Generating Diverse Realistic Data Sets

(for episode mining)

Workshop "Practical Theories of Data Mining" @ ICDM 2012

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DTAI
MACHINE LEARNING

FWO
VLAANDEREN
Fonds Wetenschappelijk Onderzoek
Research Foundation – Flanders

My Motivation

- Involved in industry cooperation
- Time-stamped event data

$$\langle (E,1),(A,12),(B,15),(C,25),(D,26),(A,36),(B,38),\ldots \rangle$$

- Approach: episode mining
    - e.g. sliding window, minimal occurrence
- Off-the-shelf miner

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NO idea what to do with patterns!

- Approach ... ining
  - e.g. sliding window, minimal occurrence
- Off-the-shelf miner

Going to the literature

- Guidance which approach to use - none
- Significance measures - (almost) none
- Guidance where in the output relevant patterns are - (almost) none
- Guarantees that patterns are found at all - (almost) none

15 years of research

Why's that?

- Few temporal (real-life) data sets
  - Locked by NDAs
- Real-life data sets have no ground truth!
  - Post-hoc evaluation by domain experts
  - Opposed to a priori class labels

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Episode mining specific

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Episode mining specific

Pattern mining problem

Straight-Up Solution

- Generate diverse artificial data w/known patterns
  - Building on Laxman's generator
- Extensively evaluate different techniques/measures
- Develop guidelines when methods expected to work

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(Related episodes and HMMs)

Comparative Data Mining

A detour to knowledge discovery

1. Get hands on real life data
2. Generate artificial data w/same characteristics
3. Mine patterns on artificial & real life data
4. Use relationship known & mined patterns on artificial data to select patterns from real data

Laxman's generator

- n sequential patterns
- length N
- alphabet size M
- length of data sequence
- noise probability p
- uniform distributions for noise/time stamps

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- alphabet size M
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- $n=2$, $p \in [0.2, 0.5]$
- fixed M
- no sharing/repetition of elements
- interleaved episodes
- embedded concurrently

What's "realistic"?

- Time information matters
- Events might not be logged
- There might be several patterns
  - Differently likely
- Patterns might interleave/share events/ repeat events
- Patterns might occur successively
- Not only uniform distributions

This is anecdotal

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Episodes probably time-constrained

- Time information matters
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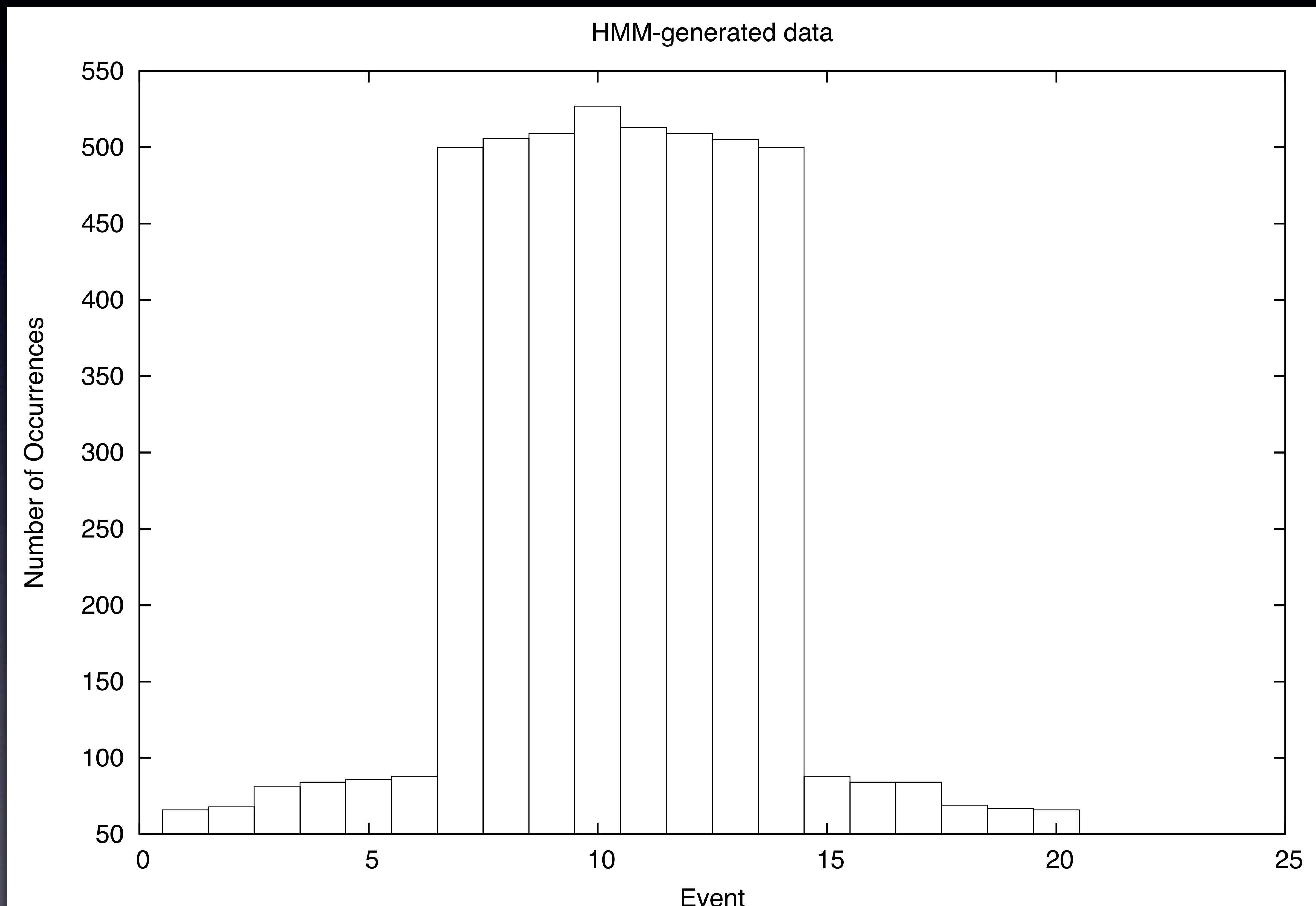
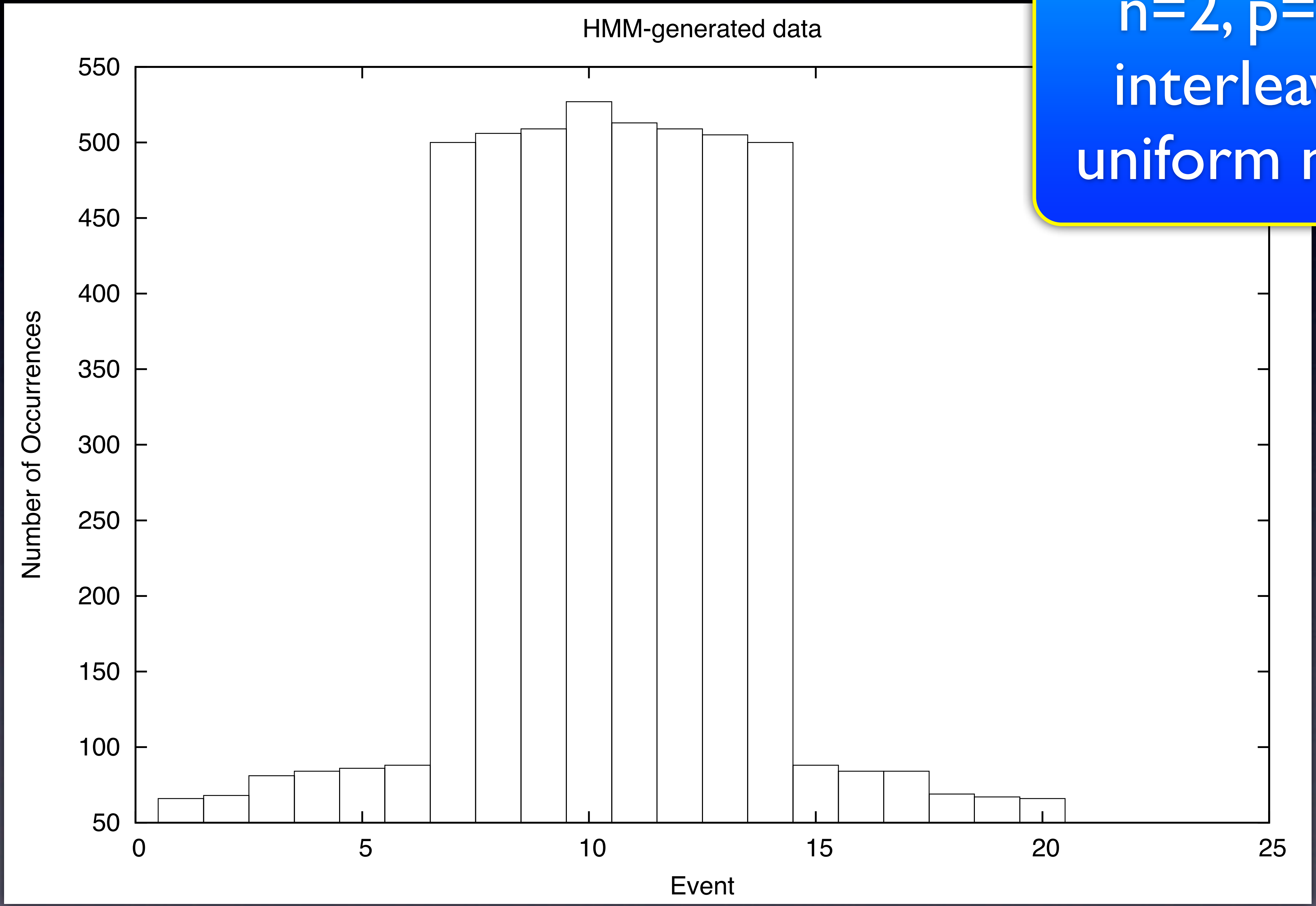
Adding parameters

- Failure (to log) probability
- Maximal delays explicit
  - Enforcement in episode
- Switches for sharing/repetition/interleaving/concurrency/weights
- Poisson distribution for noise
- (Mixture of) normal distribution(s) for delays

Different kinds of data



Different kinds of data



n=2, p=0.3
interleaved
uniform noise

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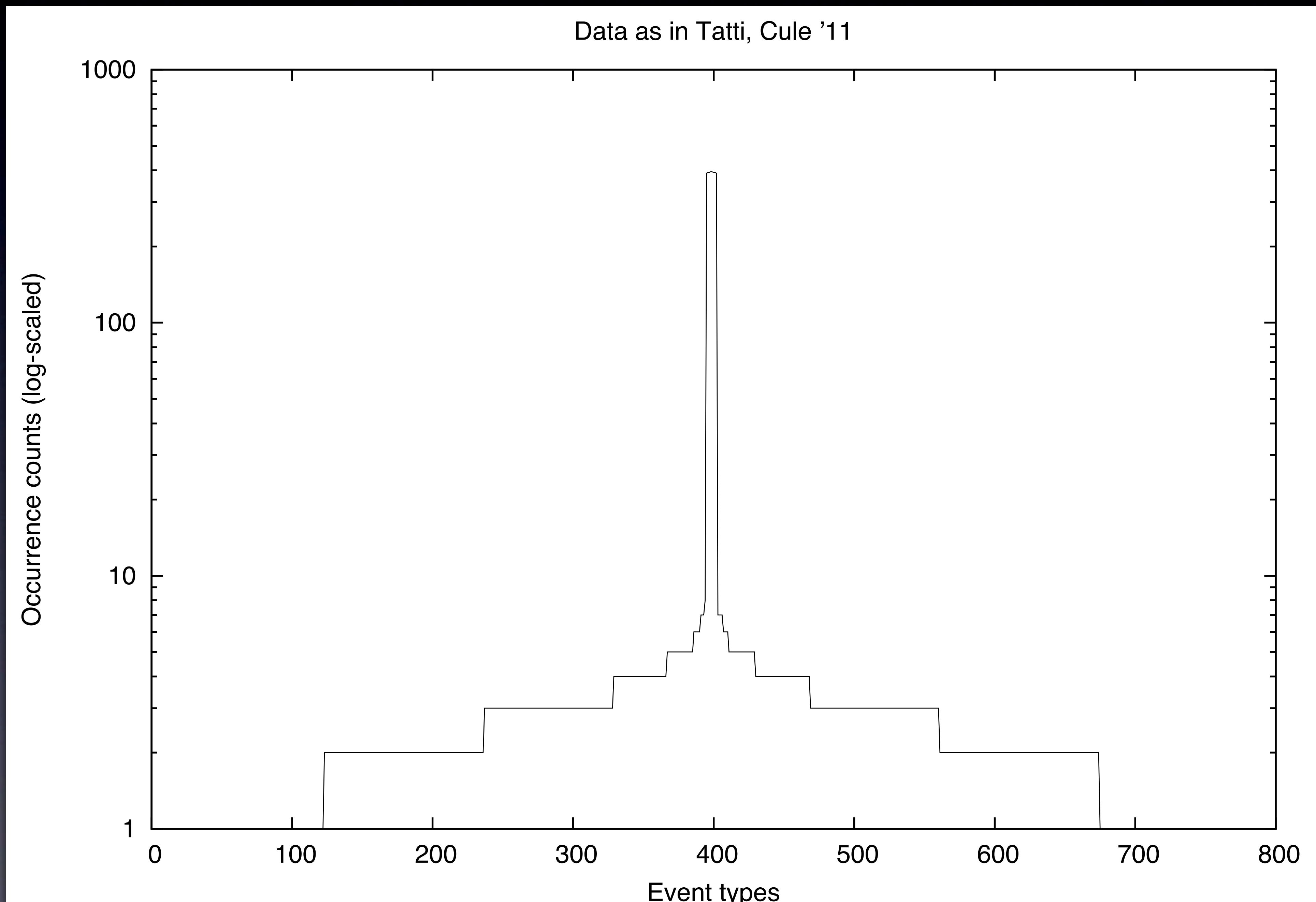

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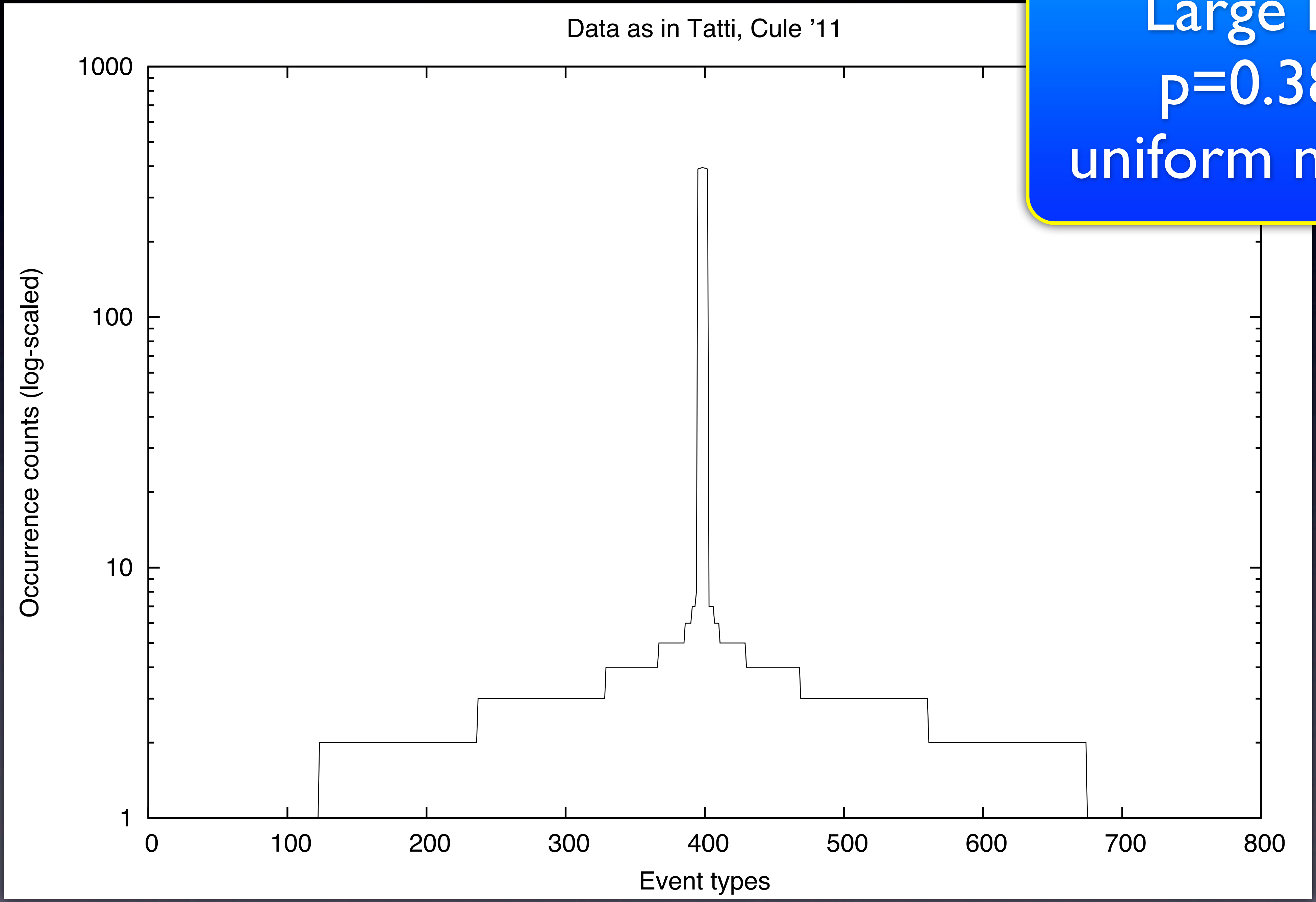

Large M
p=0.38
uniform noise

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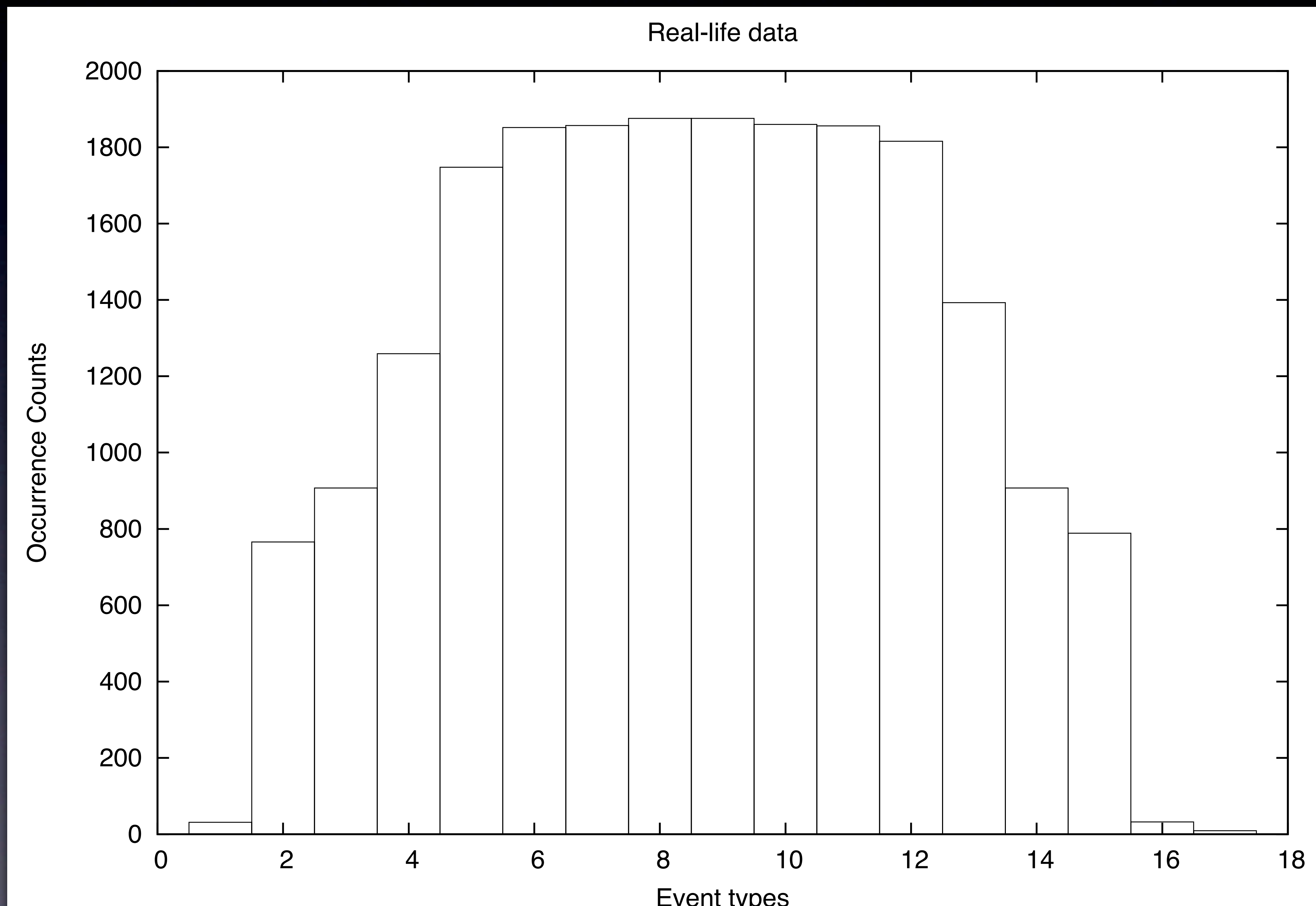

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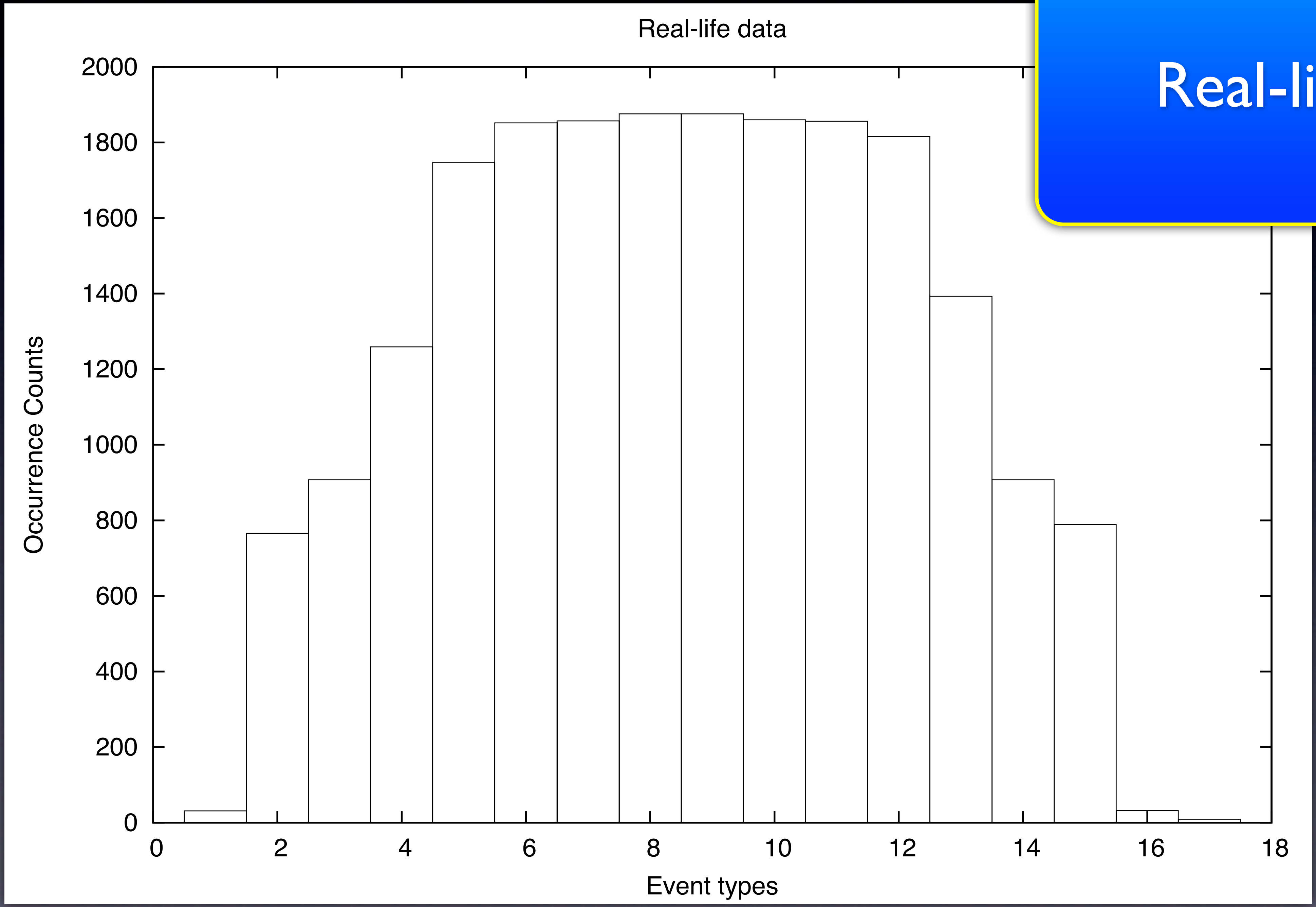
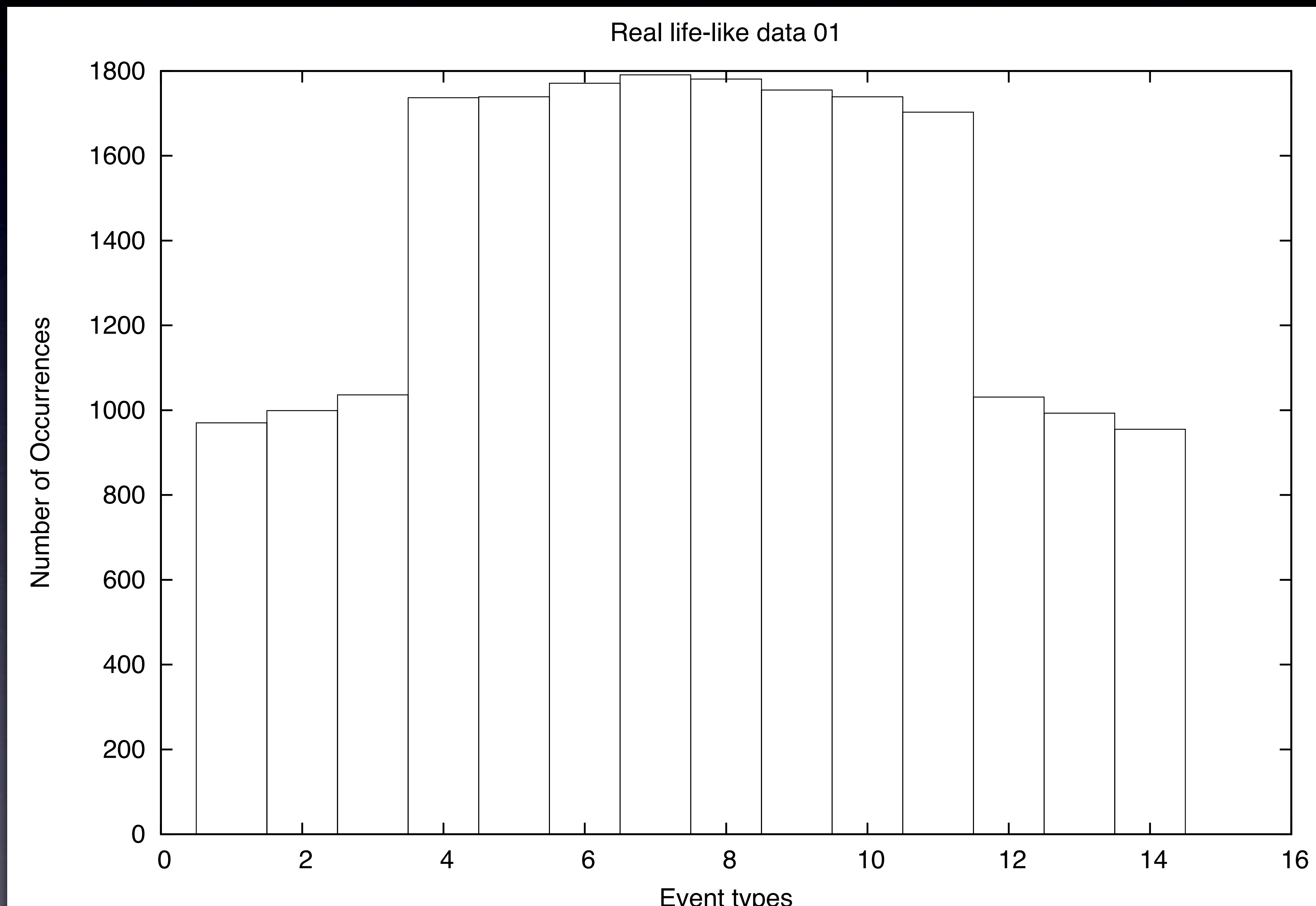


Real-life

Can I rebuild my data?



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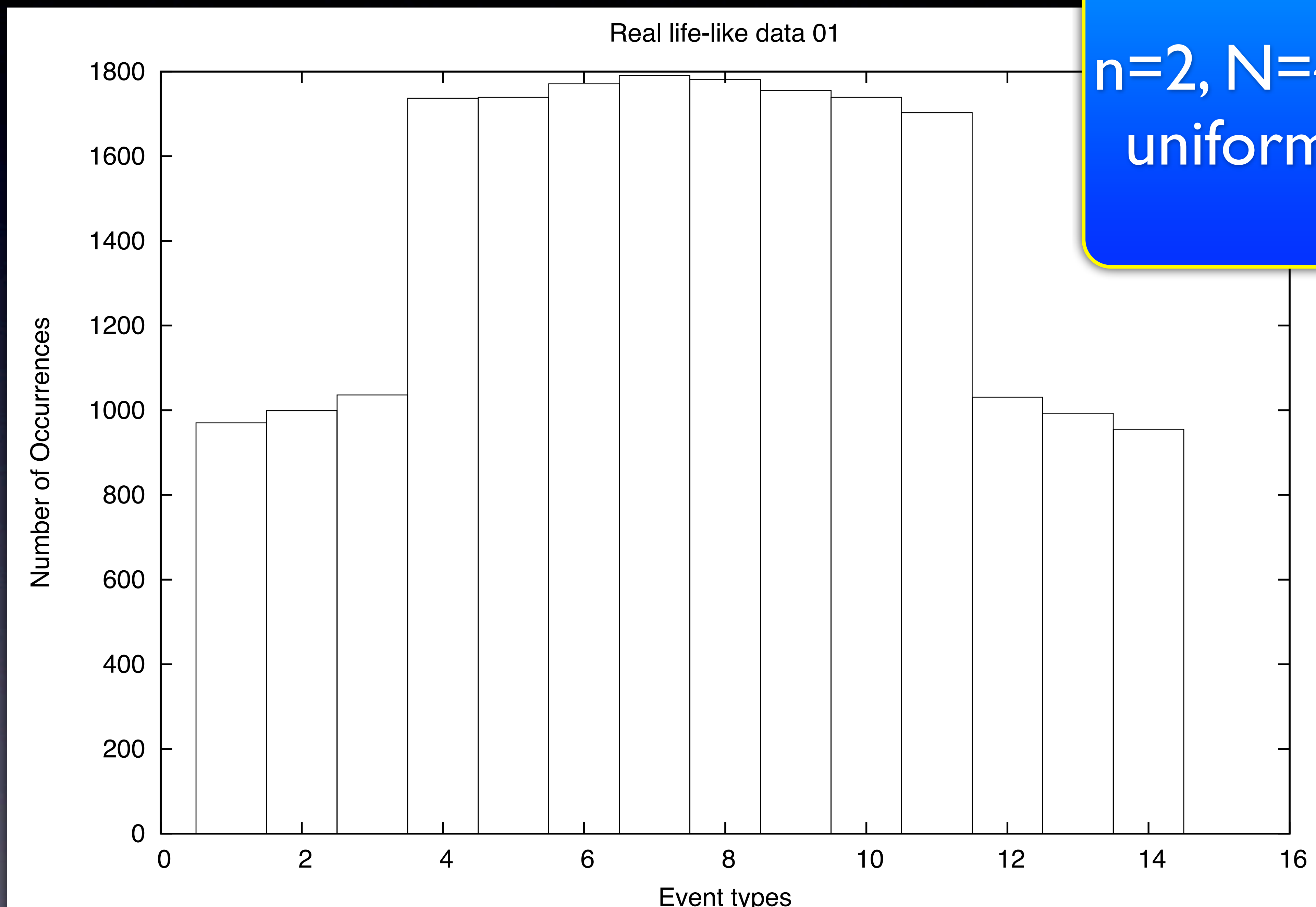

n=2, N=4, p=0.7
uniform noise

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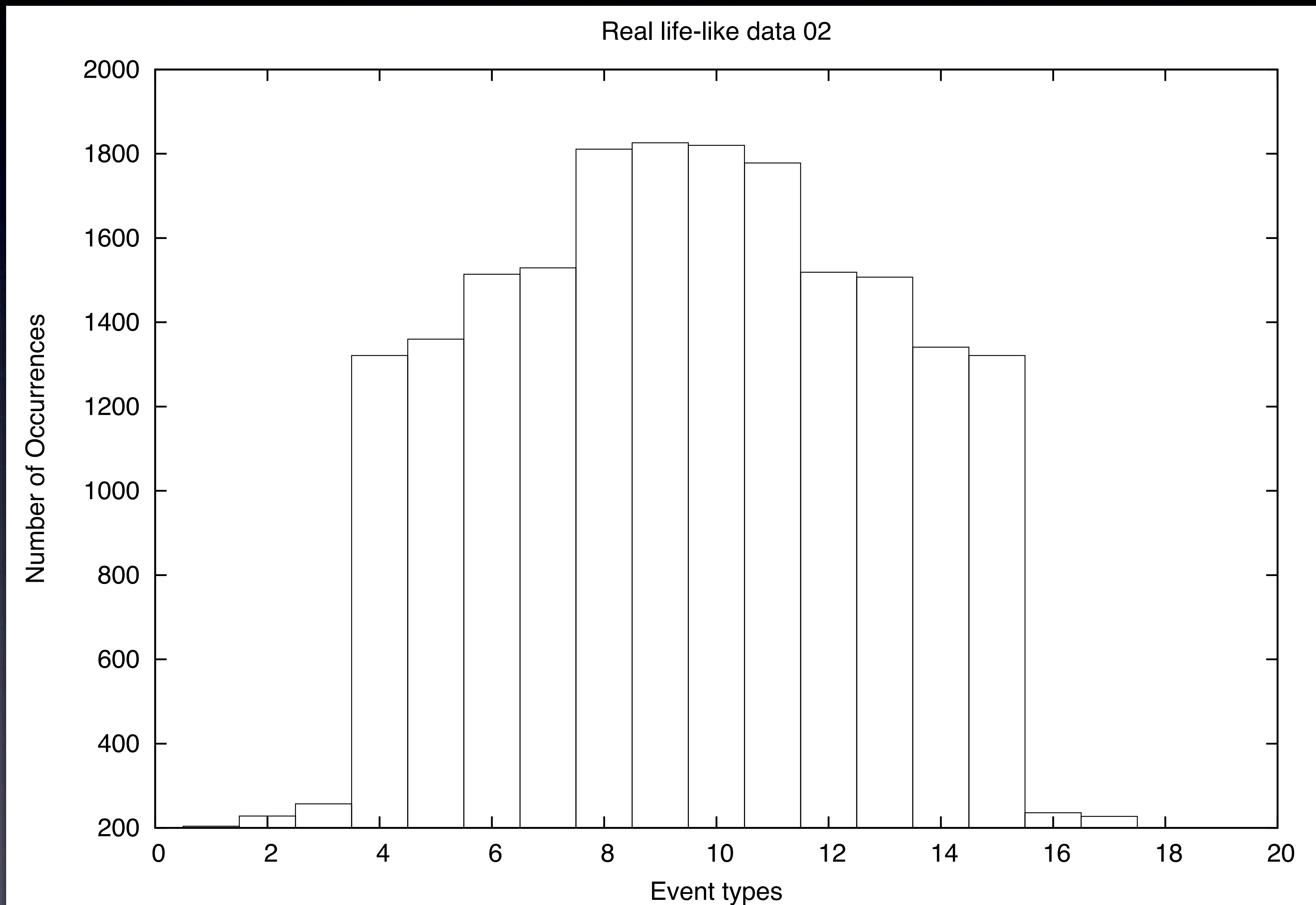

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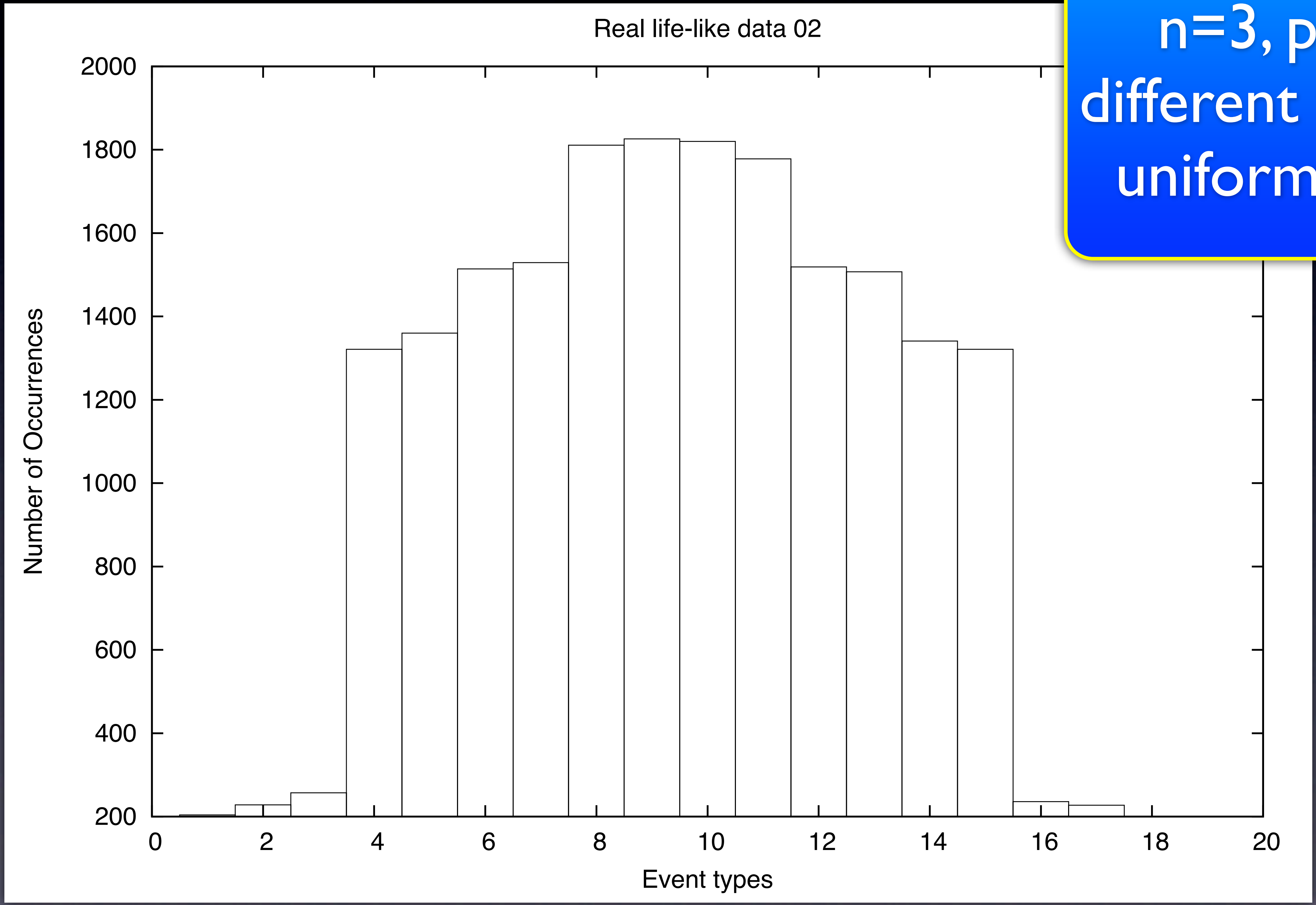

n=3, p=0.3
different weights
uniform noise

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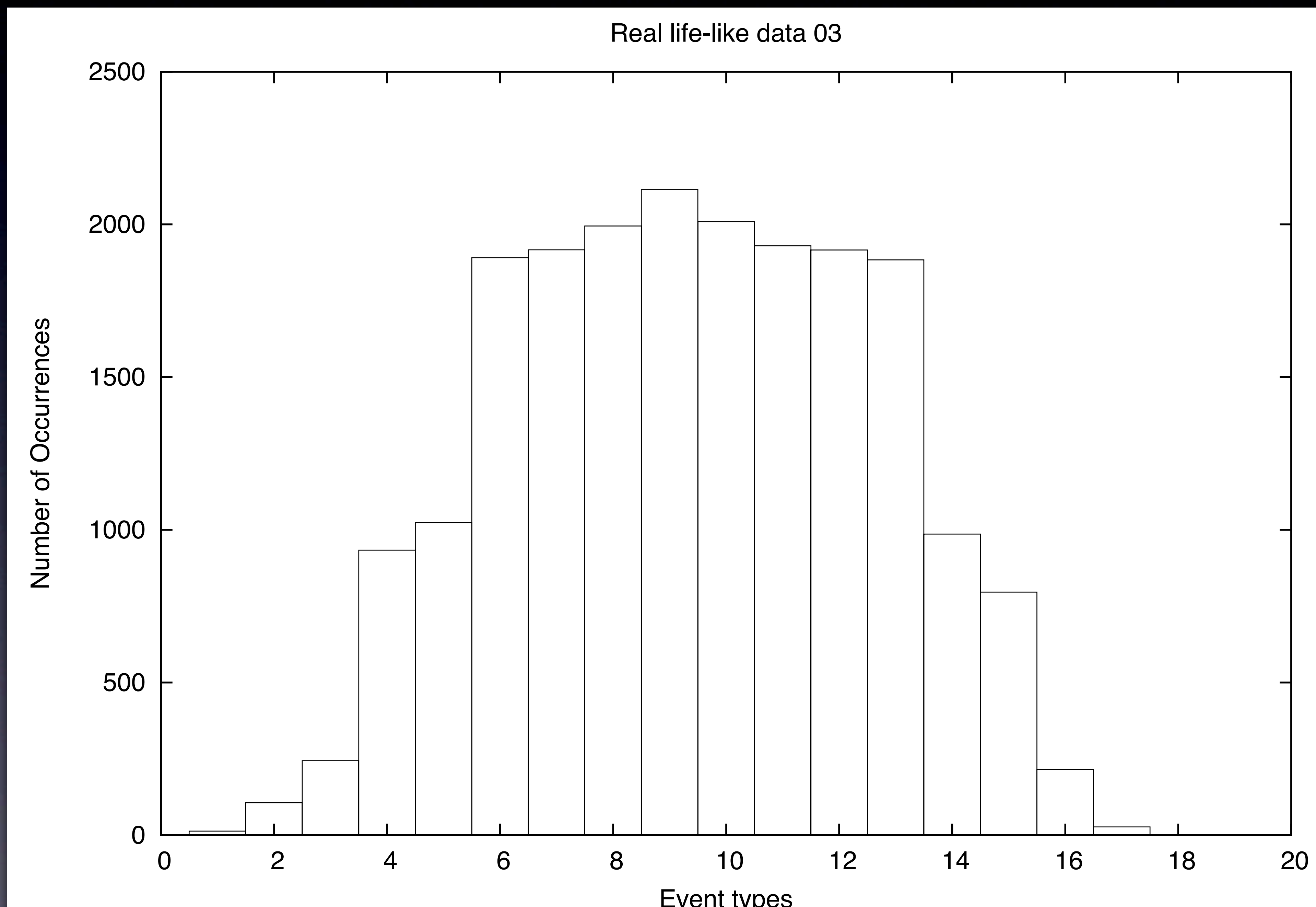

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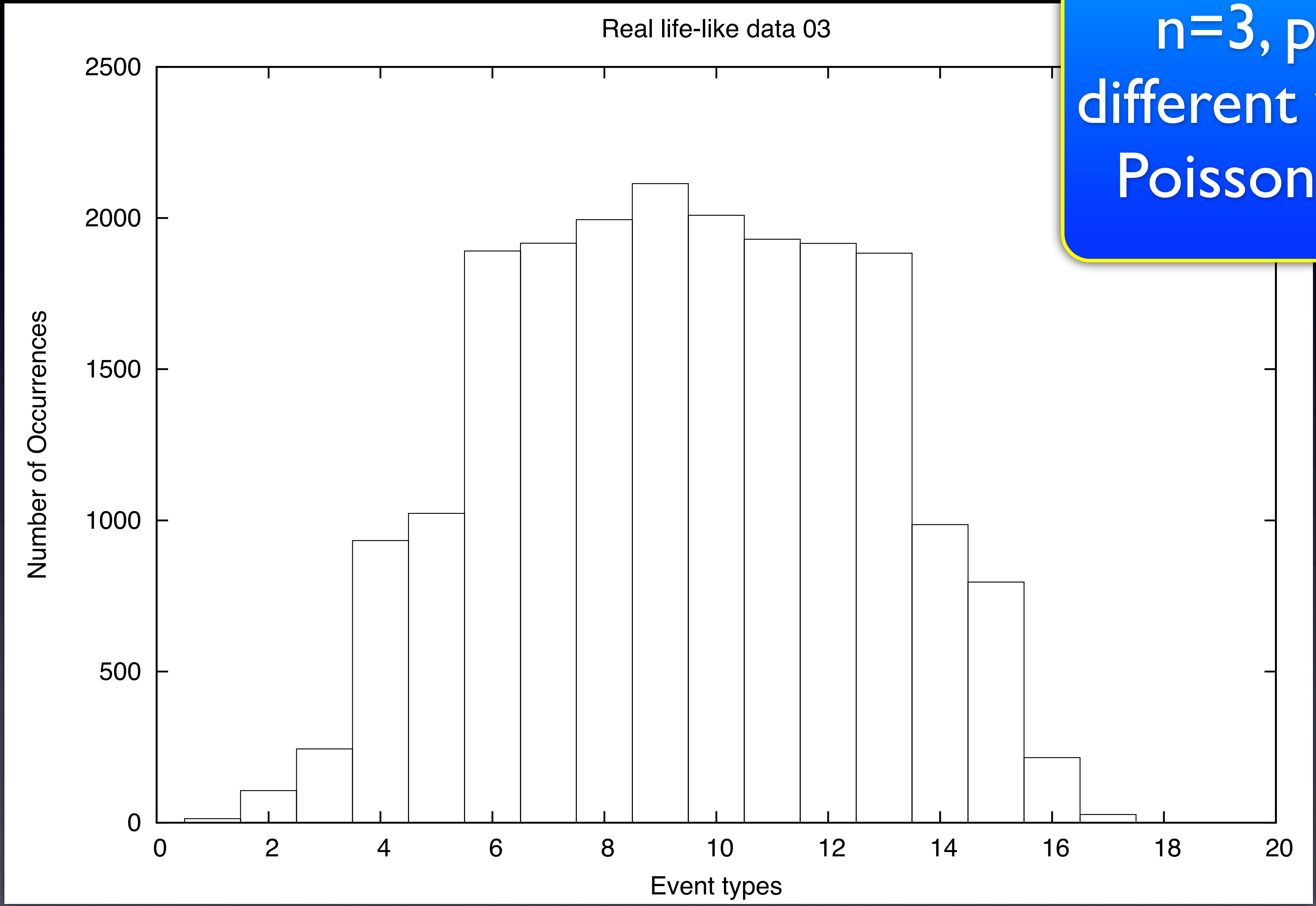

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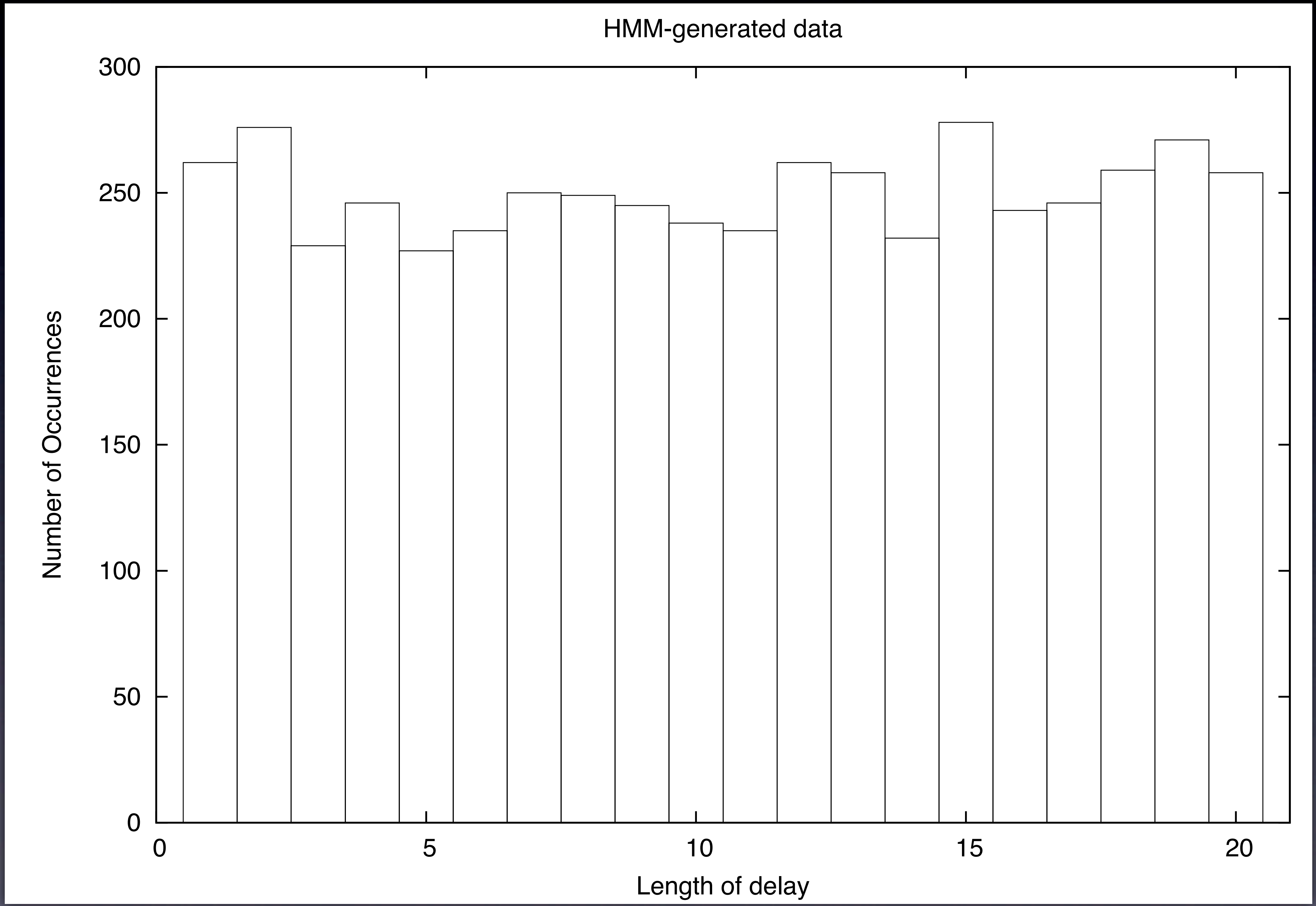
different weights
Poisson noise

Harder for time



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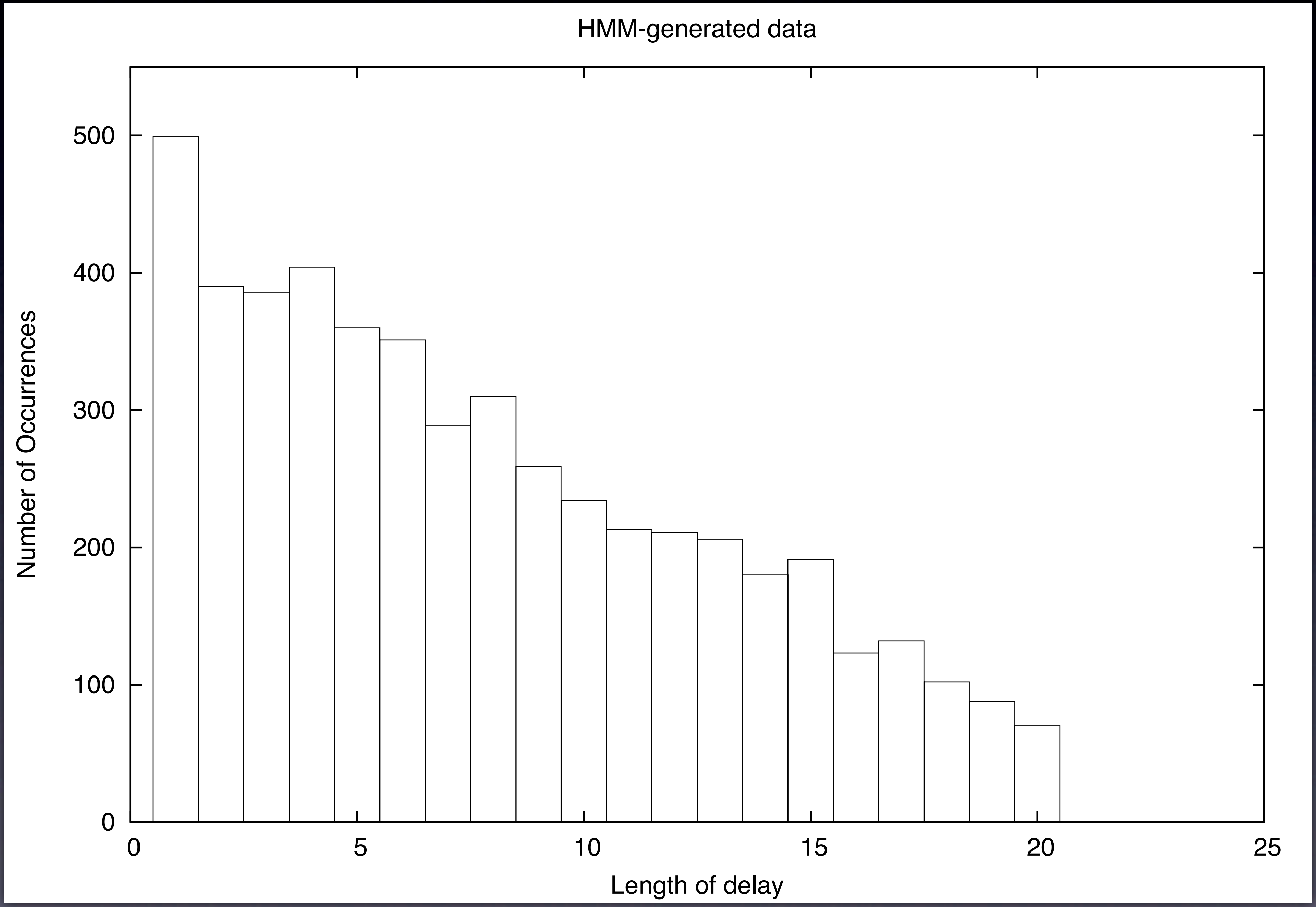

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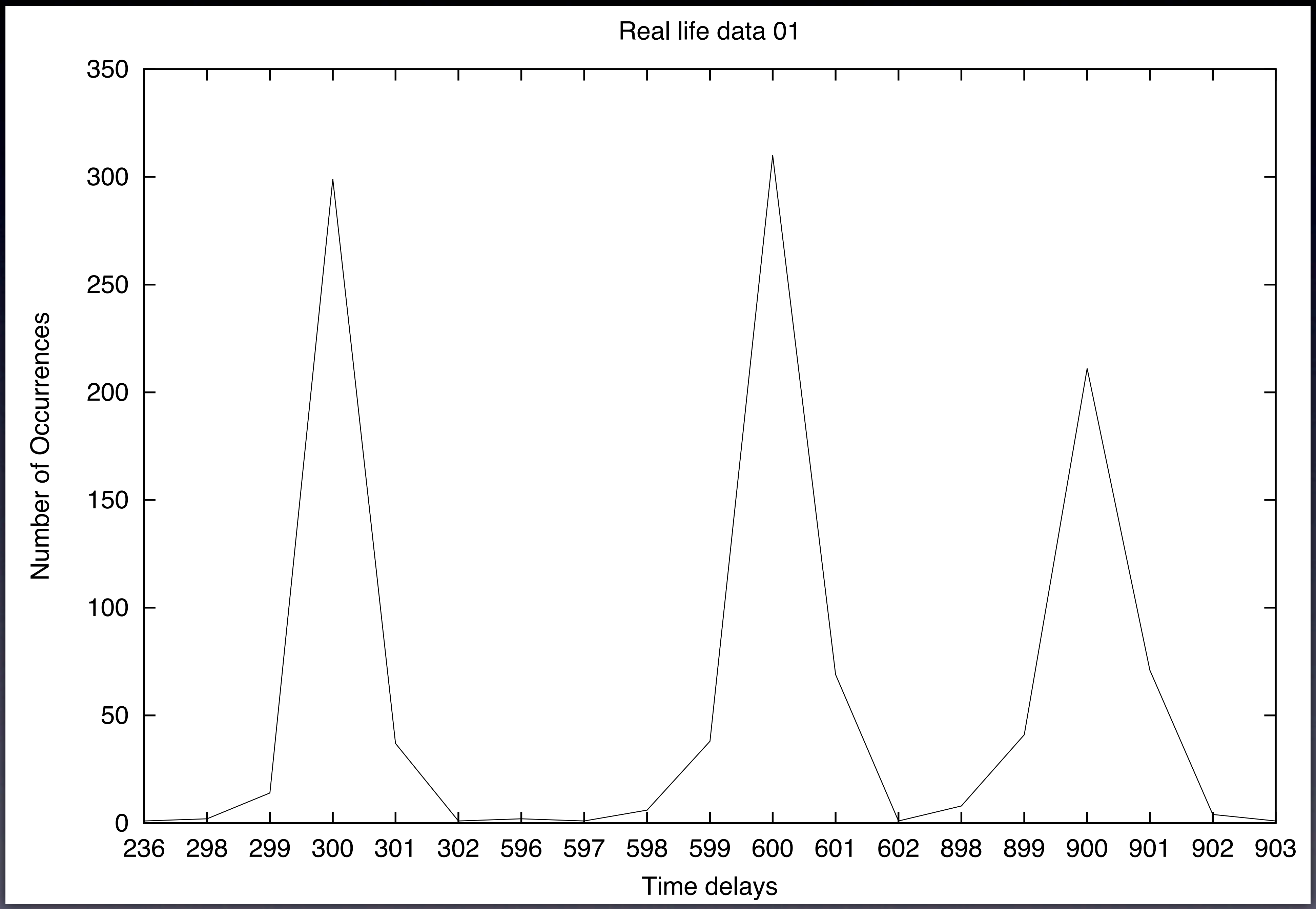

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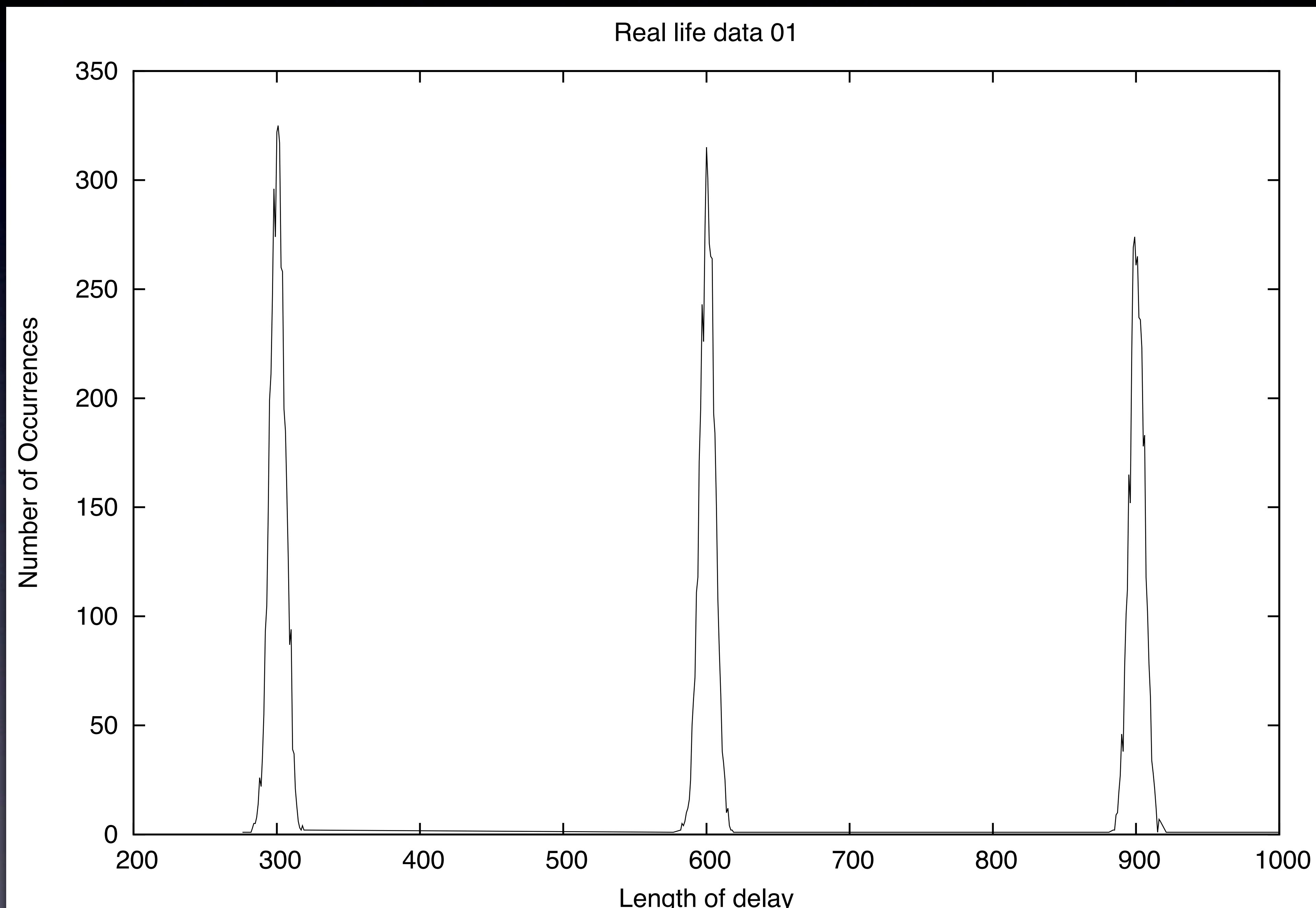

Experimental results

- Time constraint seems more important than matching semantic
- Best case: pattern within top-10
- Several patterns: **very** hard
- Real life data: patterns swamped by other stuff

Beyond episode mining

- Comparative data mining: general framework
- Currently working on itemset mining
- Extending to supervised settings:
  - Data harder to generate
  - Augment theoretical/UCI guarantees