# Making sense of hierarchical log data

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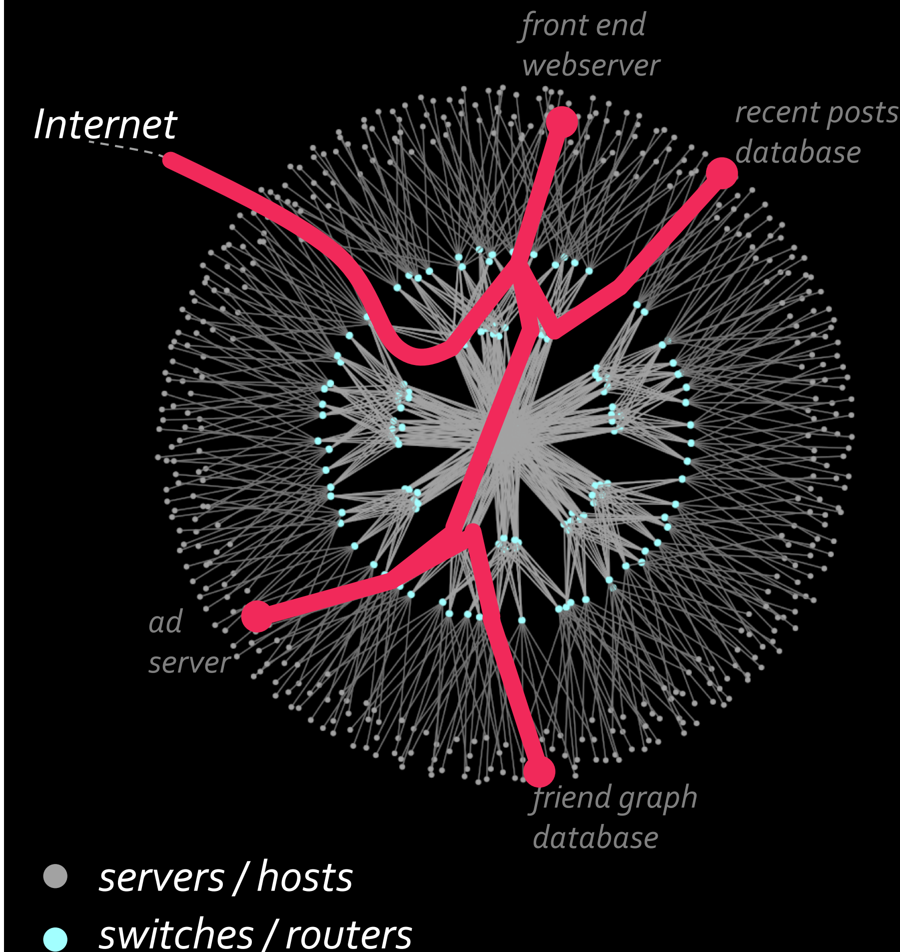
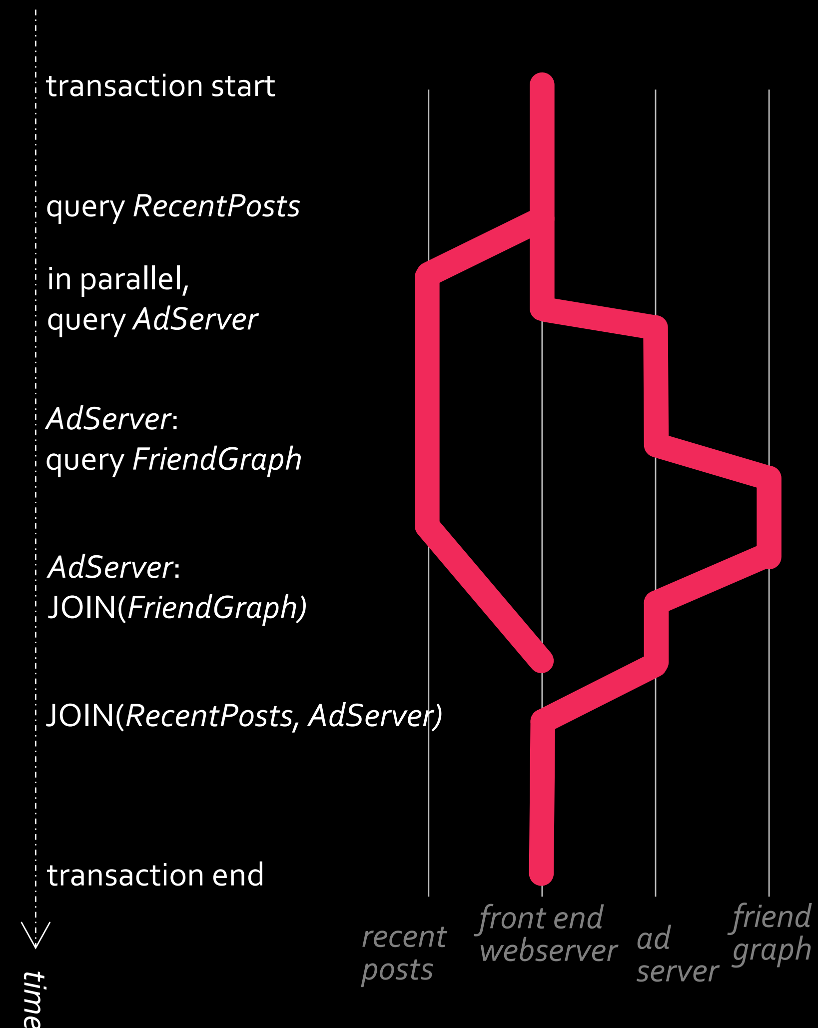
# *Debugging in a data center*

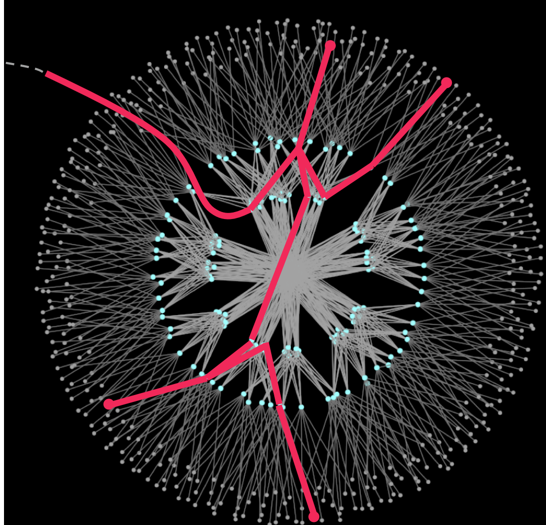


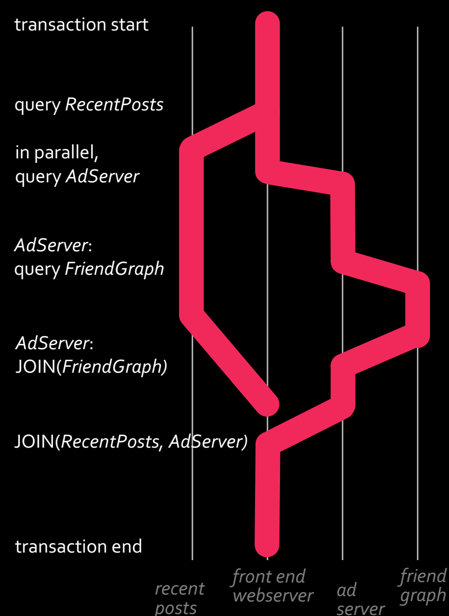
*Debugging in a data center*

DevOps notices problems with response time.

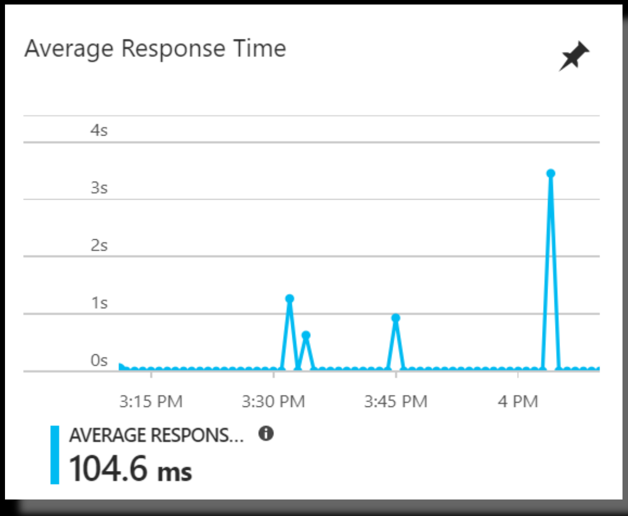
- Was there a network update, which messed things up?
- Was there a code update?
- Is there some part of the system that started churning?
- Is it because of changes in demand?
- Is it a knock-on effect from elsewhere?



Network engineer view




Programmer view

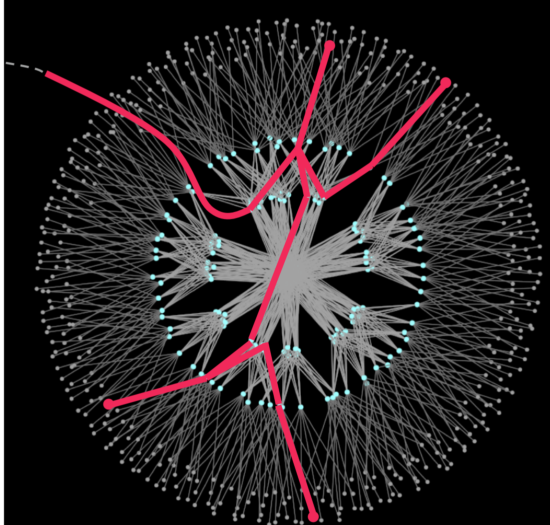



DevOps view

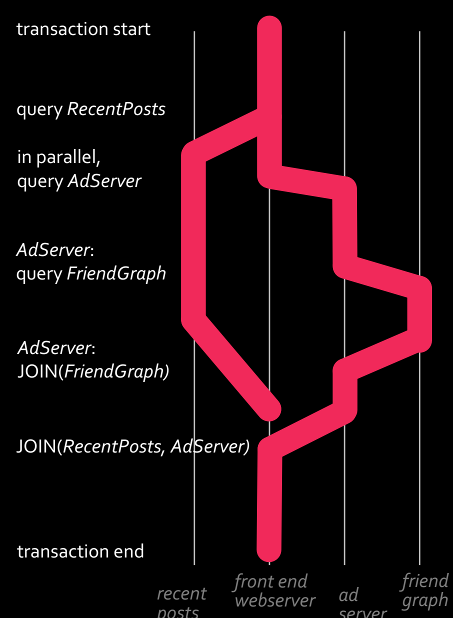
*Debugging in a data center*

True story:

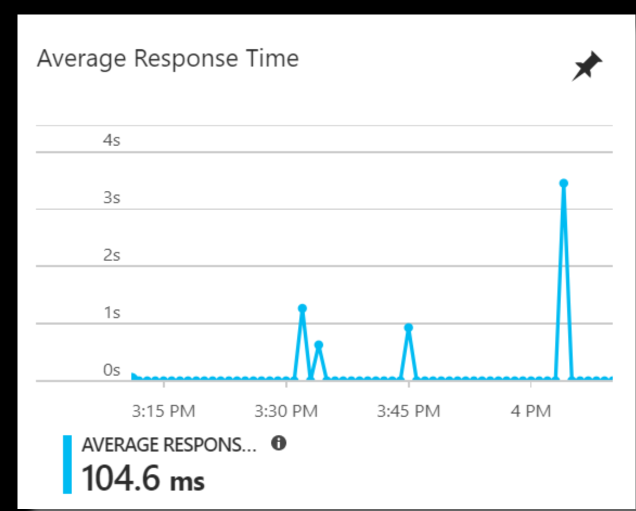
- Student's peer-to-peer code runs happily, until it suddenly becomes horribly slow
- It's only slow on the campus network, not over ADSL
- Diagnosis:
  Certain workload patterns trigger a cascade of ≈12 packets
  This overwhelms the switch buffers, and the final few packets get dropped
  The code goes into timeout / recovery



Network engineer view

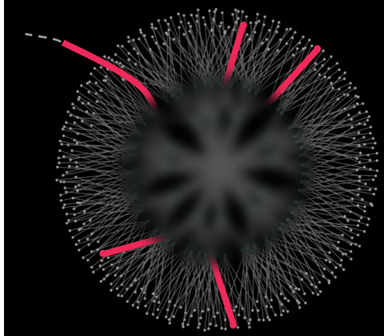


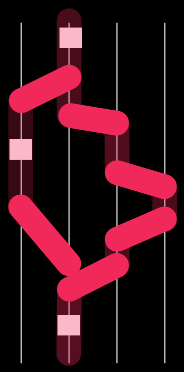

Programmer view




DevOps view

*Challenge, version 1*





Flow from INTERNET to HOST1(pid=4af) ended at t=128.3
HOST1(pid=4af) log message *“transaction type 5”*
Flow from HOST1(pid=4af) to HOST2(pid=b3c1) started at t=129.5
Flow from HOST1(pid=b3c1) to HOST2(pid=b3c1) ended at t=132.0
HOST2(pid=b3c1) log message *“found in cache”*
Flow from HOST1(pid=4af) to HOST5(pid=ee22) started at t=130.0
...

If we have logs of flows,
plus the process ID that each flow belongs to,
plus occasional programmer-generated log messages,

but we don’t know the network state or the code,

how can we diagnose problems?

# *State of the art: AppDynamics*


- The operator manually assigns labels:
  to transaction types, and to classes of server
- AppDynamics reports average statistics grouped by these labels

*Challenge, version 2*

Based on logs at an intermediate level of abstraction,

we want unsupervised learning

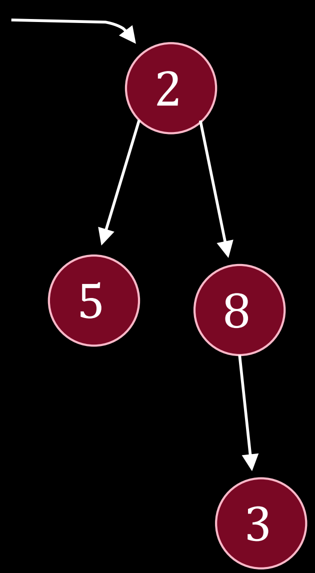
- of clusters of code structure
- of how code behaviour is influenced by network infrastructure
- of how the network infrastructure responds to code choices

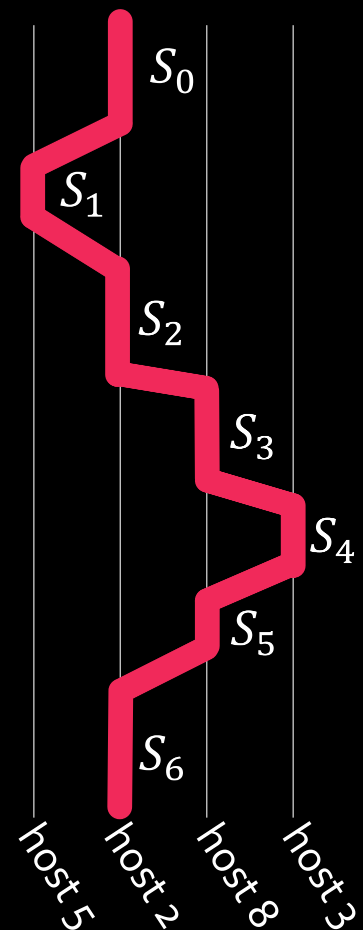
to give the operator insight into what's happening and why.

# *A stylized machine-learning model* *in the spirit of*
Grammar Variational Autoencoder (*Kusner, Paige, Hernández-Lobato, 2017*)

## First, write the transaction as a sentence in a grammar of state transitions and actions.

(Here I'm restricting attention to trees, encoded via depth-first traversal. All the bells and whistles, e.g. interaction with infrastructure, parallel calls, and programmer log messages, can be added.)

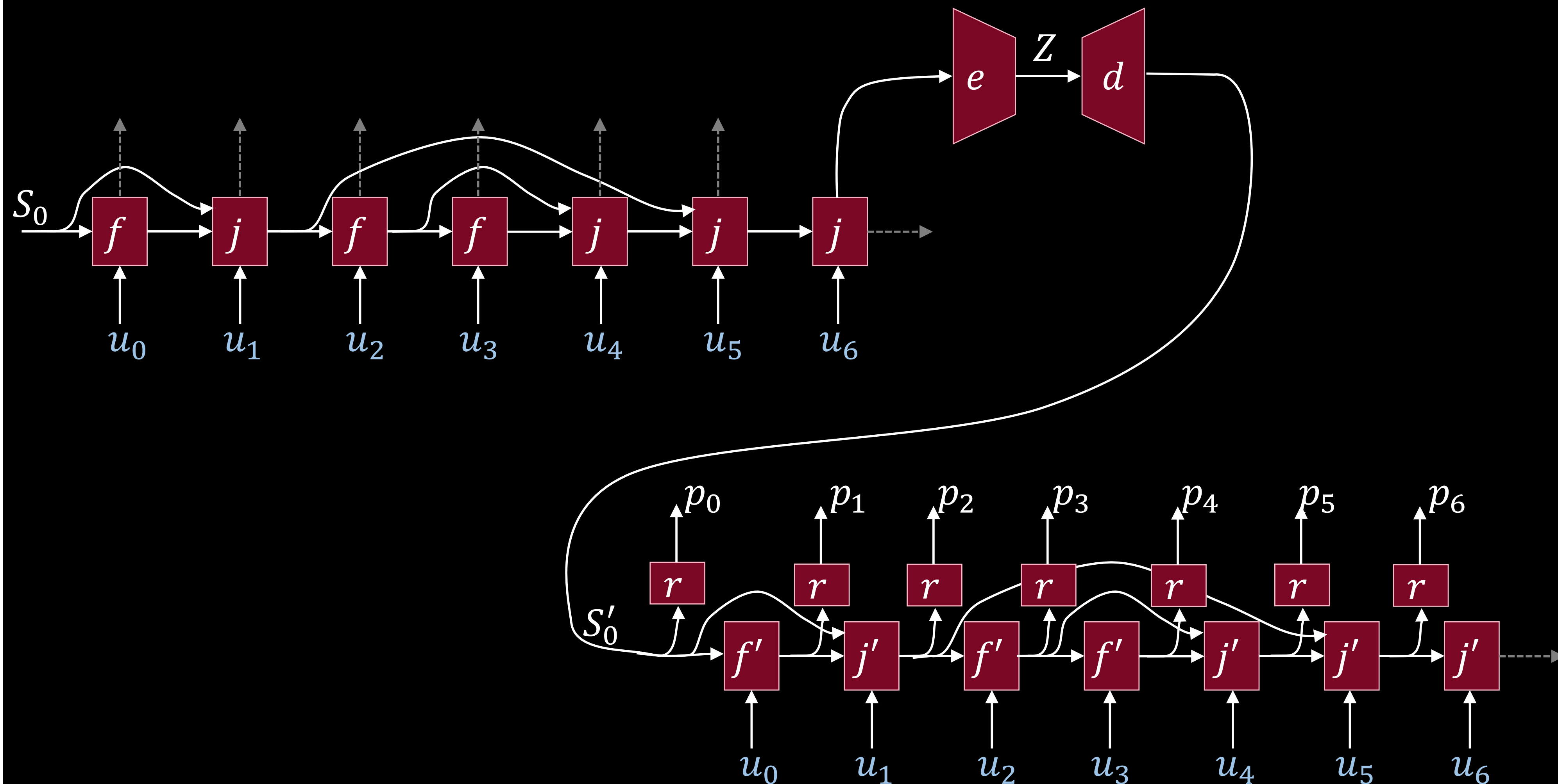



$S_0 = 0$
$u_0 = \text{"fork[host5]"}$
$S_1 = f(S_0)$
$u_1 = \text{"join"}$
$S_2 = j(S_0, S_1)$
$u_2 = \text{"fork[host8]"}$
$S_3 = f(S_2)$
$u_3 = \text{"fork[host3]"}$
$S_4 = f(S_3)$
$u_4 = \text{"join"}$
$S_5 = j(S_3, S_4)$
$u_5 = \text{"join"}$
$S_6 = j(S_2, S_5)$
$u_6 = \text{"join"}$

# *A stylized machine-learning model* in the spirit of
Grammar Variational Autoencoder (*Kusner, Paige, Hernández-Lobato, 2017*)

Second, train an autoencoder: a neural network that learns to reconstruct the sequence.



# *A stylized machine-learning model* in the spirit of
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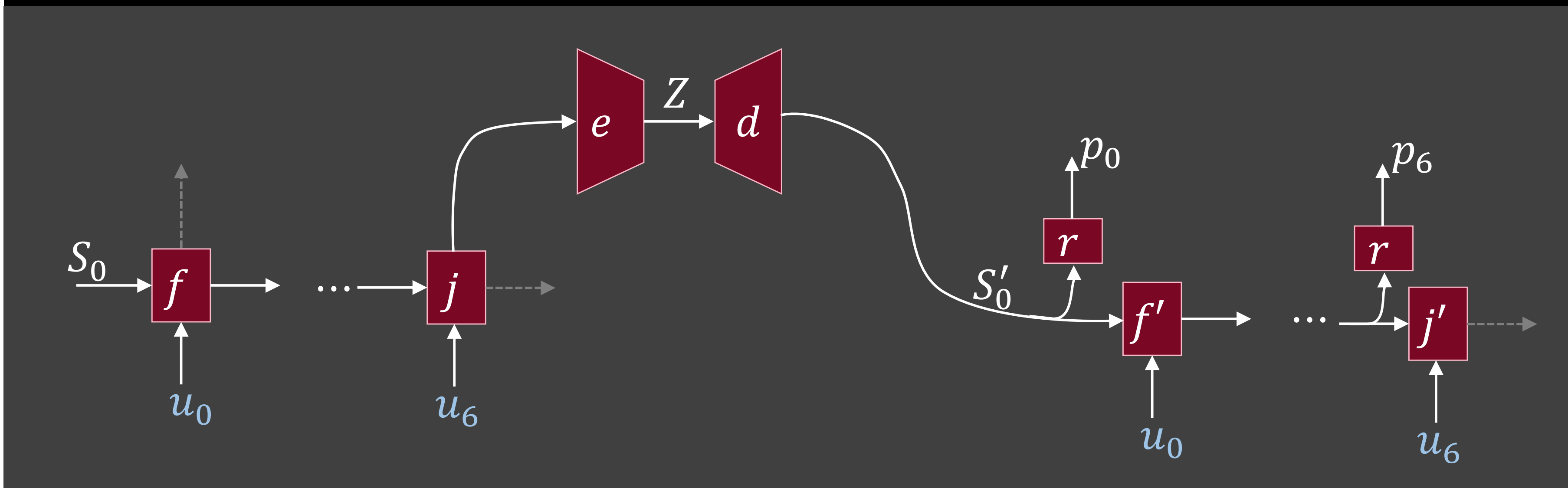
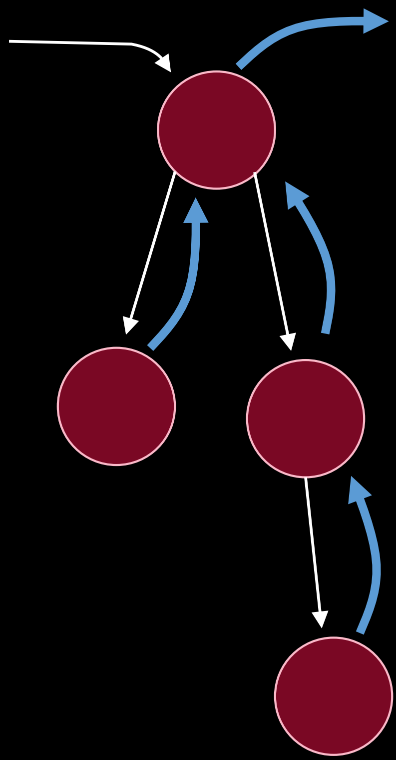



| | |
|---|---|
| $S_0, S_0'$ | high-dimensional vectors |
| $Z$ | low-dimensional vector: the latent representation |
| $u_i$ | actions, embedded into vectors |
| $p_i$ | vectors that encode distributions over actions |
| $f, j, f', j', e, d, r$ | functions parameterized by weights, trained to minimize |

$$\text{loss} \quad = \sum_{\text{transactions } t} \quad \sum_{\text{steps } i \text{ in } t} \log p_i(u_i) \quad + \quad \text{regularizer}(\text{distribution of } Z)$$

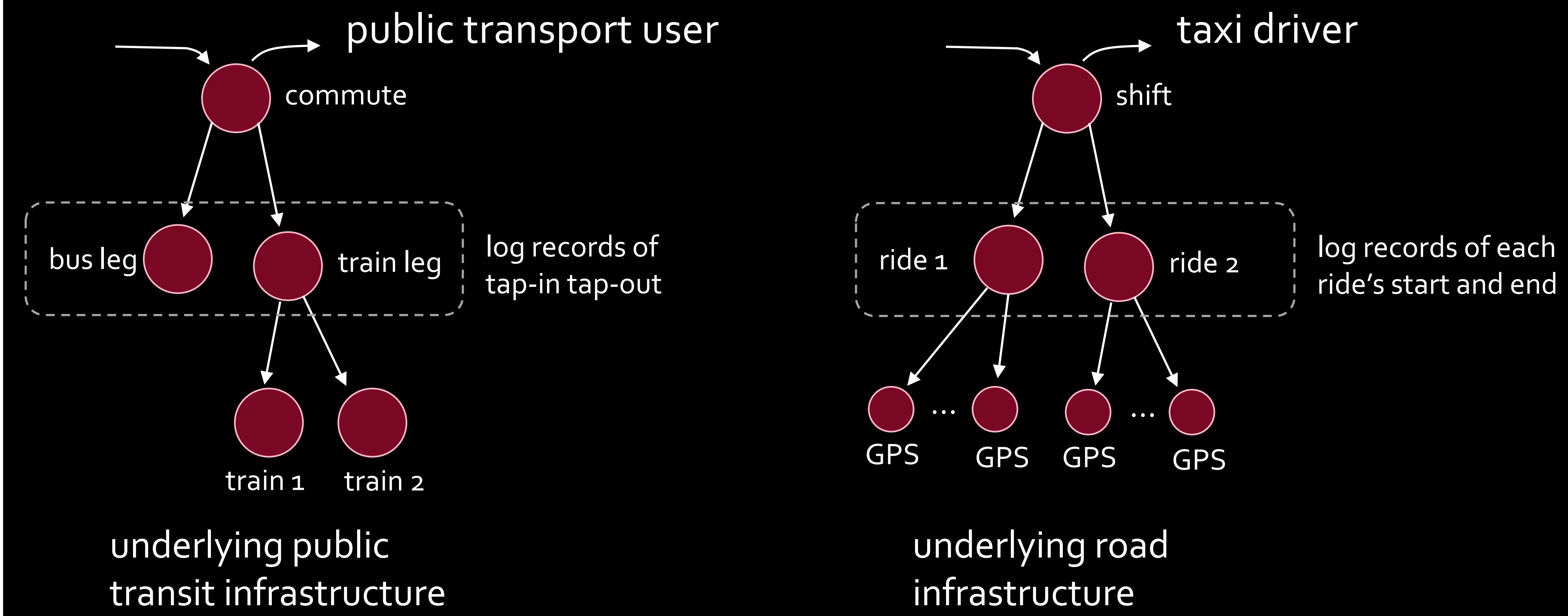


The latent variable $Z$ encapsulates

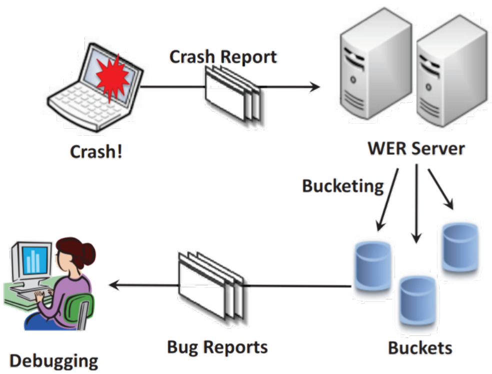
- *intent:*
  how a transaction's code is split into subrequests
- *experience:*
  how the next choice is affected by the experiences of subrequests

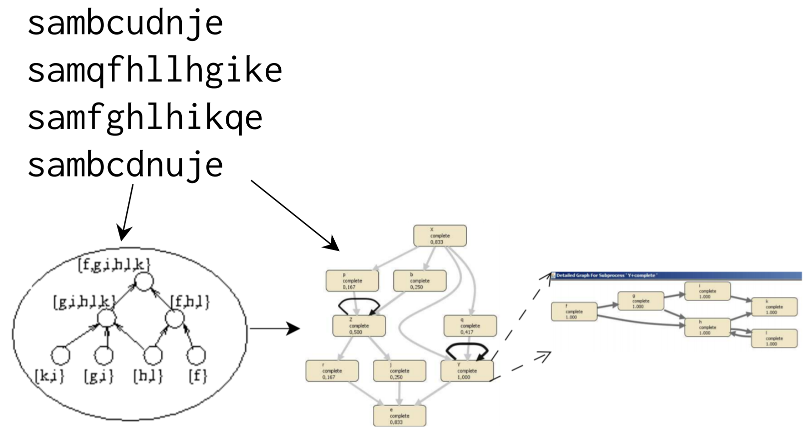
It is an unsupervised way to group similar transactions. It should be a good basis for interactive visualization / investigation.

*This type of data arises in many societal networks.*



## *Log files are everywhere, but they're hard to make sense of.*




Analyzing Windows telemetry, to identify common call stacks at the time of crashes.

*Debugging in the (very) large: ten years of implementation and experience*
Glerum, Kinshumann, et al. (SOSP 2009)

*ReBucket: a method for clustering duplicate crash reports based on call stack similarity*
Dang, Wu, et al. (ICSE 2012)

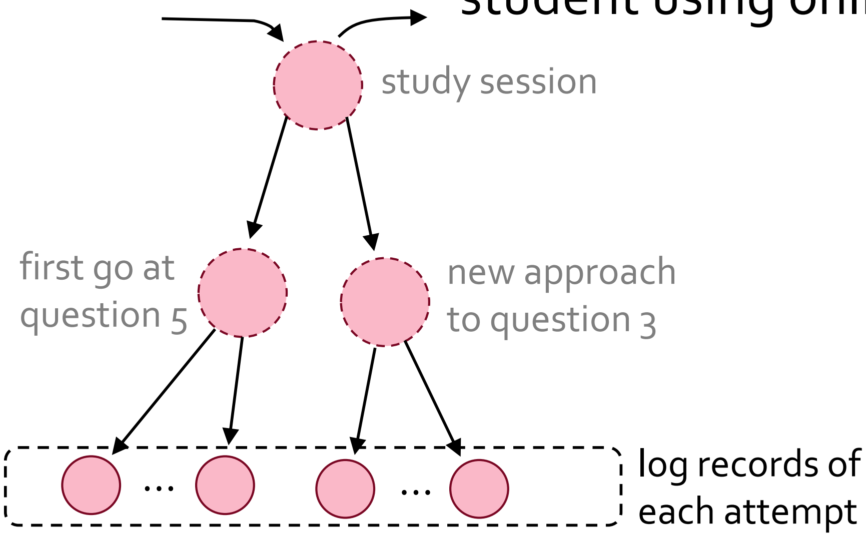
Mining event logs of processes (businesses, hospitals, home sensors) to discover dependencies and to highlight common subprocesses.

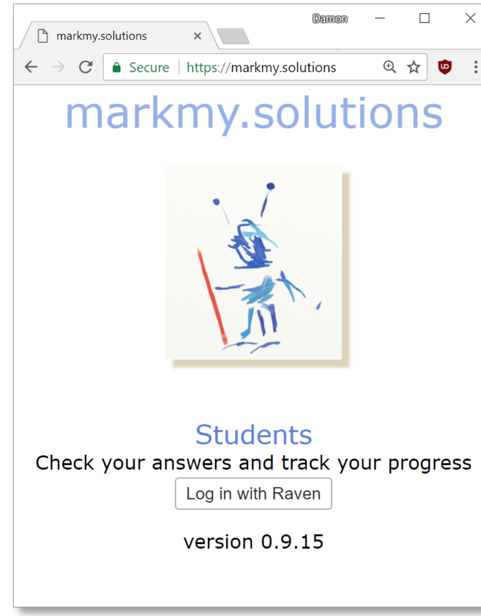
*Structure identification in layered precedence networks*
Kong, Katselis, Beck, Srikant (CCTA 2017)

*Mining context-dependent and interactive business process maps using execution patterns*
Li, Bose, van der Aalst (Business Process Management 2010)

*All sorts of structured human activity fall in this general category*
*(and data centers are the perfect laboratory, because of reproducibility and privacy)*

student using online grading




*Challenge v3*

Based on log records at a low level of abstraction,
infer the latent hierarchical structure of the activity.

(Deep learning for Natural Language Processing manages to learn something like grammar. Log records are surely easier!)

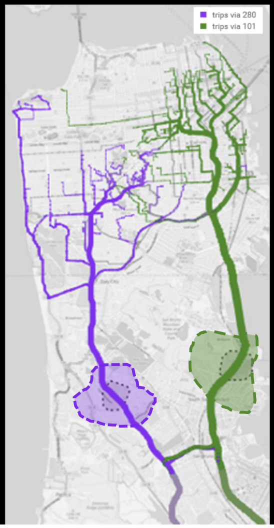
# *Challenge v4*
# *Build systems for working with this sort of data.*

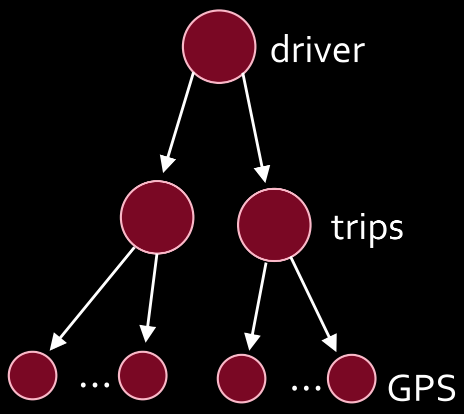
- Build databases that make it easier / faster to manipulate hierarchical data

  *FDB: A query engine for factorised relational databases*
  Bakibayev, Olteanu, Závodny (Proc VLDB 2012)

- Excel, Tableau, etc. are wedded to flat tabular data.
  Invent tools for users to interact with hierarchical data.

  *Example interaction:*
  *"Label some GPS coordinates, use these to up-label the trips, use these to down-label all their GPS coordinates."*



*Challenge v4*
*Build systems for working with this sort of data.*

- **The Synecdoche Engine**

  To understand data about richly structured behaviour, it's often helpful to look at illuminating anecdotes.