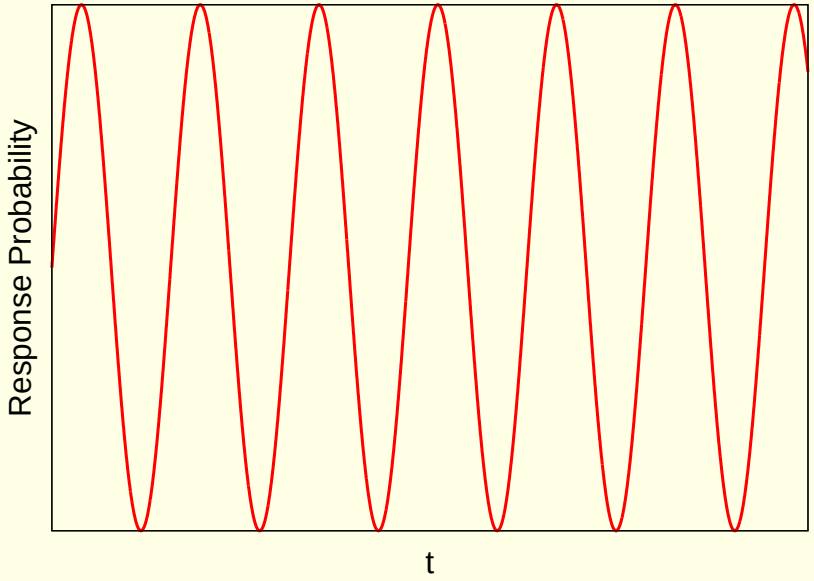
Parameters:
time constant, maximum probability

Currently implemented options

GaussianOption



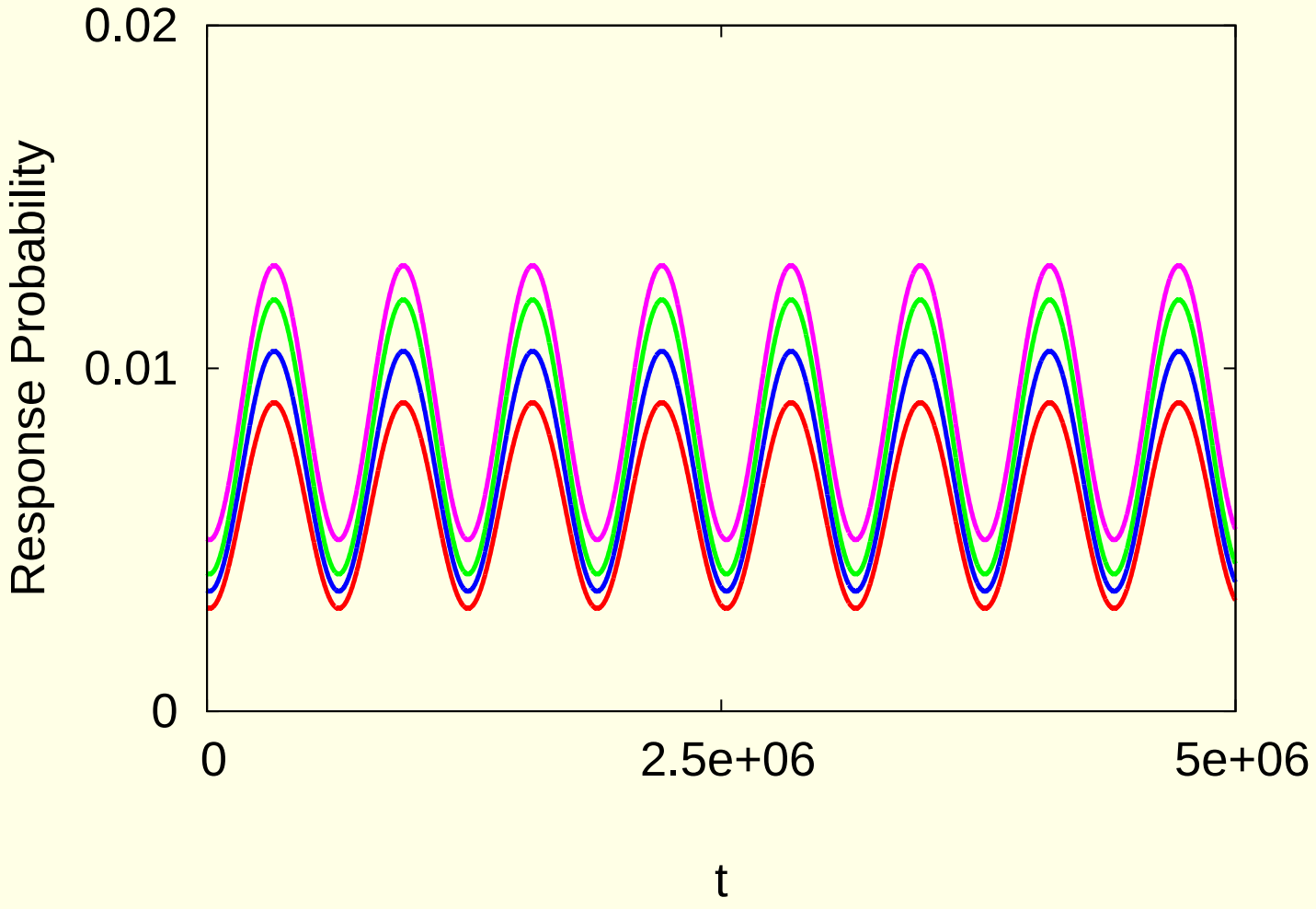
SinusoidalOption



Parameters:
mean, variance, maximum probability
phase offset, frequency, amplitude, amplitude offset

Visitors implemented for the challenge

SimulatedVisitorCoherentVariation



Visitors implemented for the challenge

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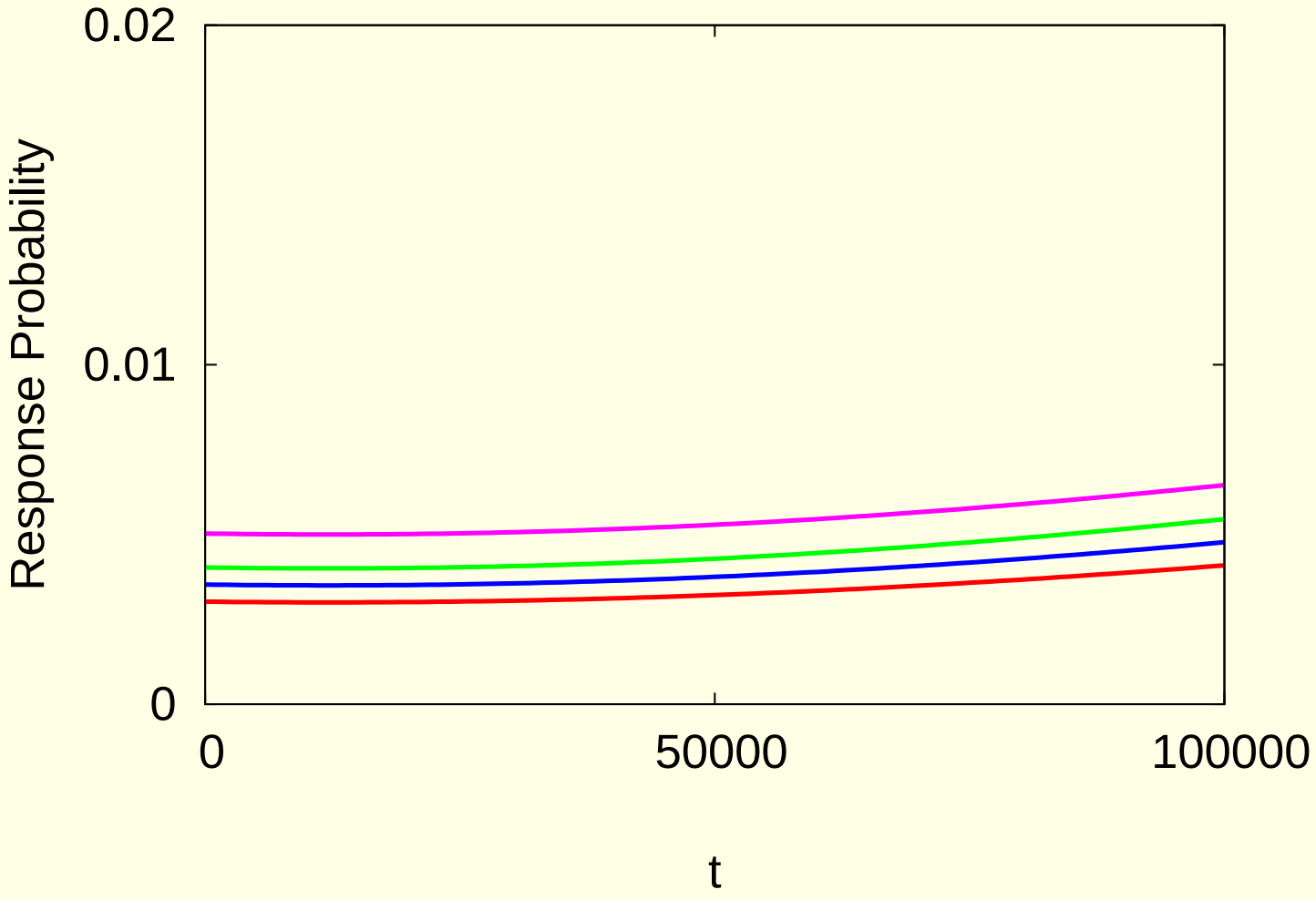
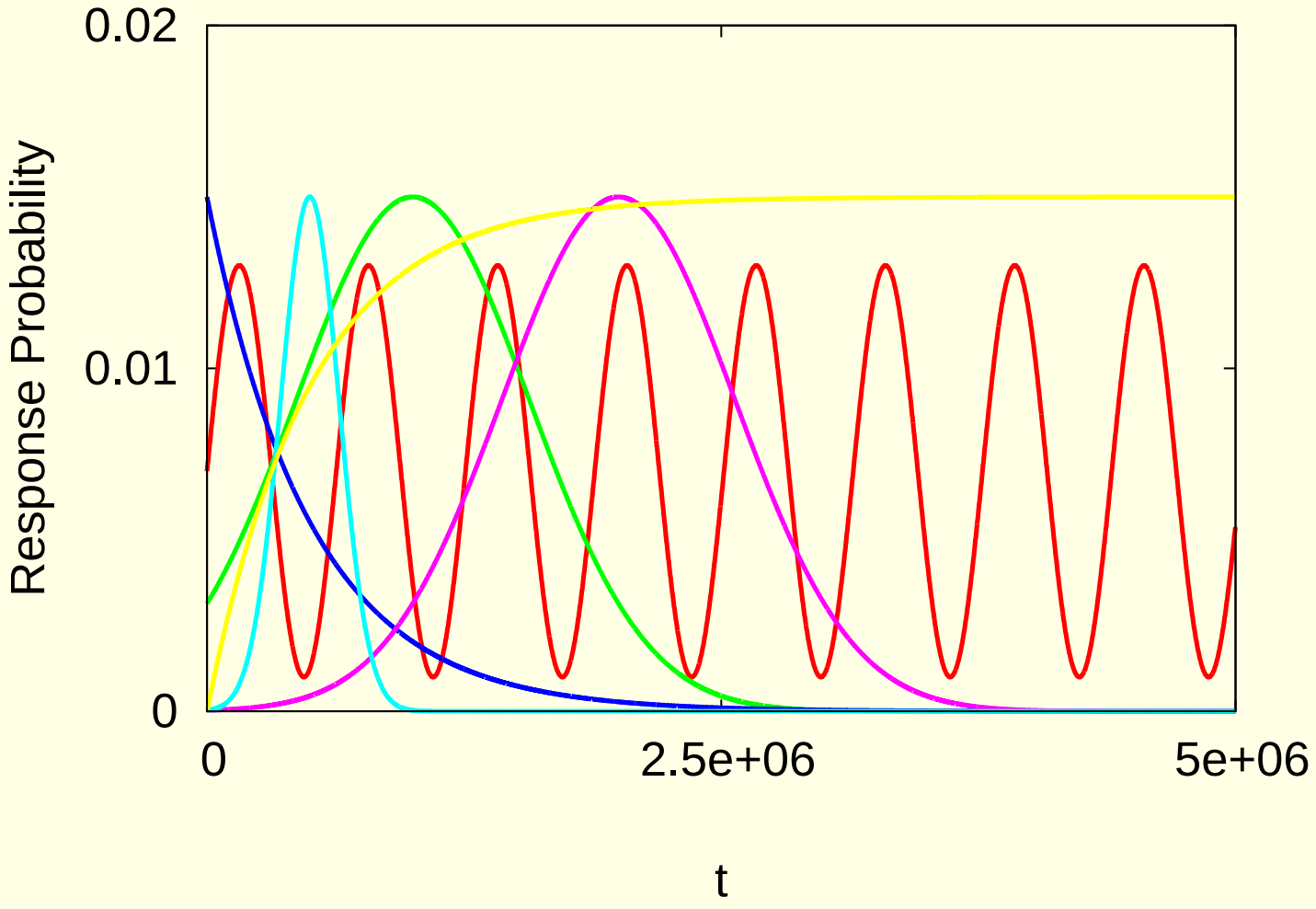


Visitors implemented for the challenge

SimulatedVisitorMixture



Visitors implemented for the challenge

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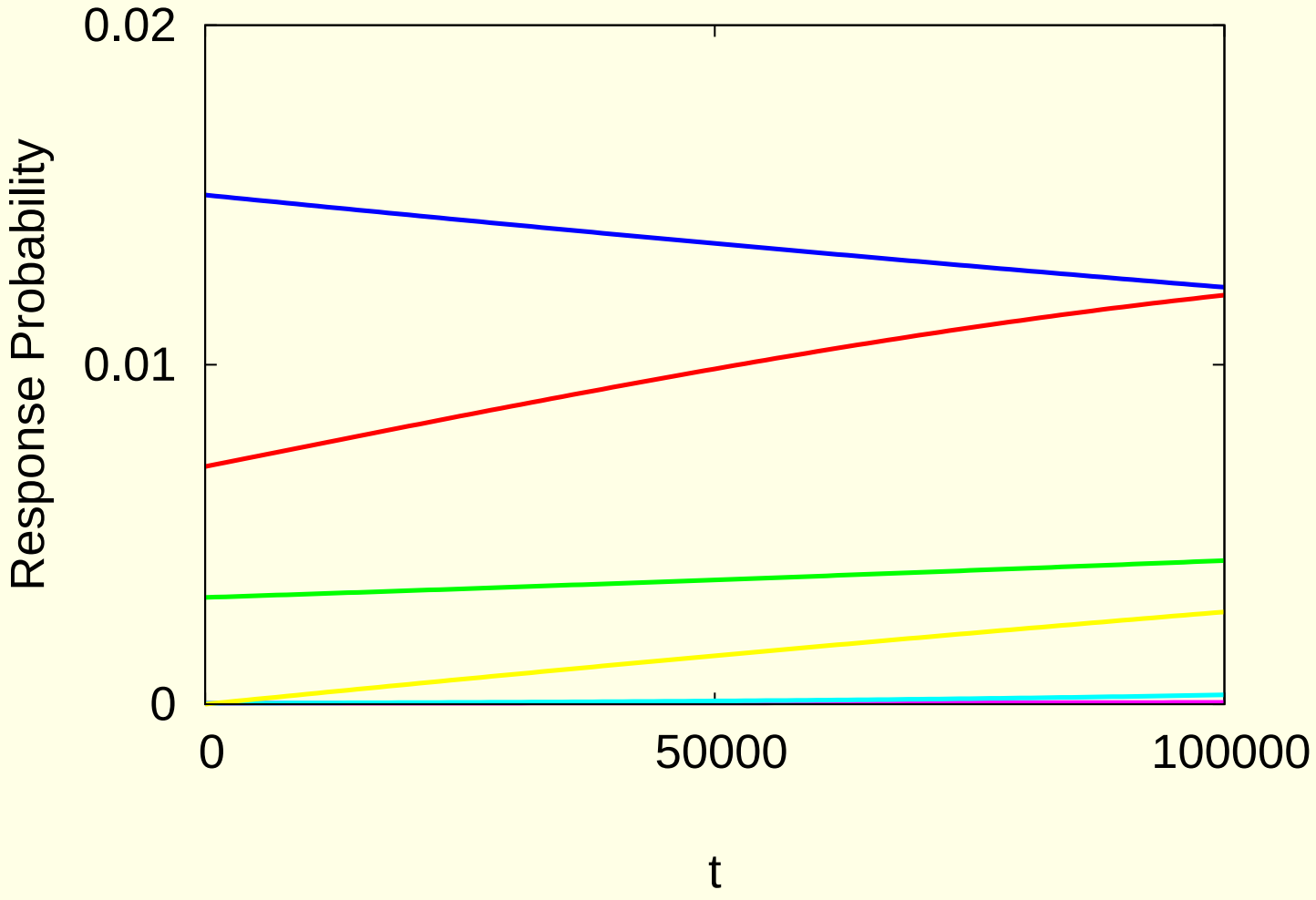
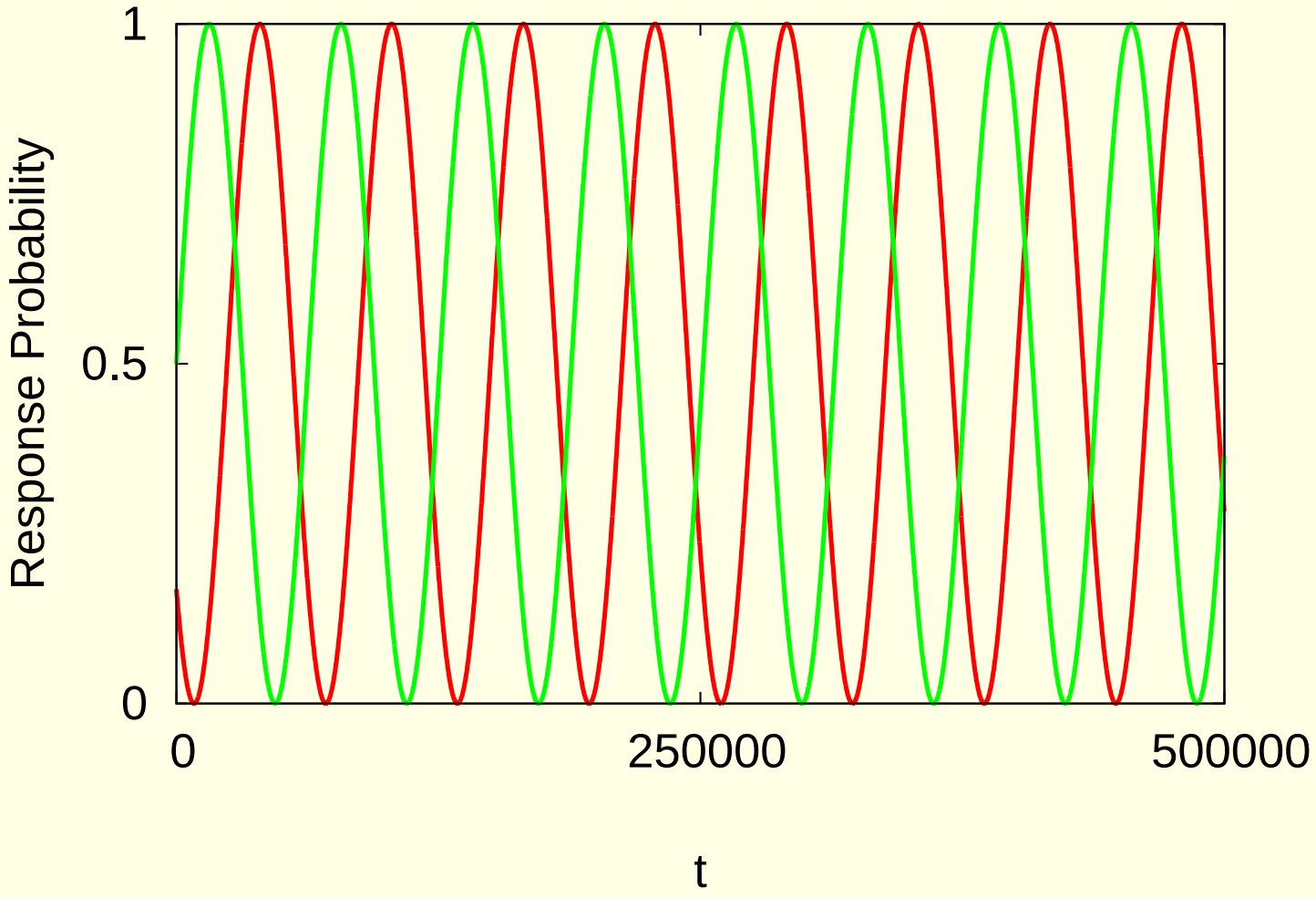


Visitors implemented for the challenge

SimulatedVisitorSimple



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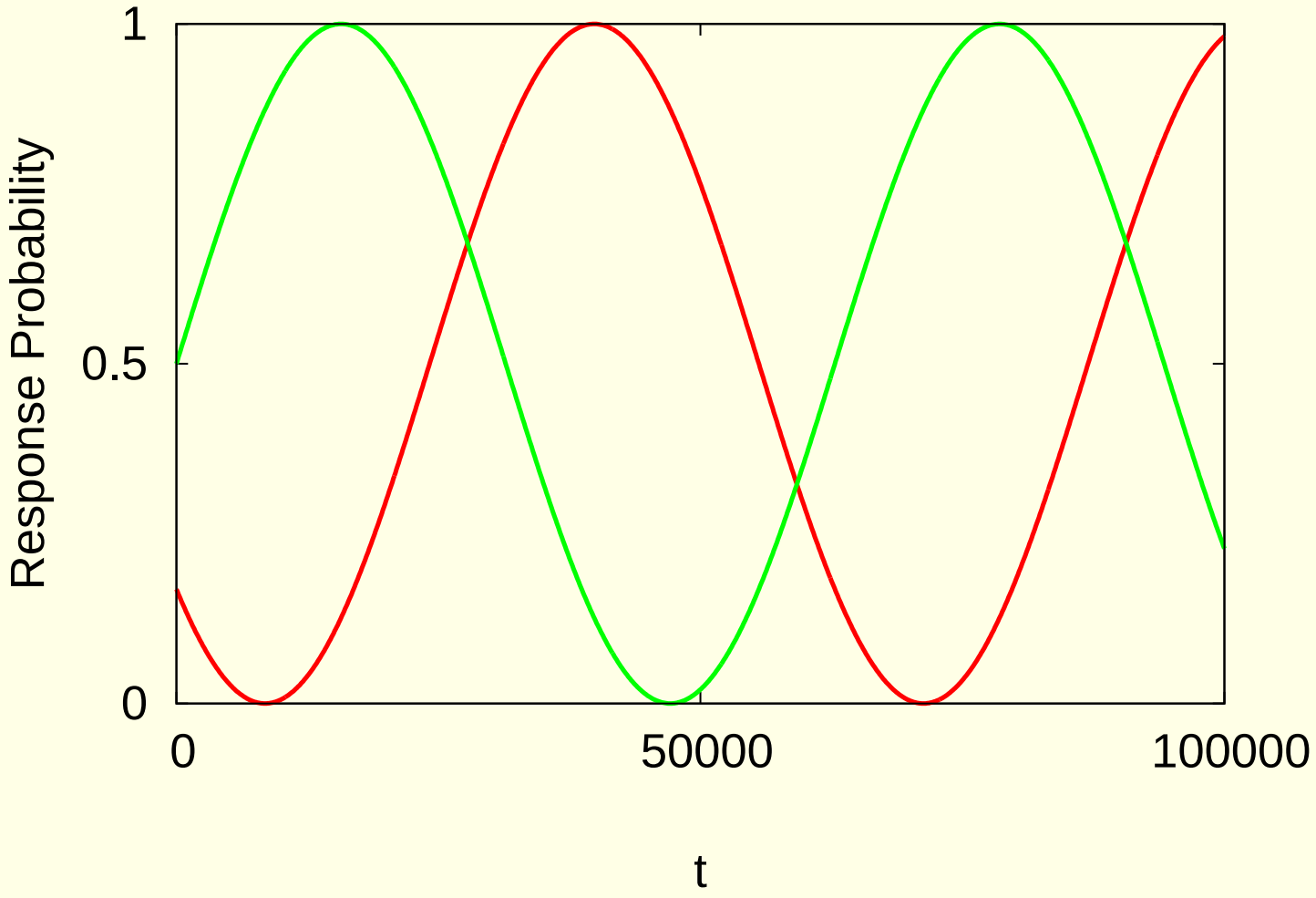

Shifting adversarial bandit algorithm

Adversarial bandits vs. random bandits:

- No statistical assumptions on how responses r_t are generated.
- Suitable for unknown, time varying success probabilities.
- The algorithm may again use upper confidence bounds.
- It keeps track of *shifts*, comparing the successes of the algorithm with the best *schedule* $t_1, \ldots, t_S$:

$$\max_{0=t_0<t_1<\cdots<t_S=T} \left(\sum_{s=1}^{S} \left[\max_{o} \sum_{t=t_{s-1}+1}^{t_s} p_t(o) \right] \right) - \sum_{t=1}^{T} r_t.$$

- Regret [ACFS'2002]: $\tilde{O}\left(\sqrt{TS}\right)$ instead of $O\left(\log T\right)$.

Shifting adversarial bandit algorithm

Parameter: S, T.

Initialization:

$\gamma = \sqrt{SK \log(KT)/T}$, $w(o) = 1$, $W = \sum_{o=0}^{K-1} w(o)$.

Repeat for $t = 1, \ldots, T$

1. Choose o_t according to $q(o) = (1-\gamma)\frac{w(o)}{W} + \frac{\gamma}{K}$.
2. If $r_t =$`true` then $w(o_t) \leftarrow w(o_t) \cdot \exp\left\{\frac{\gamma}{K}\frac{1}{q(o_t)}\right\}$.
3. $w(o) \leftarrow w(o) + W/T$.

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- By $w(o)$ an exponentially weighted "unbiased" estimate of the performance of option o is represented.

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- The term γ/K accounts for exploration.

Shifting adversarial bandit algorithm

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Repeat for $t = 1, \ldots, T$

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3. $w(o) \leftarrow w(o) + W/T$.

- The term W/T keeps weights sufficiently large such that a shift to a new best expert can be performed quickly.

Summary

- Presentation of the framework structure
- Introduction of
  - Baseline Solutions
  - Options
  - Simulated Visitors
- Identification of some problems to be addresses for phase 2 of the challenge.
- Sketch of the Shifting Bandit algorithm.