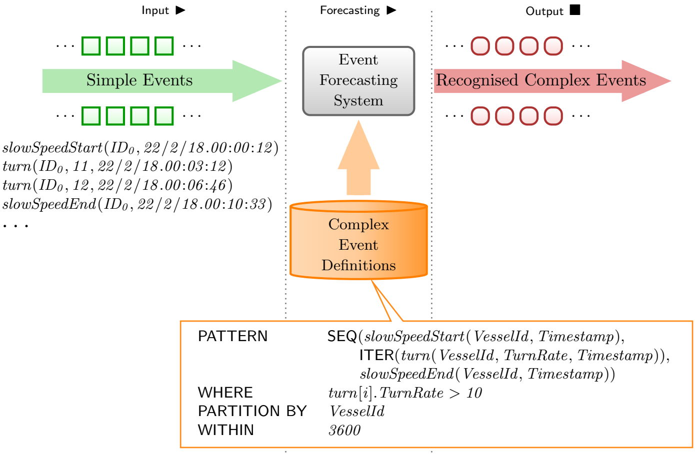
# Can Computers Understand what is Happening? Complex Event Forecasting

Alexander Artikis[1,2] and Periklis Mantenoglou[1,3]
*Slides: Elias Alevizos*[1]

[1]NCSR Demokritos, Athens, Greece
[2]University of Piraeus, Greece
[3]NKUA, Greece

https://cer.iit.demokritos.gr

# Complex Event Forecasting (CEF)*,†

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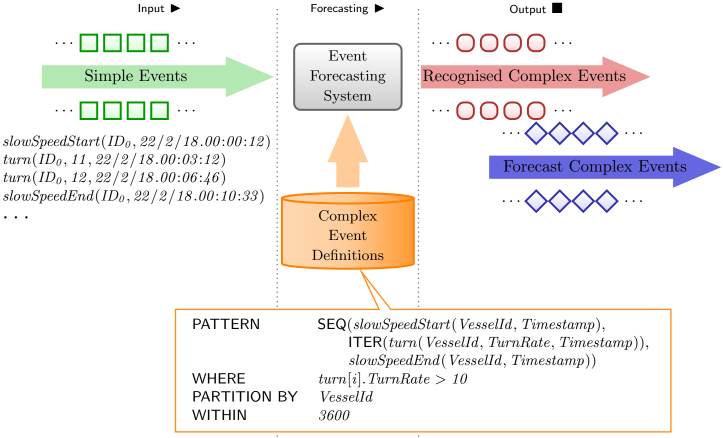


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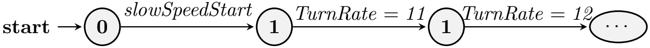


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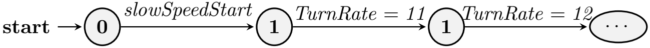


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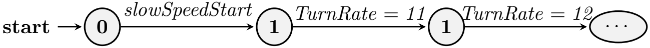


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  - Forecast the full matches.

# Wayeb: A Complex Event Forecasting system*


https://cer.iit.demokritos.gr (forecasting)

*https://github.com/ElAlev/Wayeb

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- In Machine Learning, the goal is to predict the output of a function on previously unseen input data.
  - The input data need not necessarily have a temporal dimension.
- In Complex Event Forecasting, the task is to predict the temporally future output of a function, ie the future occurrence of an event.
  - Time is thus a crucial component.
  - From the (current) timepoint where a forecast is produced until the (future) timepoint for which we try to make a forecast, no data is available.

# Complex Event Forecasting vs Machine Learning

We have Deep Learning and it seems to work. Can we go home?

Complex event forecasting:

- Formal semantics* for trustworthy models.
- Explanation — why did we forecast a complex event?
- Machine Learning is necessary. But:
  - Complex events are rare.
  - Supervision is scarce.
- More often than not, background knowledge is available — let's use it!

* Grez et al, A Formal Framework for Complex Event Recognition. ACM Transactions on Database Systems, 2021.

# Automata-based Complex Event Forecasting*

- Patterns defined as regular expressions.

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- Patterns defined as regular expressions.
- Consume streams of events and forecast when a pattern is expected to be fully matched.
- Revise forecasts to reflect changes in the 'state' of the pattern.

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  - We may also emit a future interval within which a complex event is expected.

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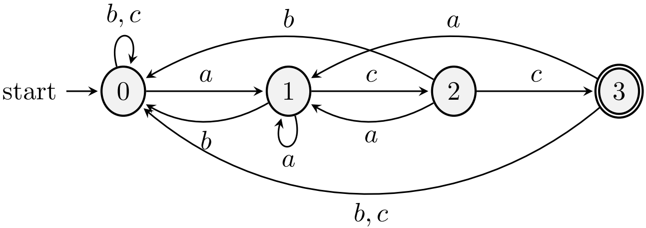
  - Calculate the waiting-time distribution for each state.
- Scan the waiting-time distributions to produce forecasts.

# Regular Expression → Pattern Markov Chain

$R = a \cdot c \cdot c.$ $\Sigma = \{a, b, c\}.$ No memory.



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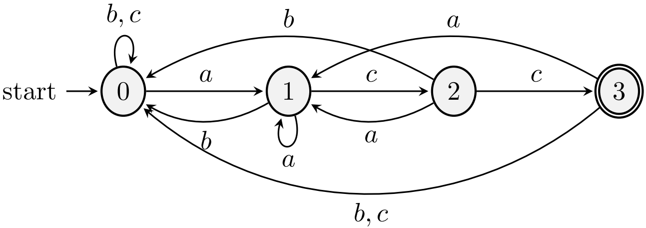
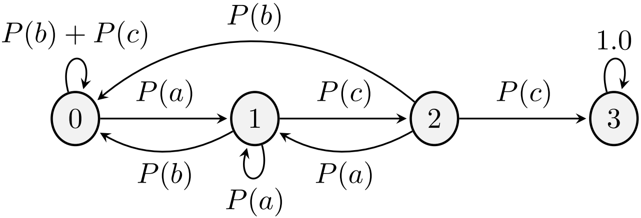
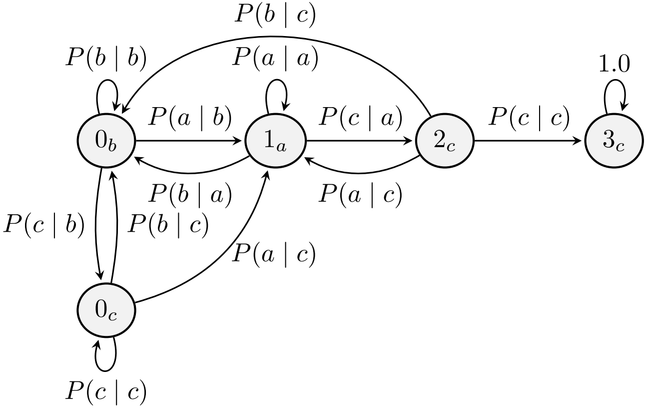


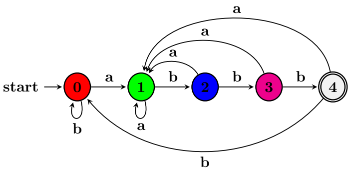
# Regular Expression $\rightarrow$ Pattern Markov Chain

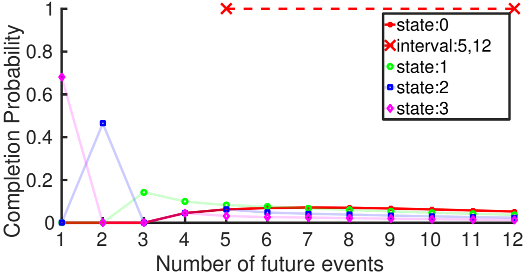
$R = a \cdot c \cdot c. \qquad \Sigma = \{a, b, c\}. \qquad m = 1.$



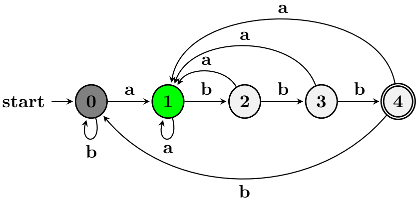
# Waiting-Time and Forecasts

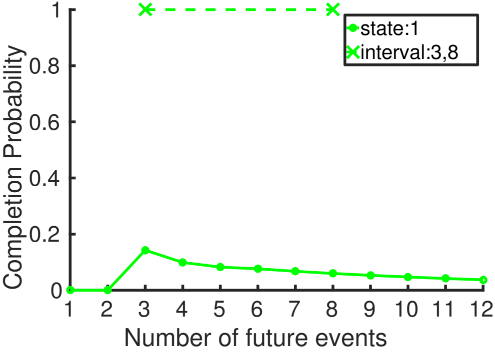
- Assume $R := a \cdot b \cdot b \cdot b$; $\Sigma = \{a, b\}$; and no memory.



# Example: $R = a \cdot b \cdot b \cdot b$.



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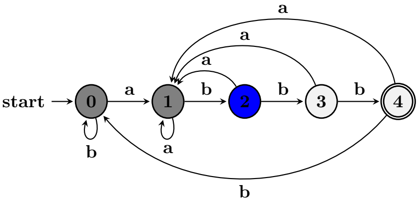


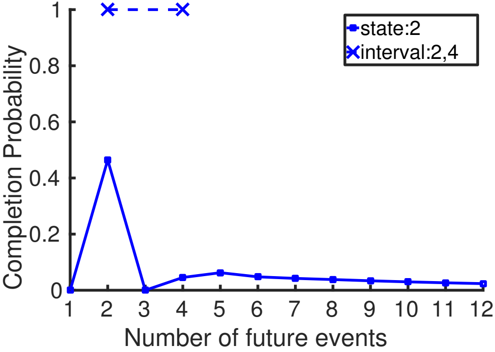

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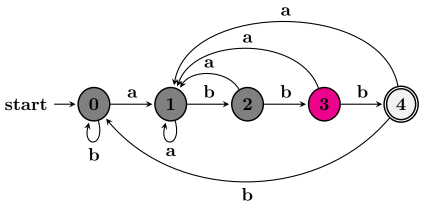


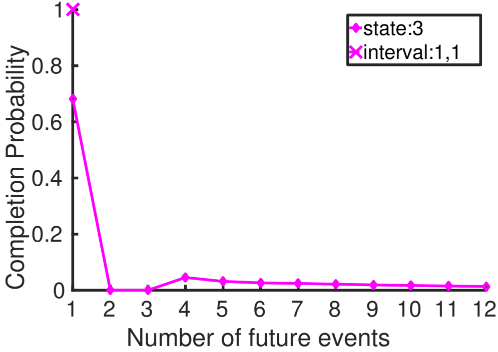

# Symbolic Automata & Variable-order Markov Models*

- Use symbolic automata.
  - Infinite alphabet.
  - Closed under concatenation, intersection, union, Kleene-star and complement; determinisable.

*Alevizos et al, Complex Event Forecasting with Prediction Suffix Trees. VLDB Journal, 2022.

# Symbolic Automata & Variable-order Markov Models*

- Use symbolic automata.
  - Infinite alphabet.
  - Closed under concatenation, intersection, union, Kleene-star and complement; determinisable.
- Use a variable-order Markov model.
  - Prediction Suffix Trees.
  - Focus on the statistically significant properties of the stream.

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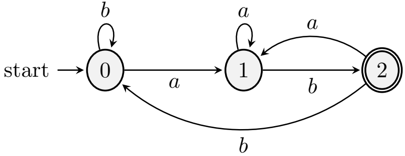
# Complex Event Forecasting with Prediction Suffix Trees



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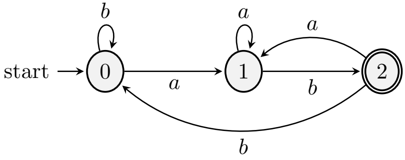


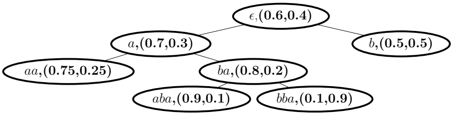

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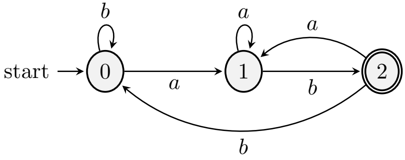
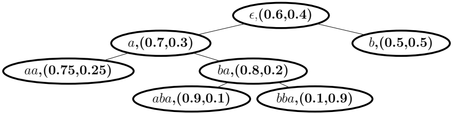
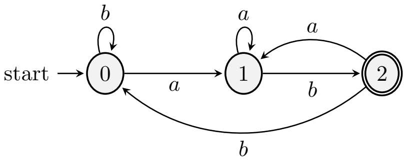


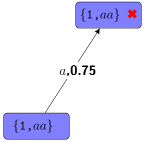

$\{1, aa\}$

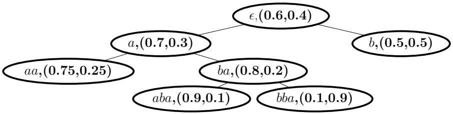



- Let's compute the waiting-time distributions.
- Assume automaton in state 1 and suffix is *aa*.
- Estimate distribution step by step, for $k = 1$, $k = 2$, etc.

# Complex Event Forecasting with Prediction Suffix Trees




- $k = 1$.
- Assume another *a* arrives. Suffix still *aa*, automaton again in state 1.
- Reaches a non-final state. Not interested.

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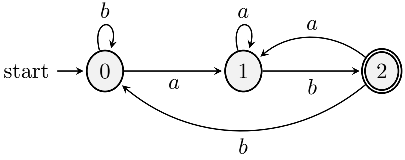


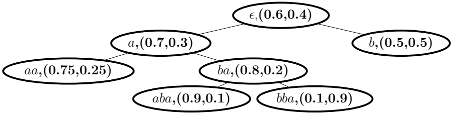


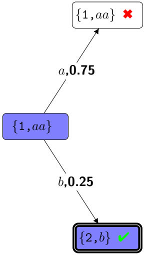


- $k = 1$.
- Assume $b$ arrives first. Suffix is $b$, automaton in state 2.
- Reaches a final state. No other options. Thus $P(W_{\{1,aa\}} = 1) = 0.25$.

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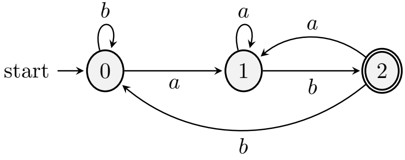


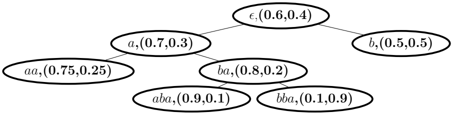


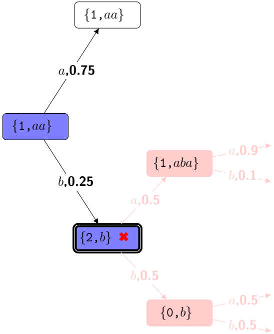


- $k = 2$.
- Assume $b$ arrives first. Suffix is $b$, automaton in state 2.
- Reaches a final state already at $k = 1$. All downstream paths pruned.

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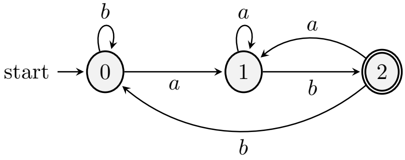


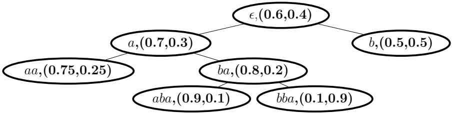


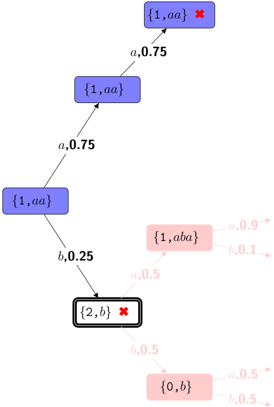


- $k = 2$.
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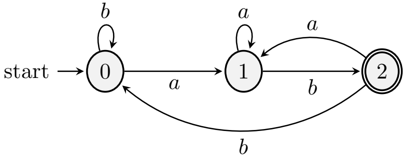


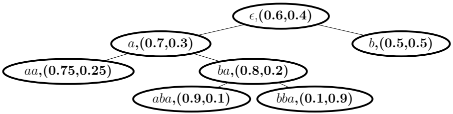


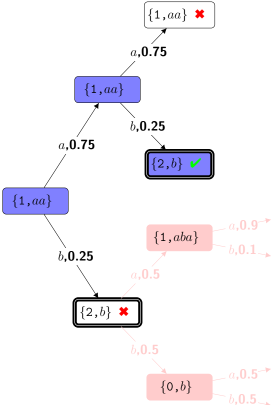


- $k = 2$.
- Assume $a$ arrives first. Then $b$.
- Reaches a final state at $k = 2$. Only path leading to a final at $k = 2$. Thus $P(W_{\{1,aa\}} = 2) = 0.75 * 0.25 = 0.1875$.

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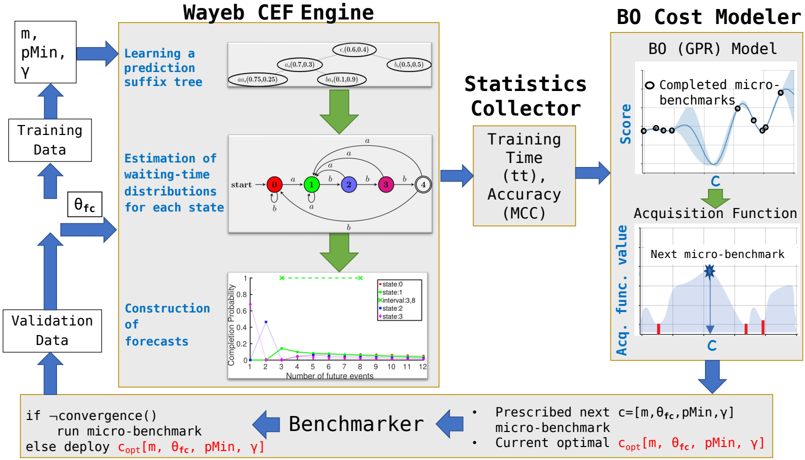
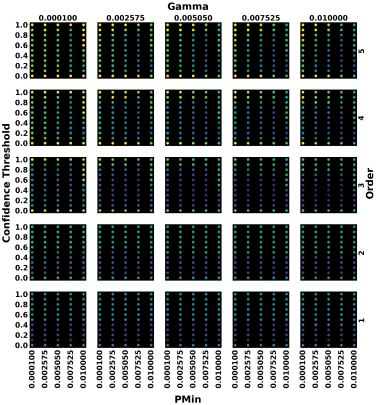
- Efficient search of the hyper-parameter space with Bayesian Optimization.

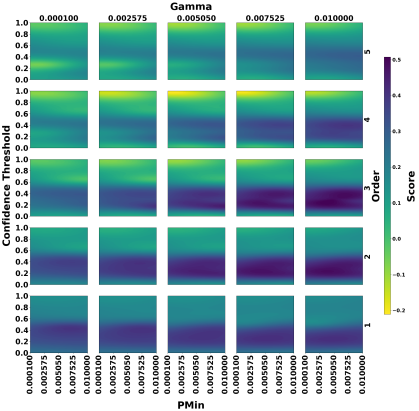
# Bayesian Optimization for Complex Event Forecasting*




*Stavropoulos et al, Optimizing complex event forecasting. Distributed and Event-based Systems (DEBS), 2022.

# Exhaustive search vs Bayesian Optimization



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Current work:

- CEF with Symbolic Register Automata*:
  - Symbolic automata with 'memory'.
  - Express *n*-ary relations between events.

*Alevizos et al, Complex Event Recognition with Symbolic Register Transducers. VLDB, 2024.