SINAPSE: Seasonal Inhomogeneous Nonconsecutive Arrival Process Search and Evaluation

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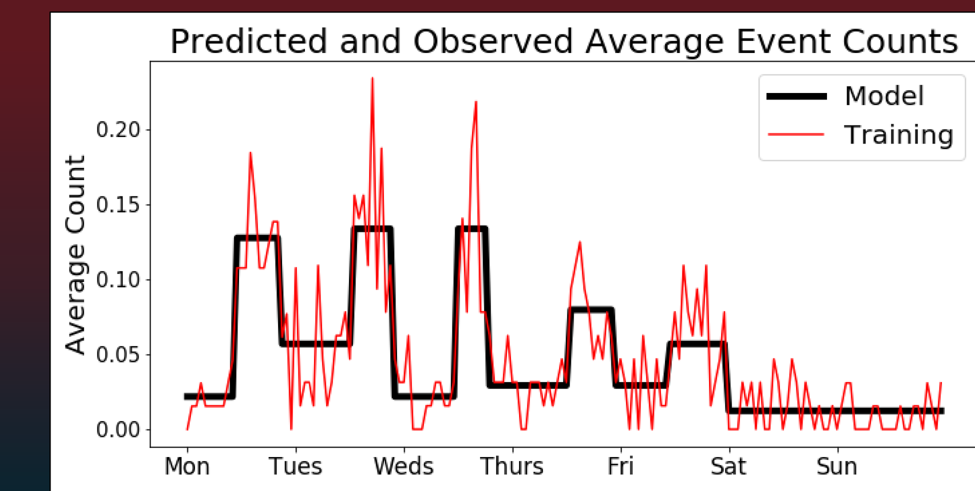
How to best model an arrival process, when:

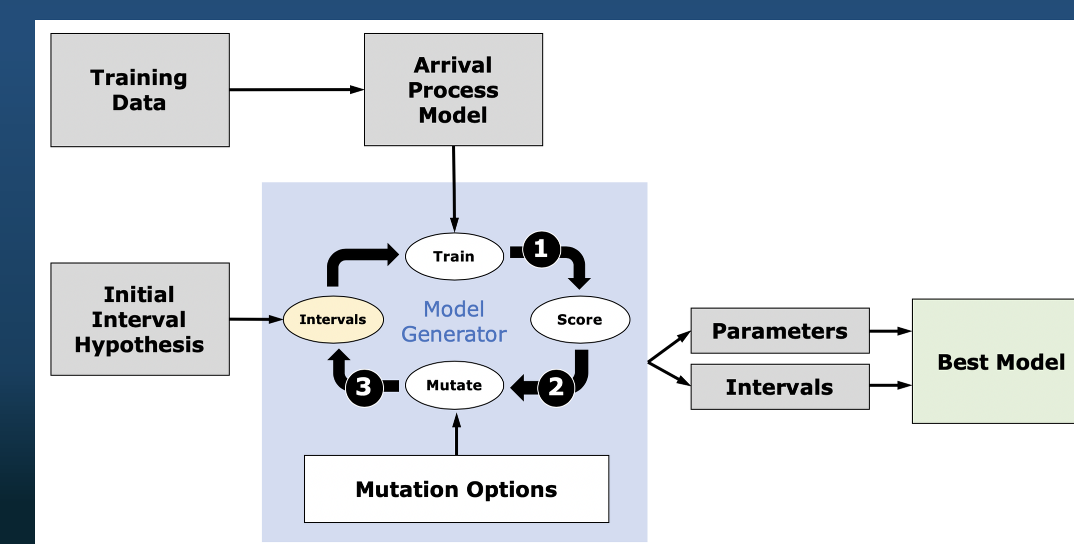
- The dataset is small and/or sparse
- The data exhibit seasonality
- The data includes points at which the parameters of the arrival process sharply change

- For example: malicious emails arriving at a company
- Few events make it difficult to model
- Behavior sharply changes by hour over the course of a week



Algorithm

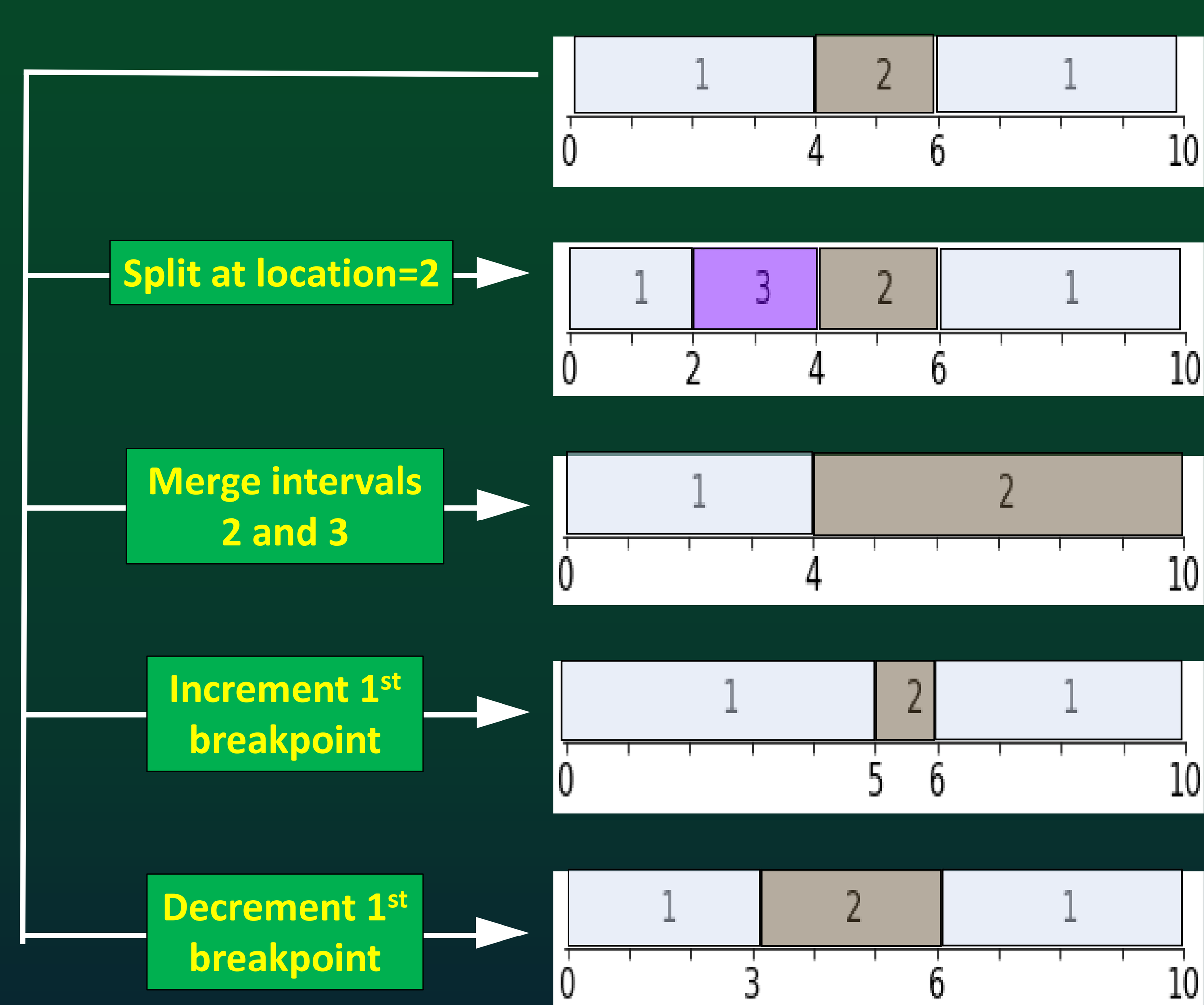
1. Start with a hypothesis division of the time period
2. Fit an arrival process model (Poisson, Negative Binomial, etc) and calculate a score (AICc)
3. Apply mutations by genetic algorithm
4. Repeat until convergence



Definitions

- Arrival process: A collection of points or events randomly placed in time
- Breakpoint: The point at which the distribution of a nonhomogeneous arrival process changes
- Interval: A closed, continuous subset of the timeline with the same set of parameters
- Regime: A collection of intervals, not necessarily contiguous, in which the point process follows a single set of parameters

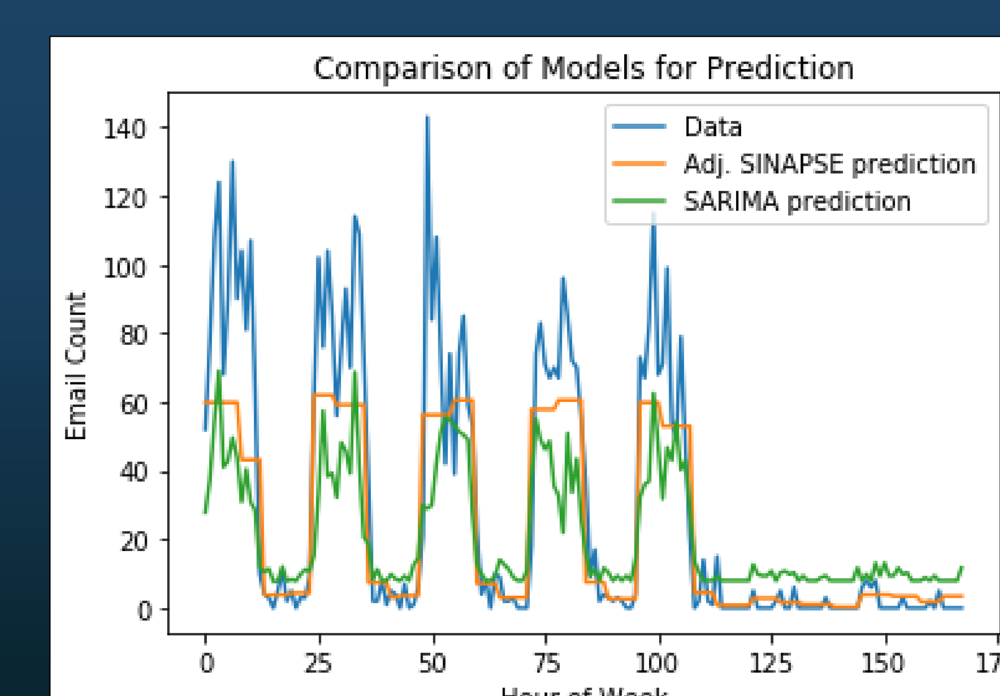
Intervals and Mutation

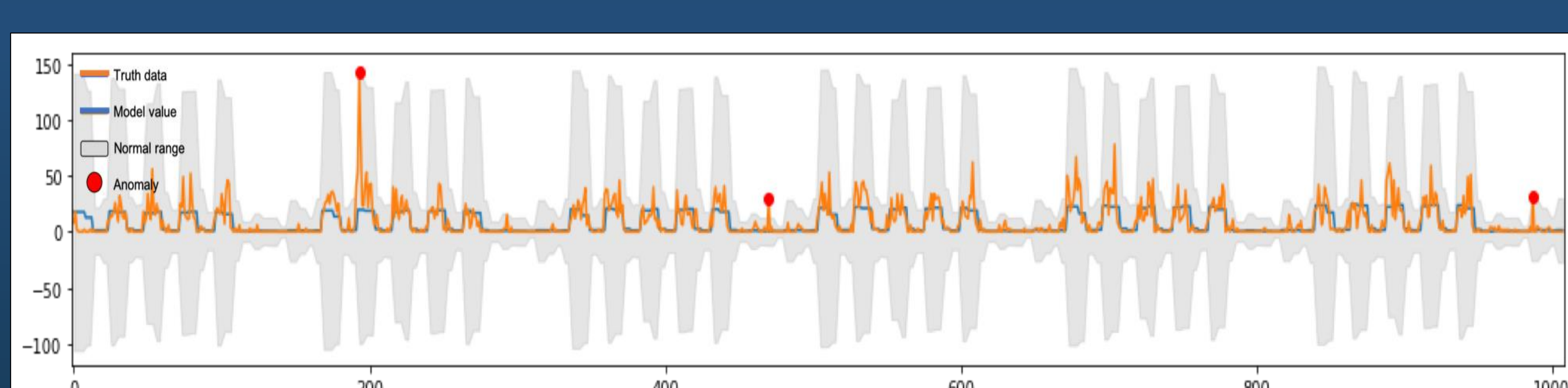


- Define an Interval: Divide the repeated period (often week) into intervals and assign intervals to regimes. Alternatively, start with homogeneous model (one interval and regime)
  - Interval regimes can be discontinuous, allowing a single set of parameters to govern disconnected time periods
- Mutate an Interval: allow for exploration of a space with an indefinite number of dimensions through breakpoint additions, deletions, increments, and decrements
  - Mutation driven by genetic algorithm to optimize a score or information criterion (AICc)
  - Balances modelling accuracy with overfitting by penalizing the number of parameters used

Application to seasonal prediction

- Use of an information criterion and discontinuous regimes leads to more parsimonious model
  - Models are less prone to overfitting
- Automatically group regions with similar occurrence patterns together identifying seasonal components
- Train on small and sparse datasets, automatically adjusting the complexity of the model to suit the data
- Comparison of SINAPSE to SARIMA model fits:





Application to anomaly detection

- SINAPSE-fit models inherently model the variance, which allows threshold-setting
- Example of 6 weeks of trend-adjusted data from the Enron dataset
- Red points correspond to anomalies

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