Unfolding Physiological State

Mortality Modeling in Intensive Care Units

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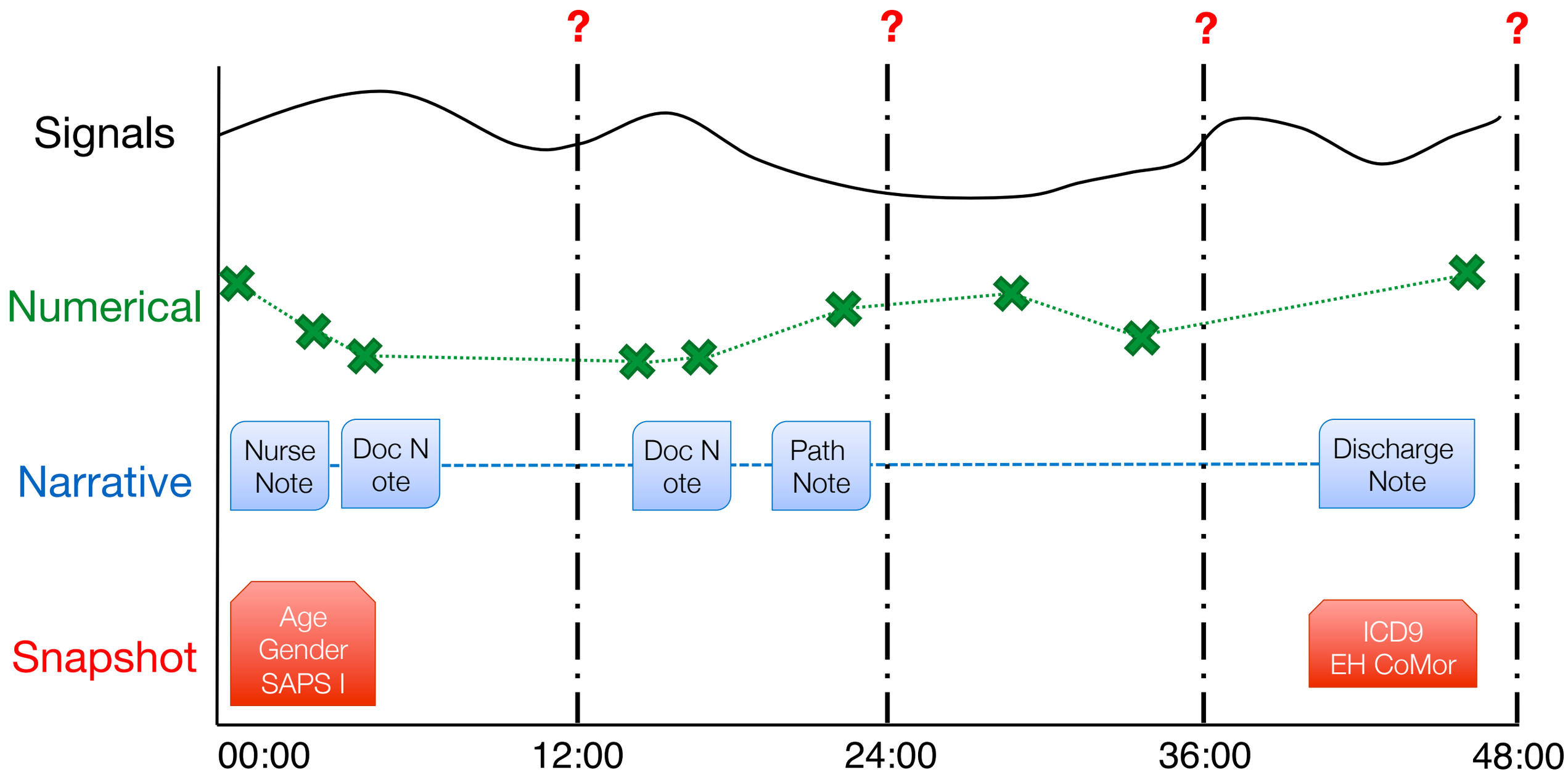
We've Got A Really Big Problem

- ICUs are busy, and carestaff are often inundated with information.
- How do I figure out which patient needs my attention?
- Use mortality as acuity surrogate.

Lots of Data Sources



What Do We Already Know?

- In 2009, 118 validated mortality prediction tools published.**
  - Modest accuracy
  - Large variability
  - Models based on numeric, waveform, or snapshot data
  - Snapshot data (e.g. ICD9) is not “realtime” or actionable

- A good predictive rule must be*:
  - Accurate in a wide variety of clinical settings
  - Easy to incorporate into routine clinical practice
  - Improves prognostic accuracy

* Grady, Deborah, and Seth A. Berkowitz. "Why is a good clinical prediction rule so hard to find?." *Archives of internal medicine* 171.19 (2011): 1701-1702.

** Siontis, George CM, Ioanna Tzoulaki, and John PA Ioannidis. "Predicting death: an empirical evaluation of predictive tools for mortality." *Archives of internal medicine* 171.19 (2011): 1721-1726.

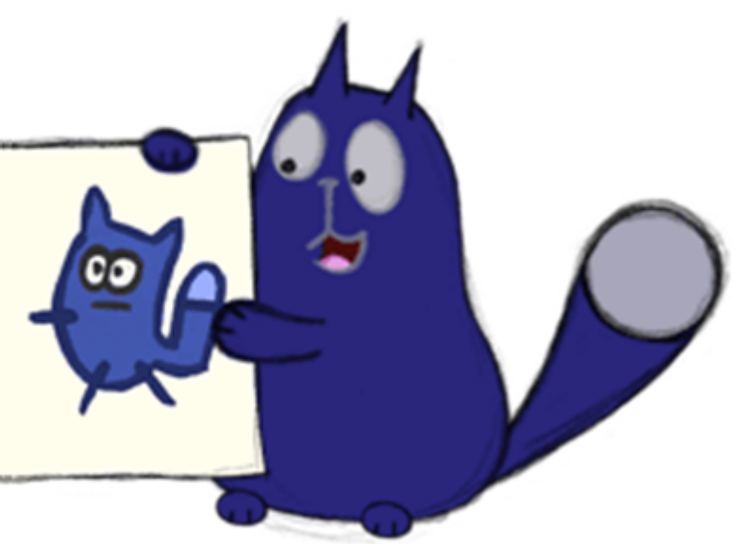
Every Cat Needs a Plan

- Create forward-facing models every 12 hours that only use data what would have actually been available, or “realtime” data.

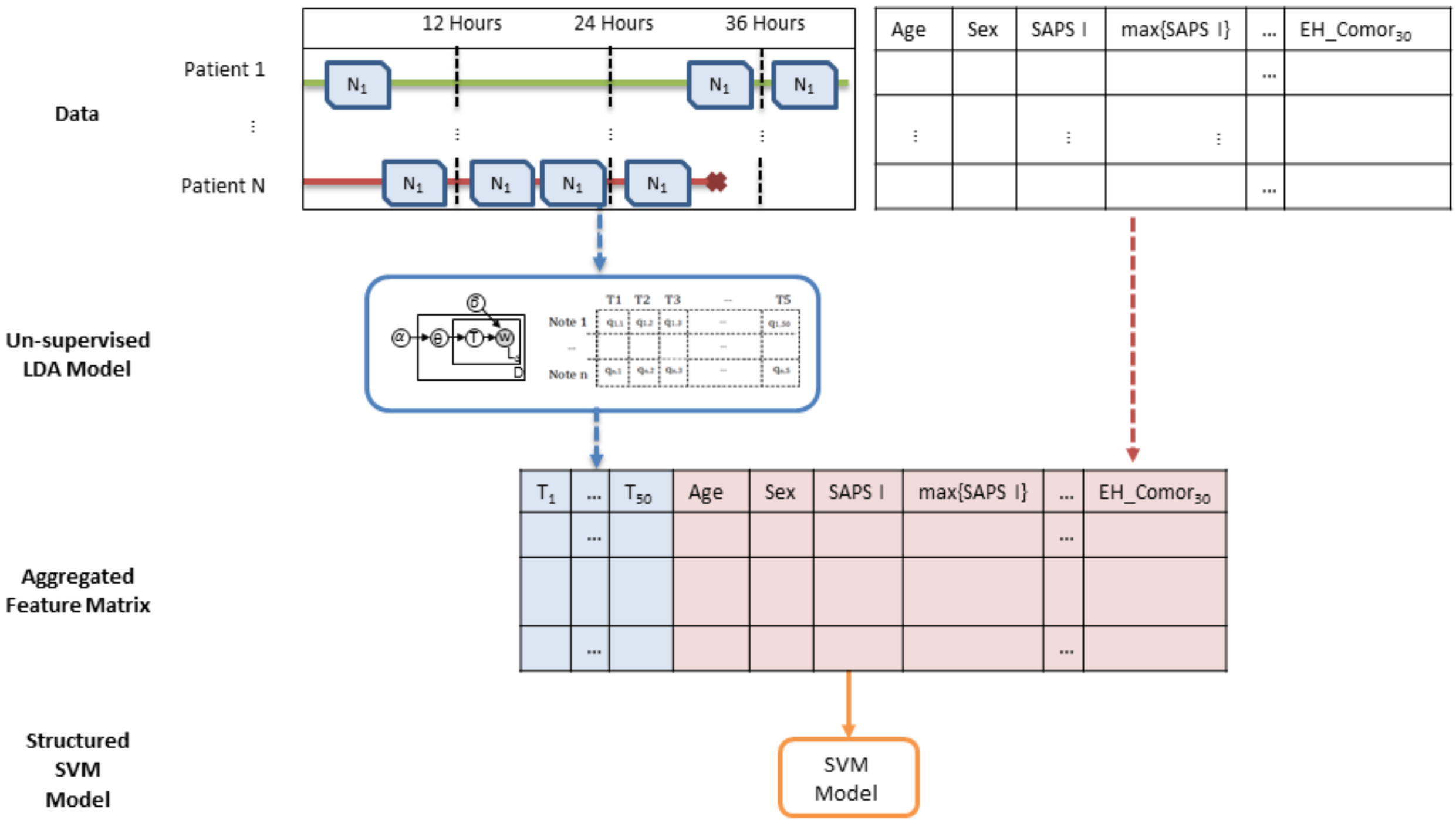
- Incorporate clinical text with snapshot data.

- Measure performance on mortality prediction in-hospital, at 30-days and 1-year post-discharge.

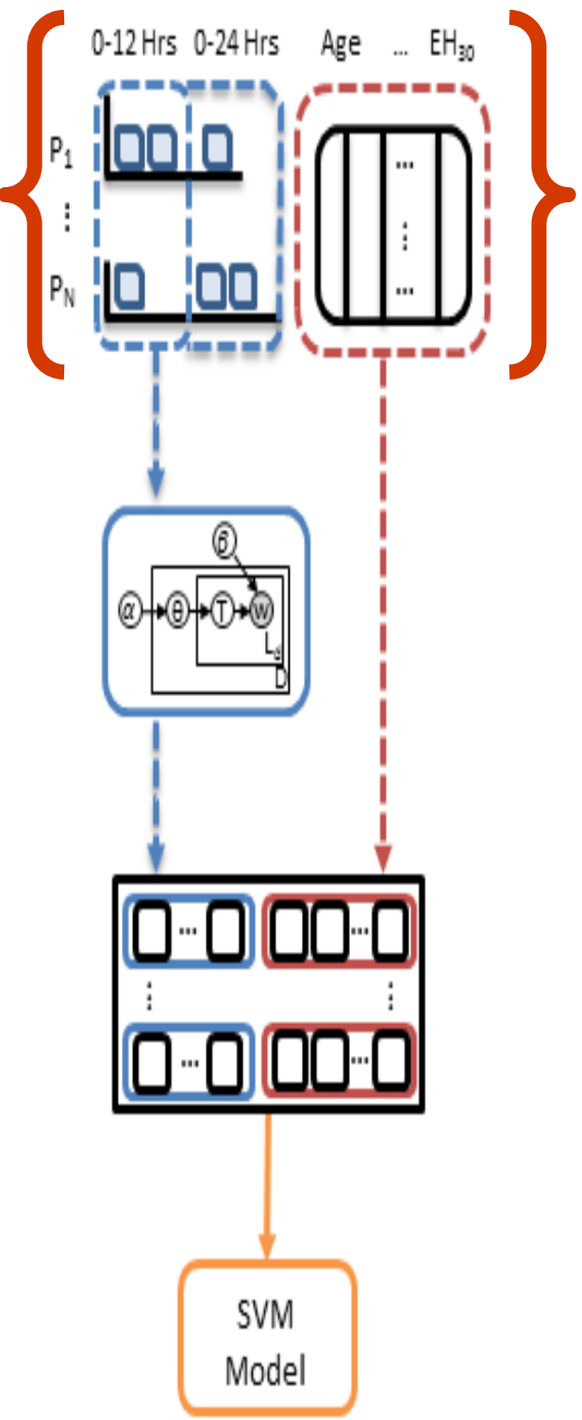
Hypothesis: Text information decomposed into topic features adds value to snapshot data.



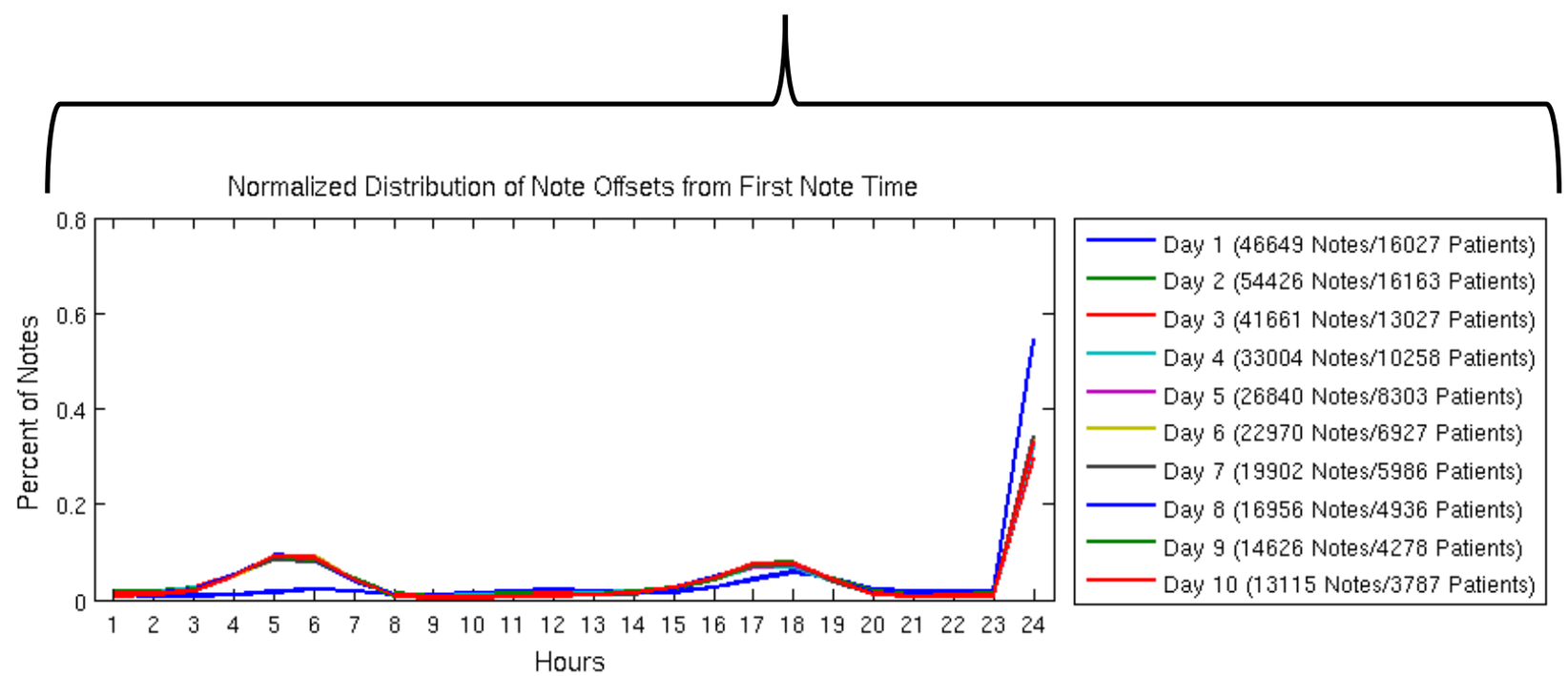
Model Setup: Overview



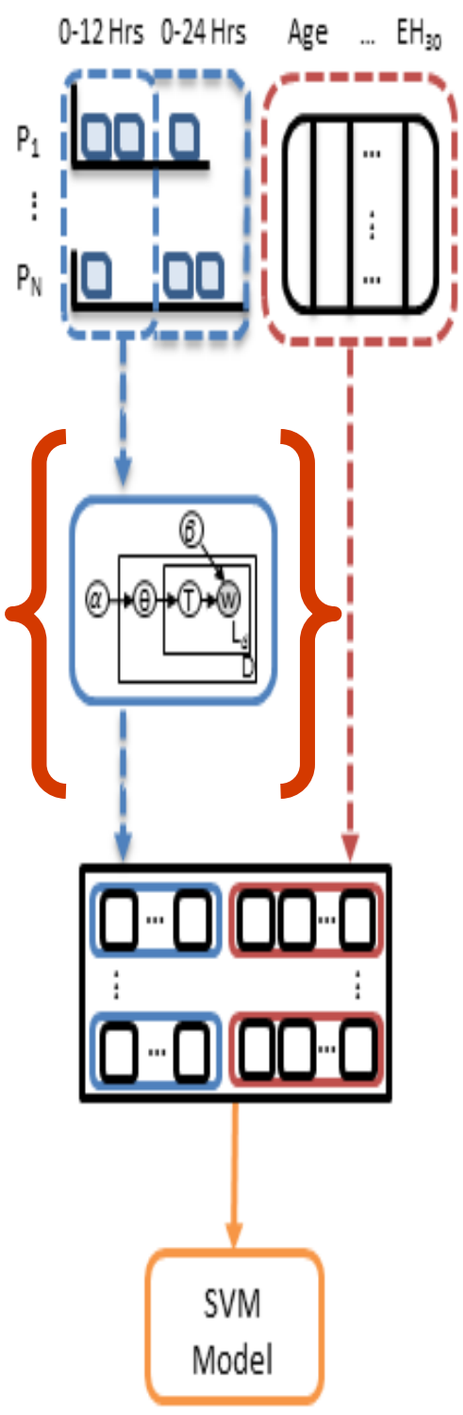
Model Setup: Data

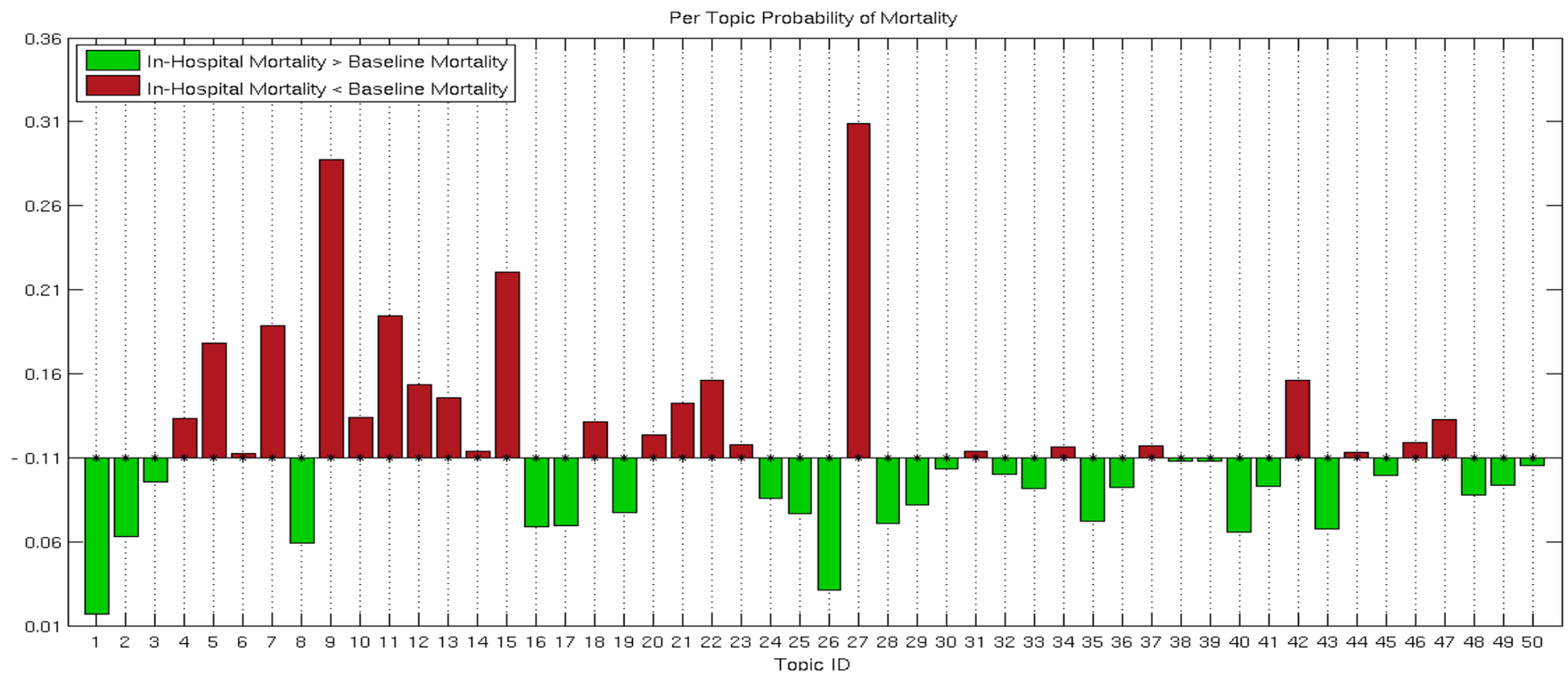


- Use 19,308 adult patient records
- Gather per-patient snapshot information
- Collect 473,764 notes
  - Use only first admissions
  - Ignore discharge summaries



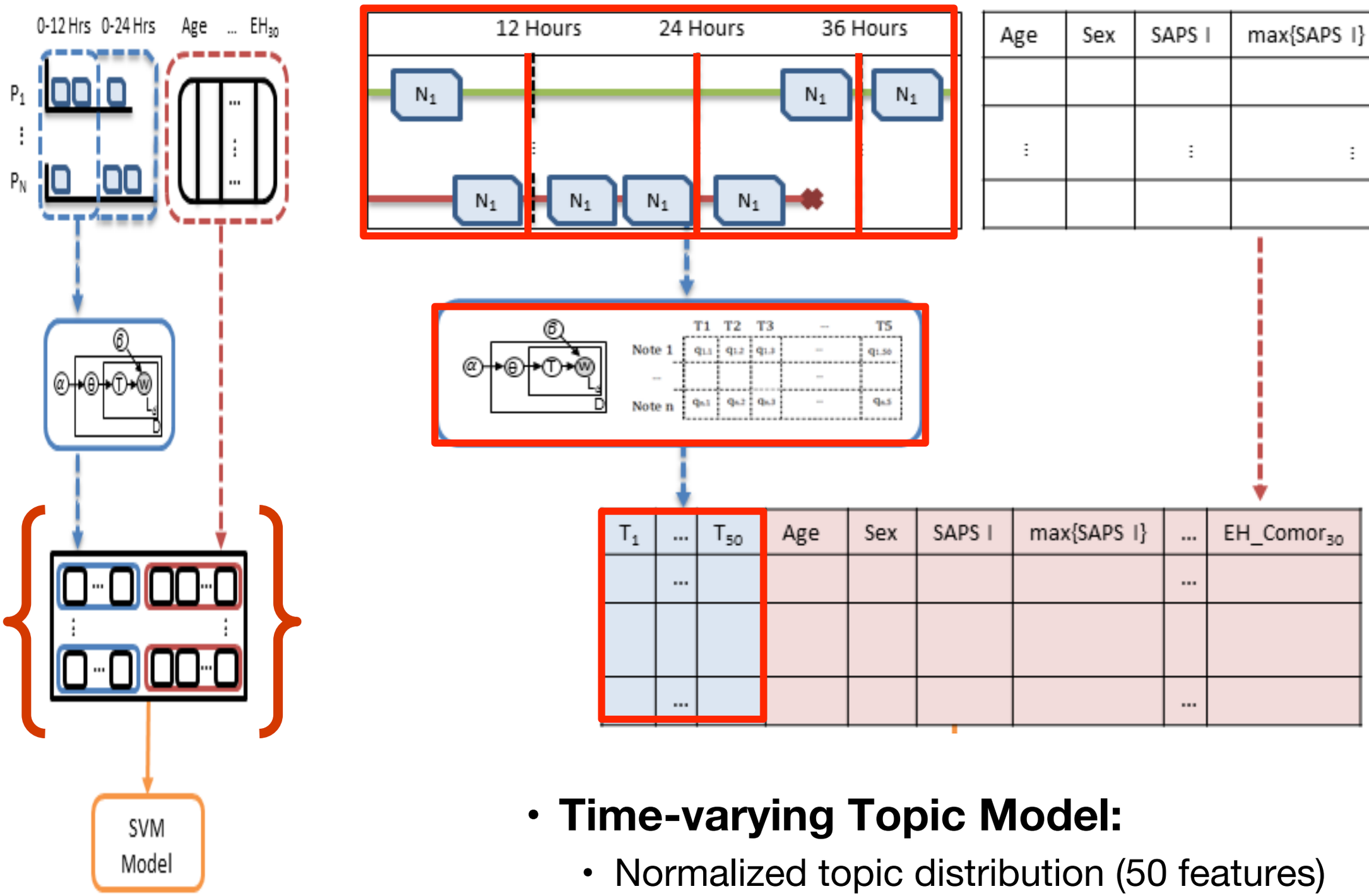
Model Setup: Latent Topic Features





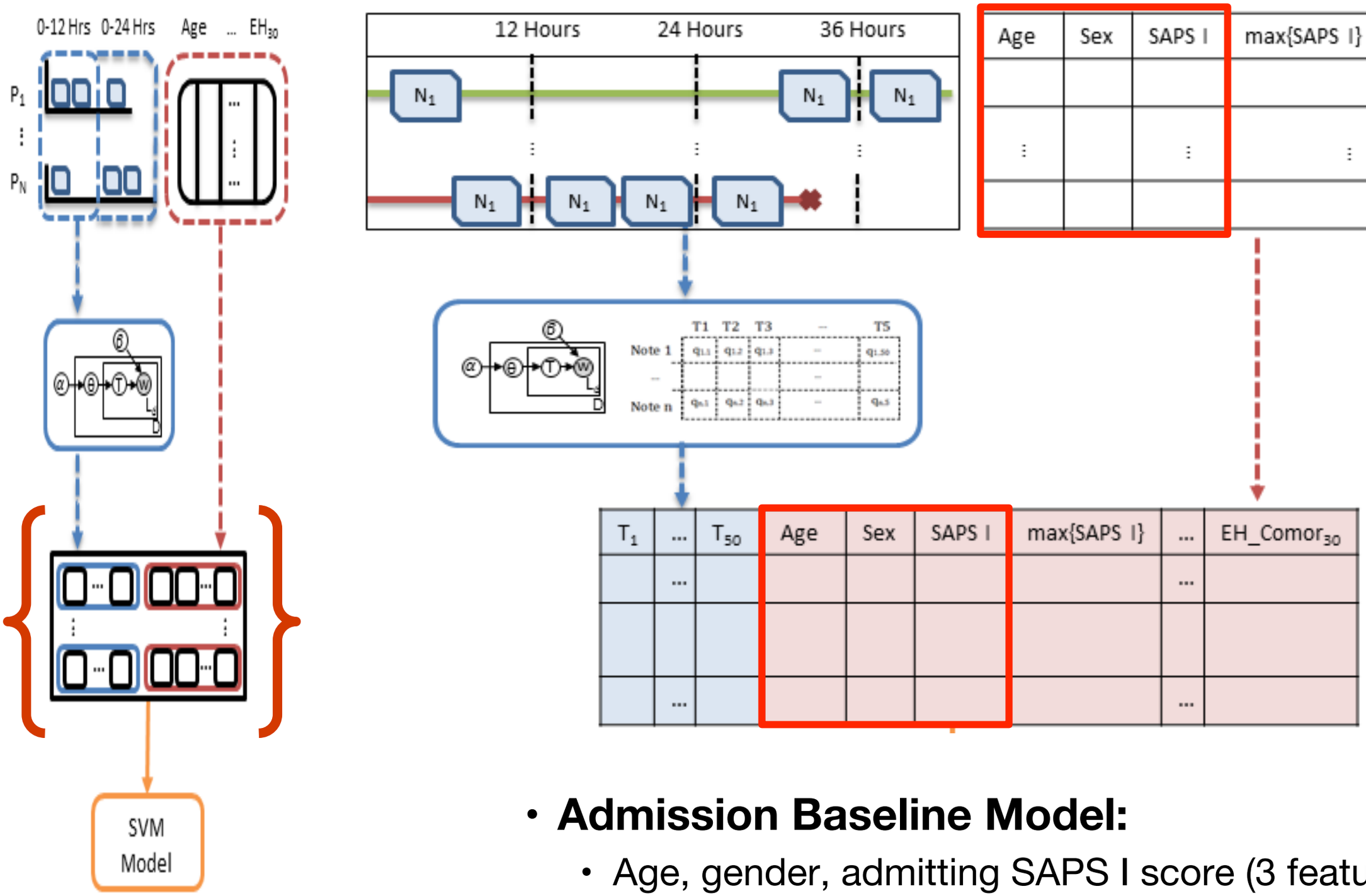
	Topic #	Top Ten Words	Possible Topic
In-Hospital Mortality	27	name family neuro care noted status plan stitle dr remains	Discussion of end-of-life care
	15	intubated vent ett secretions propofol abg respiratory resp care sedated	Respiratory failure
	7	thick secretions vent trach resp tf tube coarse cont suctioned	Respiratory infection
	5	liver renal hepatic ascites dialysis failure flow transplant portal ultrasound	Renal failure
Hospital Survival	1	cabg pain ct artery coronary valve post wires chest sp neo	Cardiovascular Surgery
	40	left fracture ap views reason clip hip distal lat report joint	Fracture
	16	gtt insulin bs lasix endo monitor mg am plan iv	Chronic diabetes
1 Year Mortality	3	picc line name procedure catheter vein tip placement clip access	PICC line insertion
	4	biliary mass duct metastatic bile cancer left ca tumor clip	Cancer treatment
	45	catheter name procedure contrast wire french placed needle advanced clip	Coronary catheterization

Model Setup: Time-varying Topics



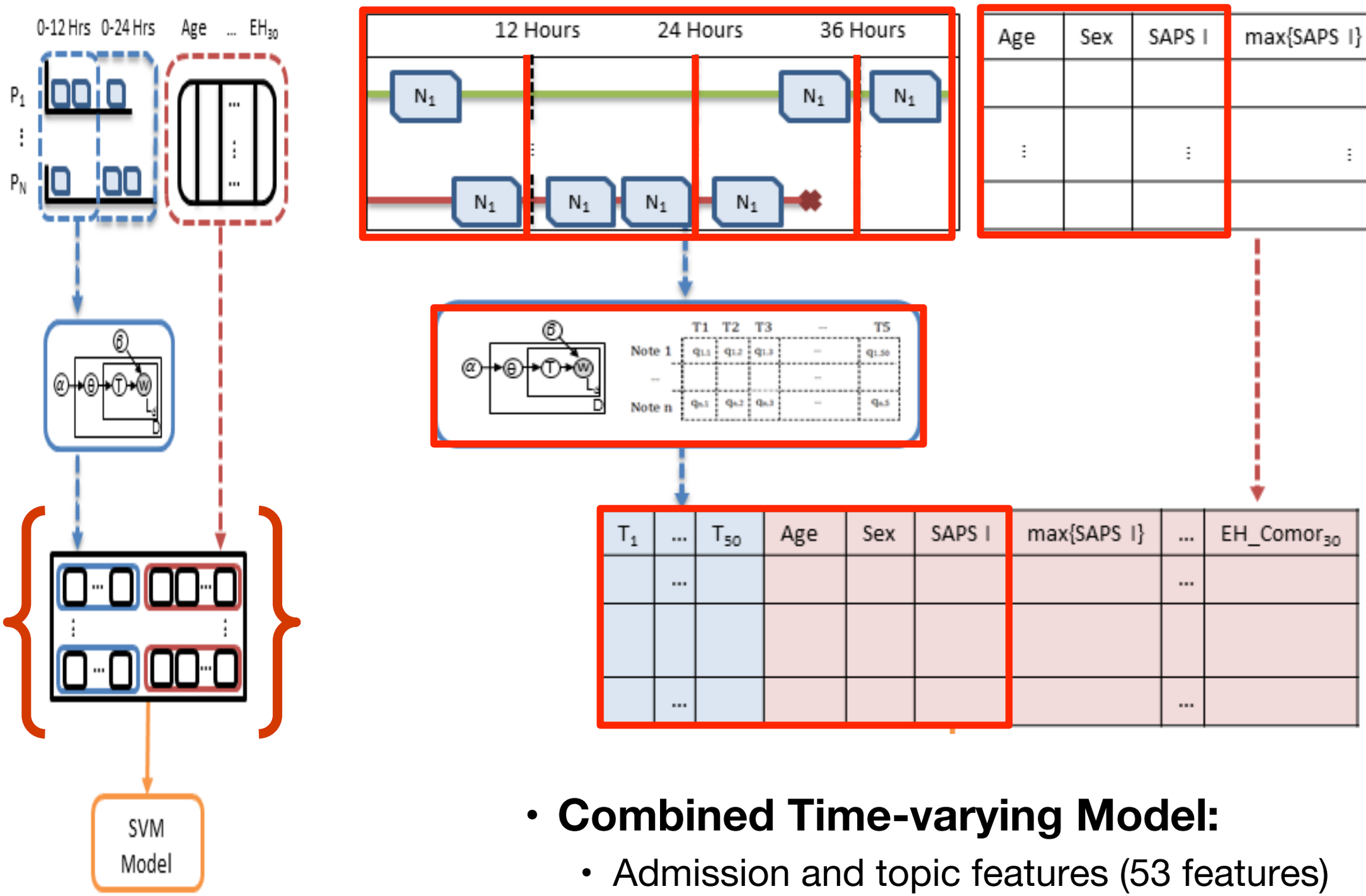
- **Time-varying Topic Model:**
  - Normalized topic distribution (50 features)

Model Setup: Admission Baseline



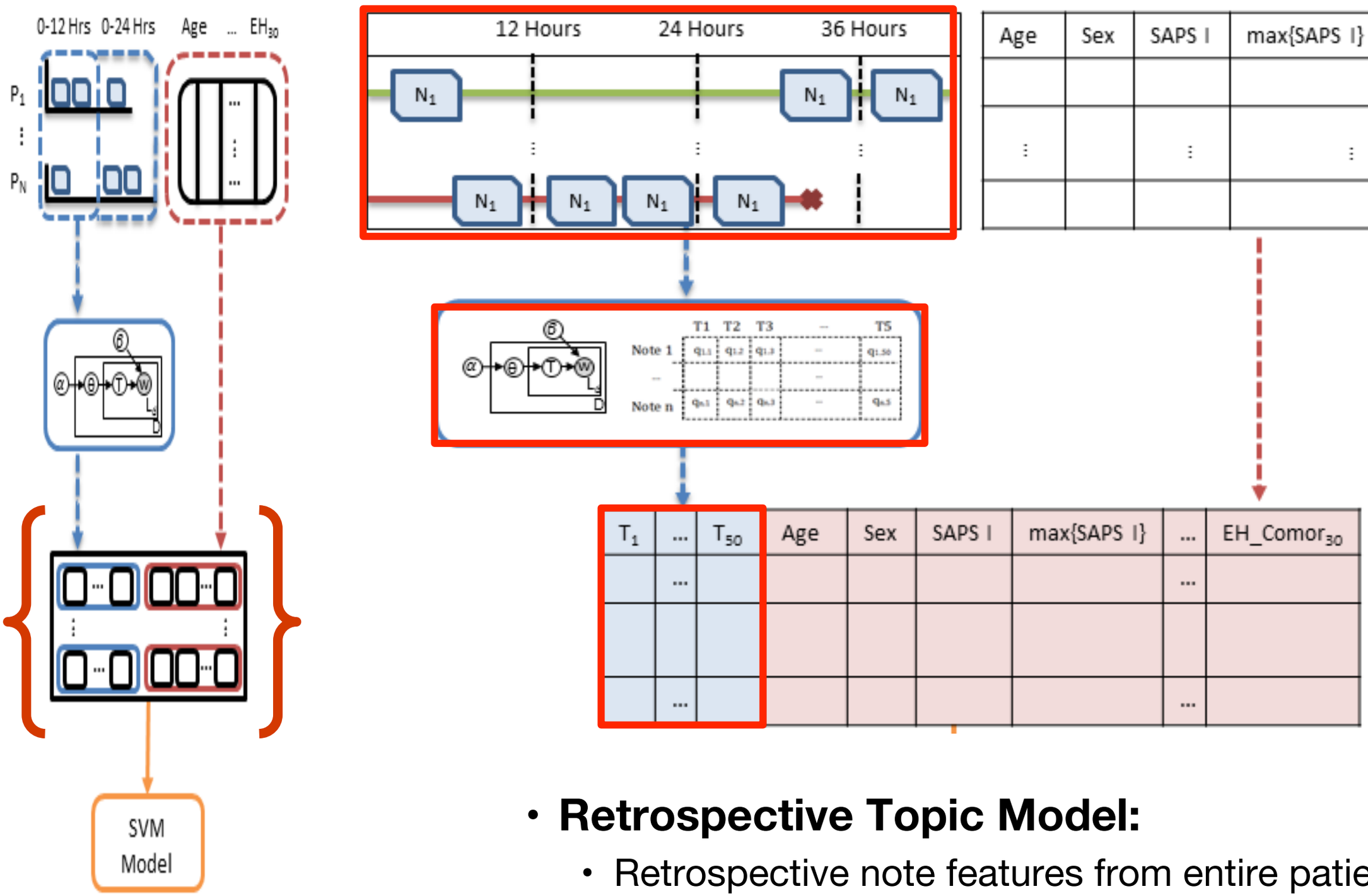
- **Admission Baseline Model:**
  - Age, gender, admitting SAPS I score (3 features)

Model Setup: Combined Time-varying



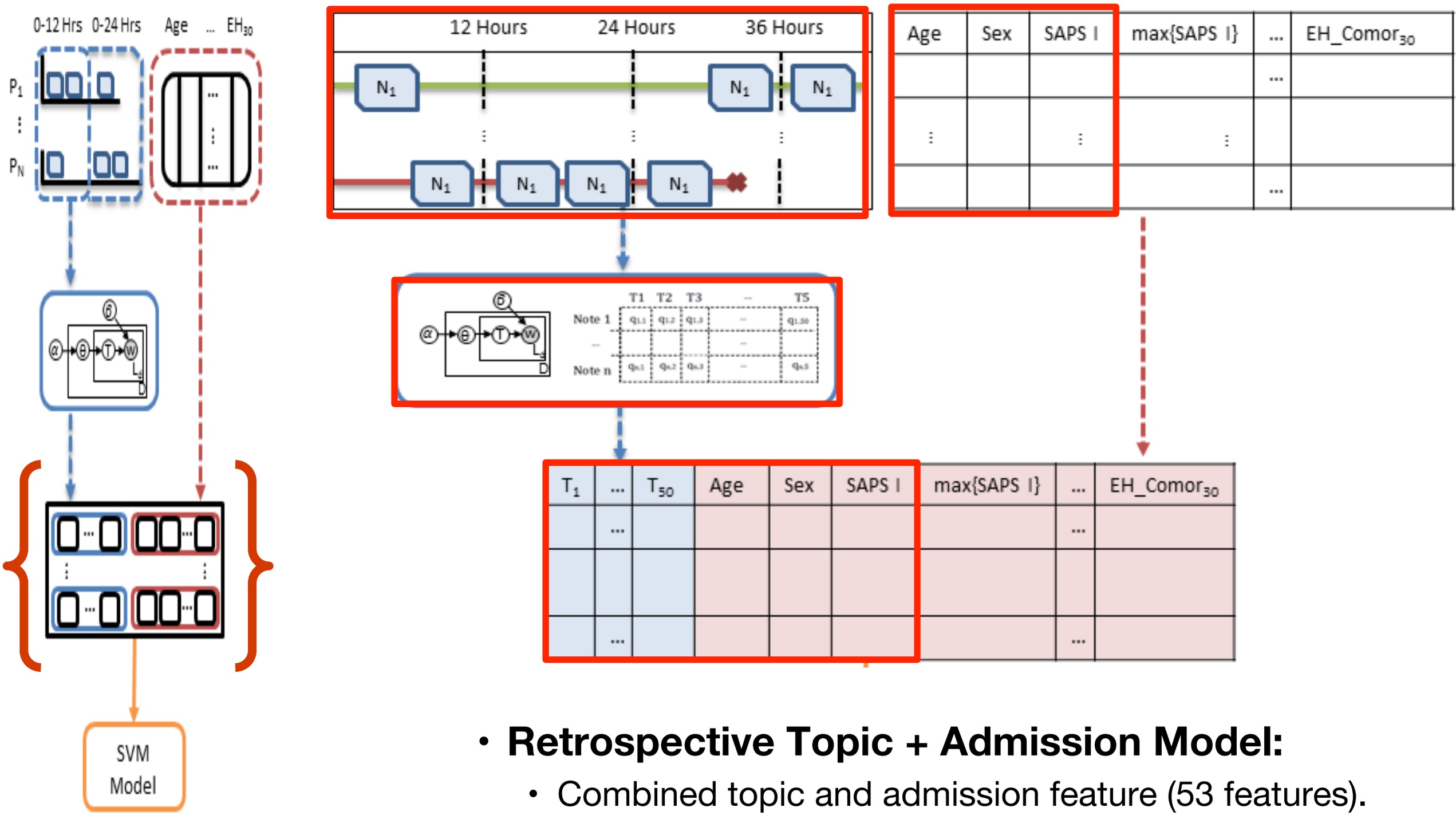
- **Combined Time-varying Model:**
  - Admission and topic features (53 features)

Model Setup: Retrospective Topics



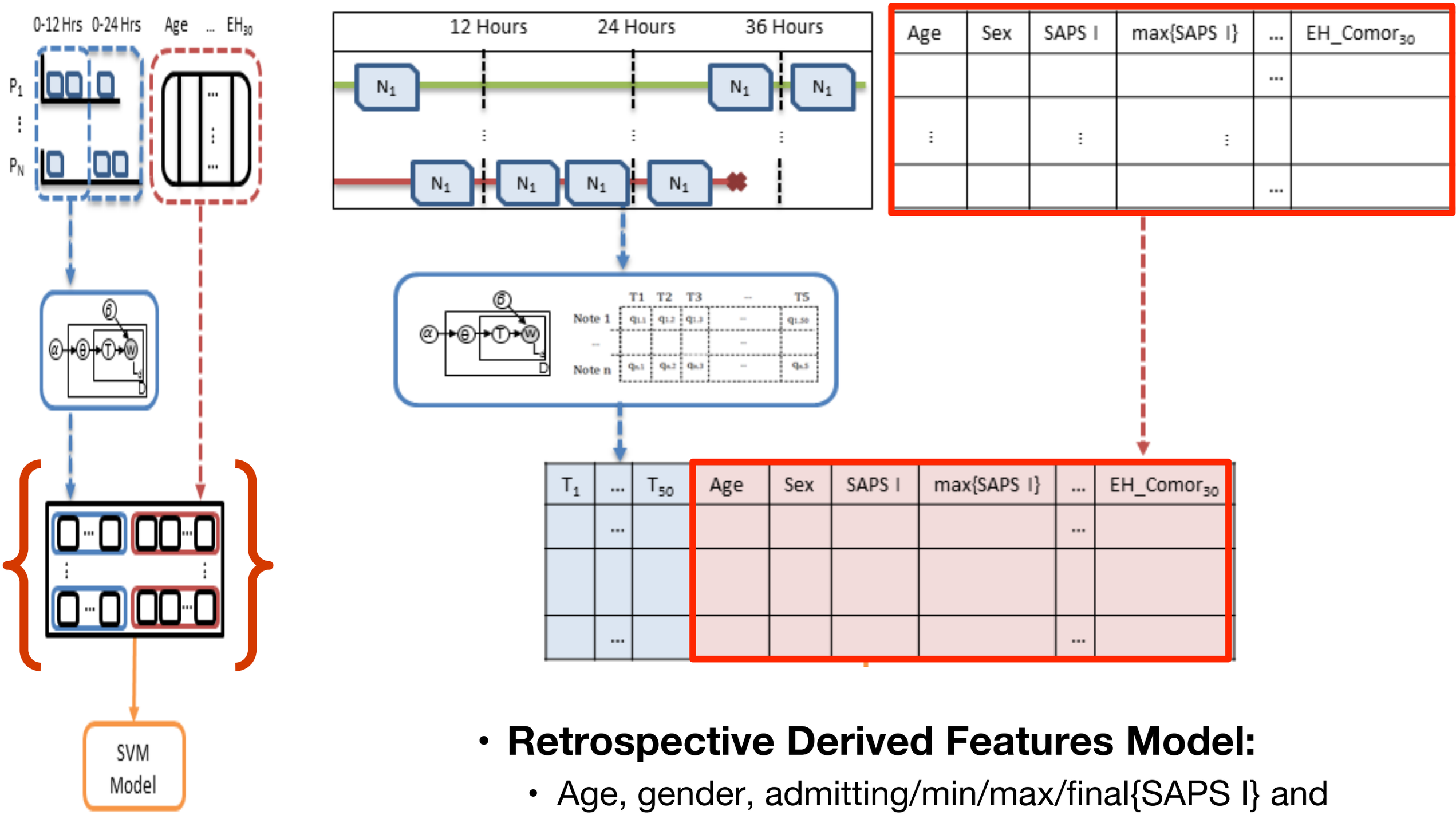
- **Retrospective Topic Model:**
  - Retrospective note features from entire patient stay (50 features).

Model Setup: Retrospective Topics + Admission



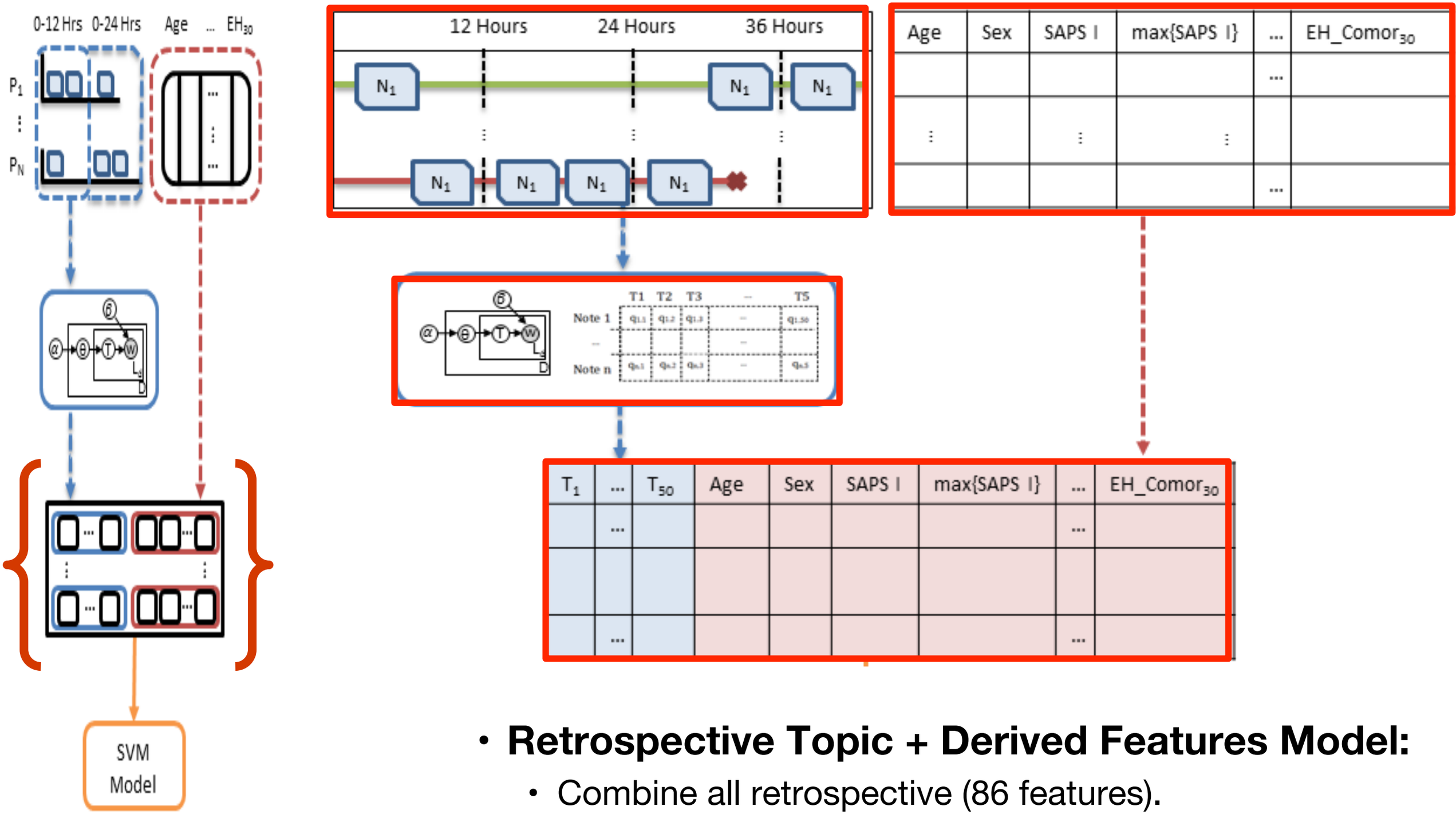
- **Retrospective Topic + Admission Model:**
  - Combined topic and admission feature (53 features).

Model Setup: Retrospective Derived



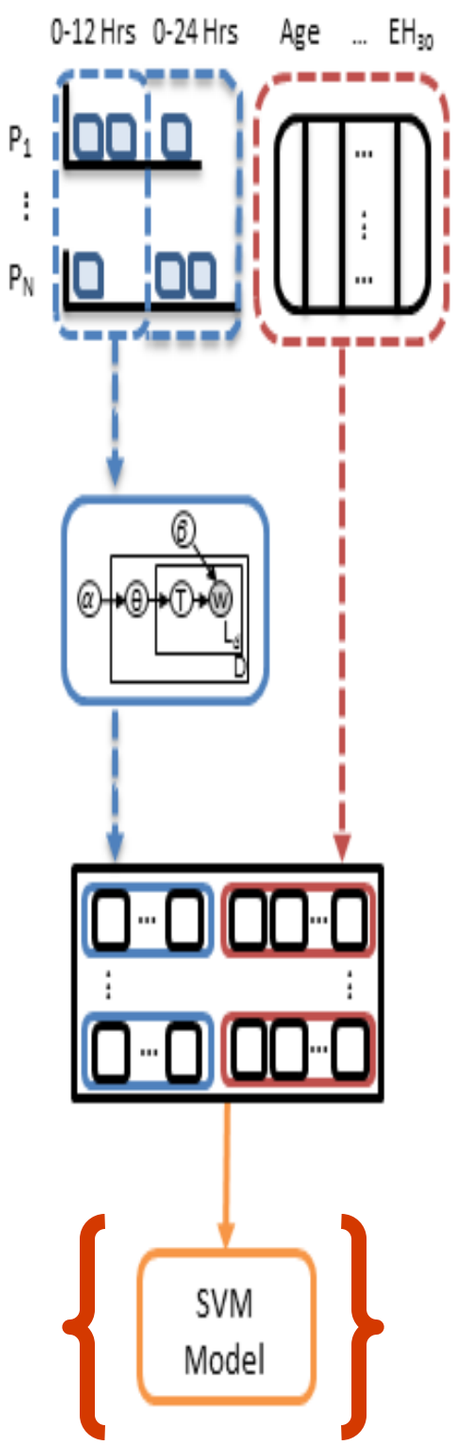
- **Retrospective Derived Features Model:**
  - Age, gender, admitting/min/max/final{SAPS I} and Elixhauser co-morbidity scores (36 features).

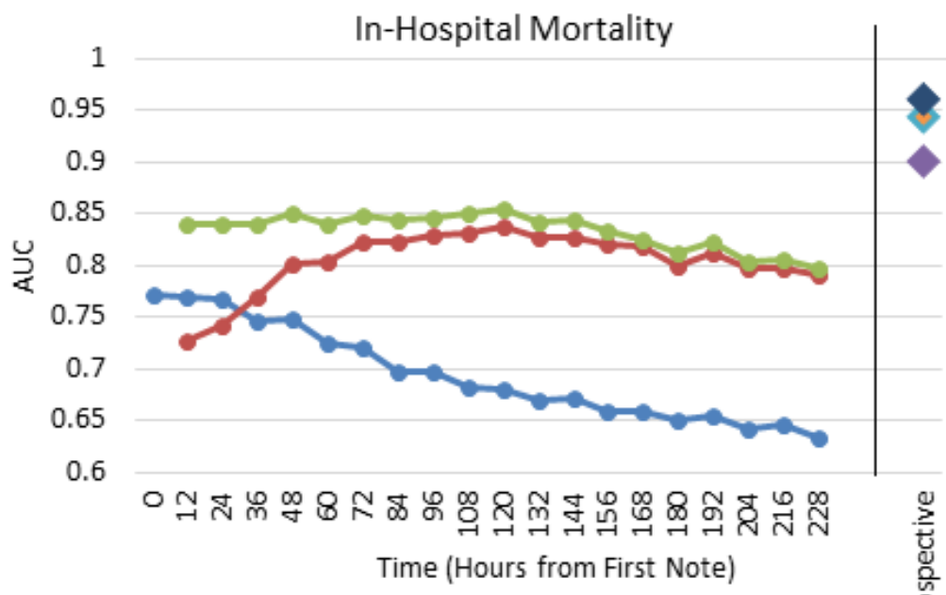
Model Setup: Retrospective Topics + Derived

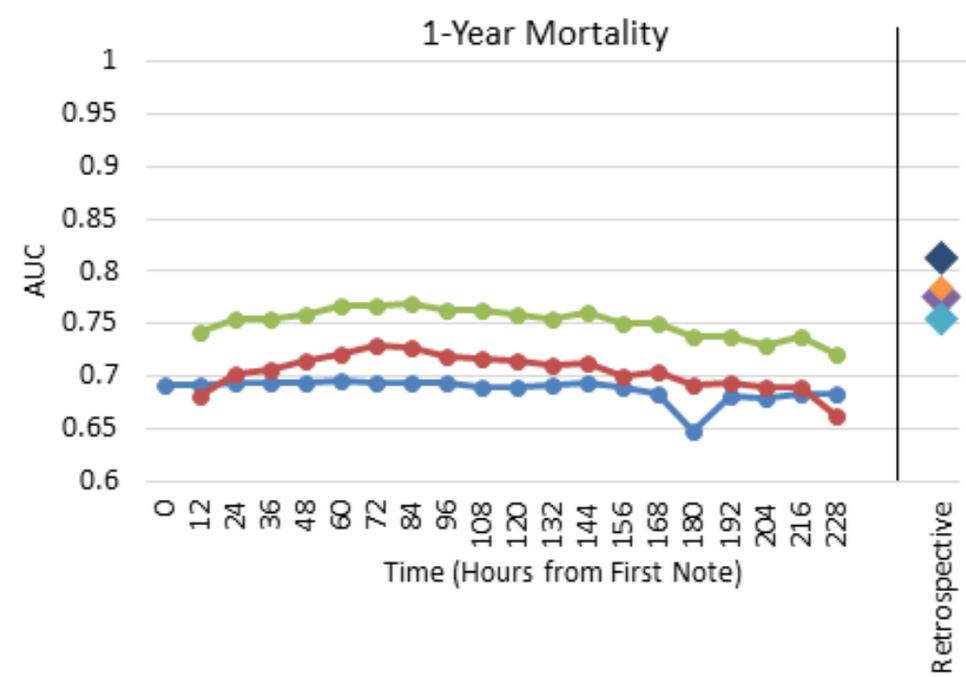


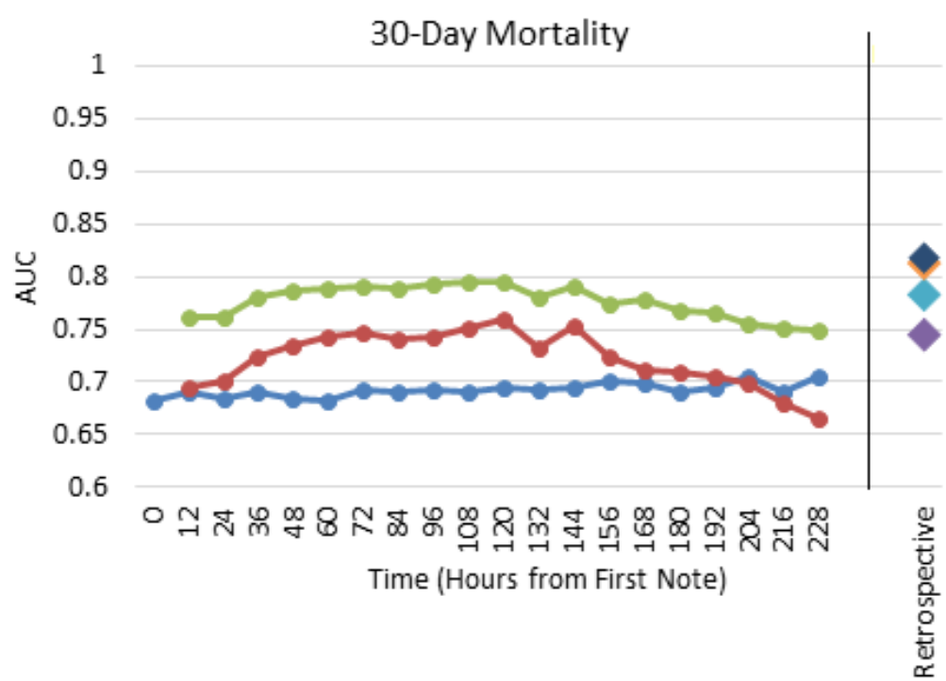
- **Retrospective Topic + Derived Features Model:**
  - Combine all retrospective (86 features).

Mortality Prediction Results









- Admission Baseline Model
- Time-varying Topic Model
- Combined Time-Varying Model
- Retrospective Derived Feature Model
- Retrospective Topic Model
- Retrospective Topic + Admission Model
- Retrospective Topic + Derived Feature Model

We Solved A Problem, So Everything Is Awesome

- Text Data Is Valuable
  - A combination of latent topic features and snapshot features worked best
- Long-term Predictions Are Harder
  - Combinations of features were best able to perform well initially and over first 24 hours.
- “Realtime” Models Are More Valuable
  - Retrospective models out-performed continuous models, but are not actionable.

Future Work

- A good predictive rule must be*:
  - Accurate in a wide variety of clinical setting
  - Easy to incorporate into routine clinical practice
  - Improves prognostic accuracy
  - Indicate effective treatment to improve outcomes

"Prediction of risk is not enough—we need evidence that prediction can lead to actions that reduce risk beyond what would occur without the prediction rule."

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Acknowledgements

Come by our poster tonight!

Thanks to:
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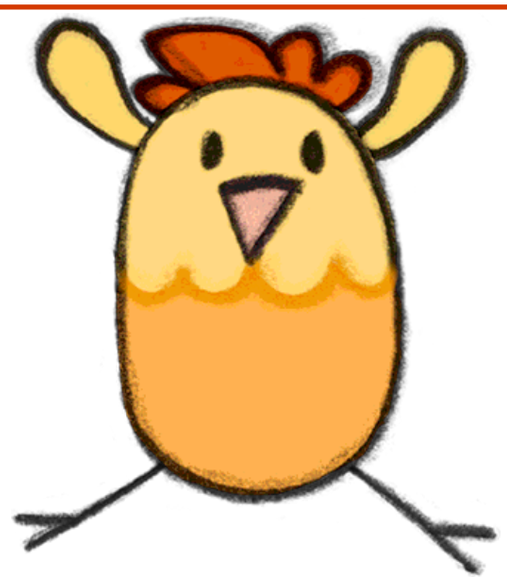
NIH NLM Biomedical Institute Research Training

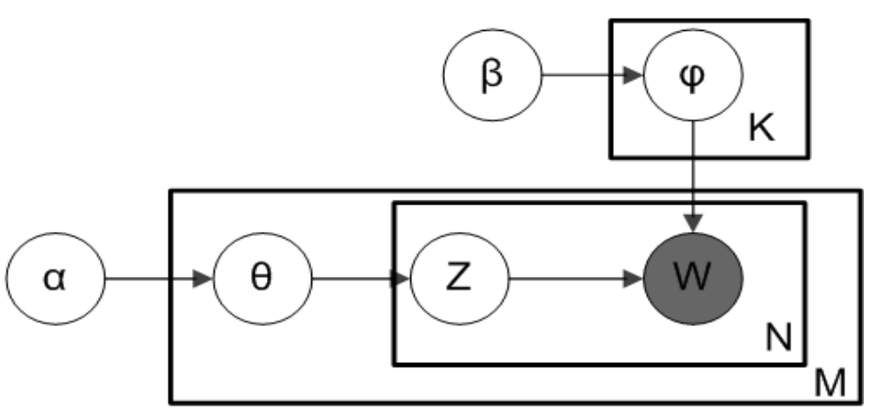


Backup

Latent Topic Inference

- Inferred topics provide weighted posterior $q_{n,k}$ for each note n and topic k such that for all n, $\sum_{k=1}^{50} q_{n,k} = 1$
- Probability of mortality for each topic as, $\theta_k = \frac{\sum_{n=1}^{N} q_{n,k} \cdot y_k}{\sum_{n=1}^{N} q_{n,k}}$

  where y_n is the mortality outcome (0 lives/1 dies).



Topics (T)

Notes	T1	T2	T3	...	T5
Note 1	$q_{1,1}$	$q_{1,2}$	$q_{1,3}$	...	$q_{1,50}$
...				...	
Note n	$q_{n,1}$	$q_{n,2}$	$q_{n,3}$	...	$q_{n,5}$

Number of patients over time goes down

Prediction

- Separate linear support vector machine (SVM) for each of three outcomes: in-hospital, 30-day, and 1-year mortality.
- Loss and class weight parameters selected using five fold cross-validation to determine optimal values.
- Class imbalances were addressed with random sub-sampling from the negative class to establish a 70%/30% ratio from:
    - 10.9% in-hospital mortality rate
    - 3.7% 30-day mortality rate
    - 13.7% 1-year mortality rate
    - Test set distributions were not modified.
- Prediction task becomes increasingly difficult over time since fewer patients have long ICU stays.
- Retrospective outcome predictions were included in order to provide relative upper bounds for each type of model.