**Goal**

Partitioning of an event sequence into the subsequences generated by the different models (without knowing the models or the mixing process).

Allows for better analysis:
- Eliminates interference between models (decoupled).
- Allows for more sophisticated analysis algorithms on the shorter subsequences.
- Massive filtering in case the events of interest are generated by a single model.

**Applications**

- Automatic classification of activities of disguised users or web bots.
- Automatic separation of randomly intermixed text from different (and unknown) natural languages.

**Benefits**

- **Extremely fast:** Linear in time with respect to the length of the event sequence.
- **Memory efficient:** Uses a small constant amount of memory.
- **Easy to implement:** The code for the algorithm is less than 200 lines.

**Limitations**

- Requires irreversible Markov chain models.
- Is unable to separate Bernoulli models.

**Experimental Results**

**Synthetic Data**

- More data improves accuracy.
- Achieves **100% accuracy** for moderate amounts of data.

The graph above shows that, most of the time, the algorithm is either 0% accurate (not enough data) or 100% accurate (enough data).

**Real Data**

Correctly separates mixtures of English and Spanish **without knowing** anything about either language or how the mixing was done.