Supplementary materials for ”A Multivariate Timeseries Modeling Approach to Severity of Illness Assessment and Forecasting in ICU with Sparse, Heterogeneous Clinical Data”

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1 Introduction

Below are supplementary materials for the AAAI 2015 paper presented by the authors.

2 Experiment I: Forecasting of Intracranial Pressure (ICP) and Mean Arterial Pressure (MAP) Timeseries: An Example

In Section 4 of our paper, we have demonstrated that the MTGP provides a significant improvement in interpolating missing values for both ICP and MAP signals, as the correlation between the two physiological variables is taken into account. This allows continuous assessment of the cerebral autoregulation mechanism measured by the interactions between ICP and MAP, which is an important indicator of secondary brain damage and mortality.

In this section, we showcase two examples to demonstrate the capability of the MTGP model in timeseries forecasting. As illustrated in Figure 2 and 1, two pieces of ICP and MAP timeseries in 10 minutes length were randomly selected for the experiment. Based on the first 8 minutes of data, both the STGP and MTGP models were employed to forecast the last 2 minutes of the time series.

It can be seen that the MTGP model greatly outperforms the STGP model. Especially for the case of MAP, the prediction variation of the STGP model start to grow rapidly as the forecasting horizon moves forward. On the other hand, MTGP is able to control the prediction variation in a much narrow region. Moreover, We also observe that, making use of the correlation between ICP and MAP, the MTGP model is able to forecast the oscillation pattern of time series.

Nevertheless, we acknowledge that a 2-minute forecasting window is probably too short for any real clinical applications. As part of our future work, we will conduct a more thorough investigation of the problem and will carry out a more systematic assessment on the proposed MTGP model's forecasting performance.

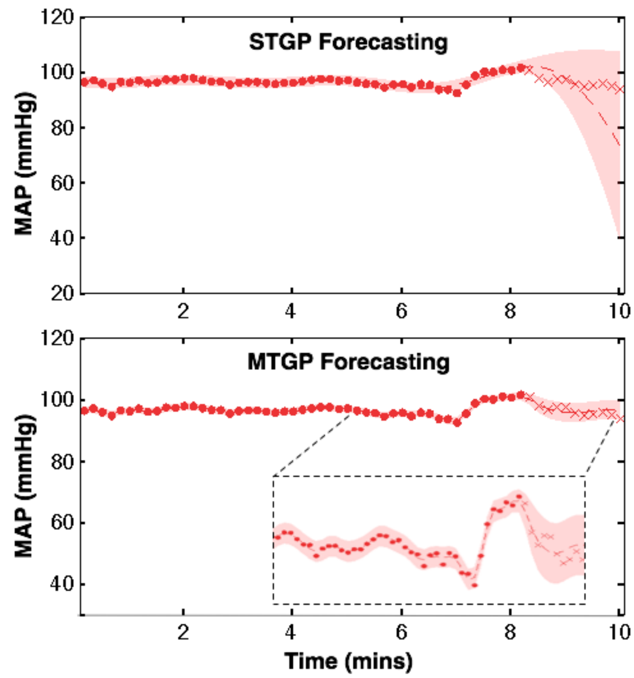

Figure 1: An example to compare the performance of MTGP and STGP on forecasting the Mean Arterial Pressure signal.

3 Experiment 2: From Heterogeneous Clinical Data to ICU Acuity Forecasting

3.1 Data

We used ICU data from the MIMIC II 2.6 database (**?**), a publicly-available, de-identified medical corpus which includes electronic medical records (EMRs) for $26,870$ ICU patients at the Beth Israel Deaconess Medical Center (BIDMC) collected from 2001 to 2008. Patient age, sex,

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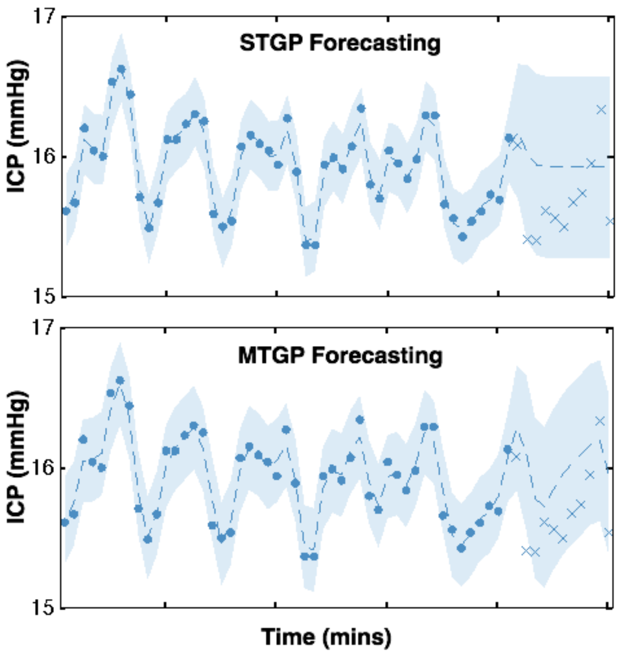

Figure 2: An example to compare the performance of MTGP and STGP on the forecasting Intracranial Pressure signal.

SAPS-II scores, International Classification of Diseases-Ninth Revision (ICD-9) diagnoses, and Disease-Related Group were extracted. Medical co-morbidities were represented by the Elixhauser scores (EH) for 30 co-morbidities as calculated from the ICD-9 codes. Patient mortality outcomes were also queried to determine which patients died in-hospital, or lived past the most recent query of Social Security records.

We extracted all clinical notes recorded prior to the patient's first discharge, including notes from nursing, physicians, labs, and radiology. The discharge summaries themselves were excluded because they typically stated the patient's outcome explicitly. Vocabularies for each note were generated by first tokenizing the free text and then removing stopwords using the Onix stopword list [1]. A TF-IDF metric was applied to determine the 500 most informative words in each patient's notes, and we then limited our overall vocabulary to the union of the most informative words per-patient. This pre-processing step reduced the overall vocabulary down to 285,840 words from over 1 million terms while maintaining the most distinctive features of each patient.[2]

Patients were excluded if they had fewer than 100 non-stop words or were under the age of 18. Specific notes were excluded if they occurred after the the end of the day in which a patient died or was discharged (e.g. radiology or lab reports whose results were reported afterwards). The final cohort consisted of 10,202 patients with 313,461 notes. A random 30% of the patients (3,040) were held back as a test set. The remaining 70% of patients (7,162) were used to train topic models and mortality predictors. The test set contained 93,411 notes, and the training set had 220,005.

3.2 Topic Inference

Topics were generated for each note using Latent Dirichlet Allocation. Our initial experiments found no significant difference in held-out prediction accuracy across a range of 20 to 100 topics. We set hyperparameters on the Dirichlet priors for the topic distributions (α) and the topic-word distributions (β) as $\alpha = \frac{50}{numberTopics}, \beta = \frac{200}{numberWordsInVocab}$. We used 50 topics in our final experiments, and topic distributions were sampled from an MCMC chain after 2,500 iterations. This topic-modeling step resulted in a 50-dimensional vector of topic proportions for each patient for each note.

3.3 Hyperparameter Construction

We concatenated the topic vectors into a matrix q where the element $q_{n,k}$ was the proportion of topic k in the n^{th} note. Of particular interest was whether certain topics were enriched for in-hospital mortality and long-term survival. We used an enrichment measure defined by Marlin et al(**?**), where the probability of mortality for each topic is calculated as $\phi_k = \frac{\sum_{n=1}^{N} q_{n,k} * y_k}{\sum_{n=1}^{N} q_{n,k}}$, where y_n is the noted mortality outcome (0 for a patient that lives, and 1 for a patient that dies).

From the topic enrichment measure (ϕ), we chose the topics with a posterior likelihood above or below 5% of the population baseline likelihood across topics. This yielded nine topics. See Figure 3 and Table 1 for a summary of the chosen topics. The relative distributions of the in-hospital mortality probabilities for all of the 50 topics are shown in Figure 4, and Table 2 lists the top ten words for all topics.

Once notes were transformed into multi-dimensional numeric vectors, we used the MTGPs to model the per-note change in topic membership over a patient's stay. This is critical for comparing two patients' records given that patients have vastly different lengths of stay and note taking intervals depend on the care staff, clinical condition, and other factors.

We employed MTGP to learn the temporal correlation between the nine topics and the overall temporal variability of the multiple timeseries.

Table 2.

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[1] Onix Text Retrieval Toolkit, API Reference, http://www.lextek.com/manuals/onix

[2] Some medical term canonicalization parsers were also examined, but we found their outputs to be fairly unreliable for this task.

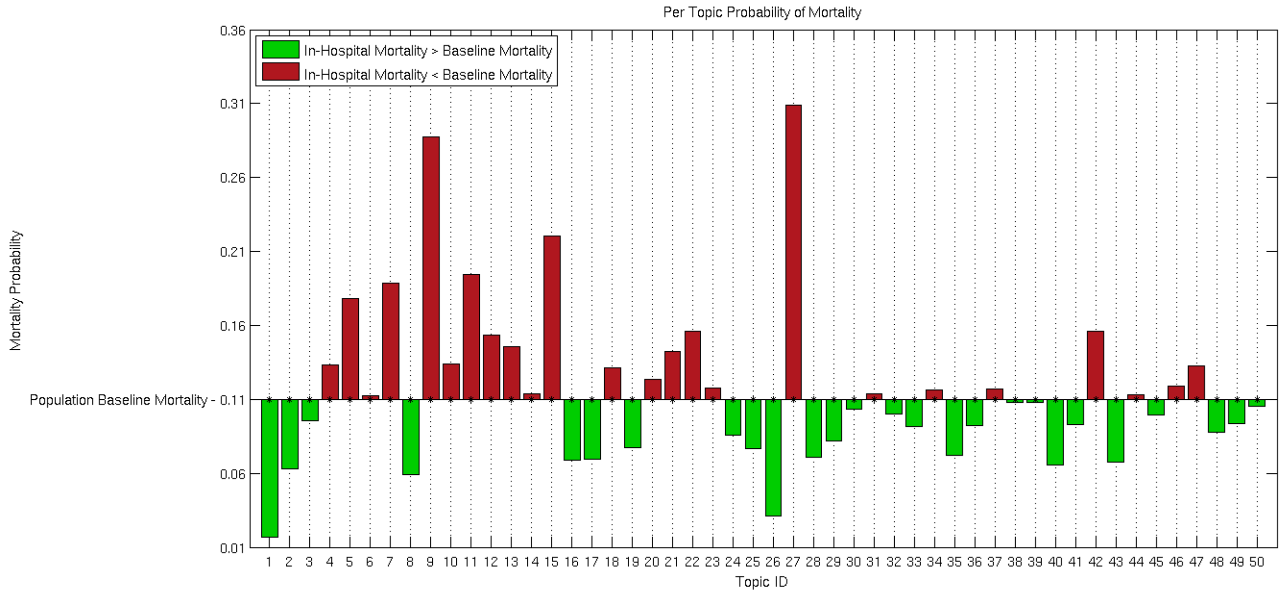

Figure 4: The probability of in-hospital mortality for each topic, indicating that topics represent differences in outcome. Probabilities are calculated as $\theta_k = \frac{\sum_{n=1}^{N} q_{n,k} * y_n}{\sum_{n=1}^{N} q_{n,k}}$ (see section **??**). Each bar shows the prevalence of a given topic k in the mortality category, as compared to the set of all patients. Bars are shown as above (in red) or below (in green) the baseline in-hospital mortality based on the value of θ_k for each topic k.

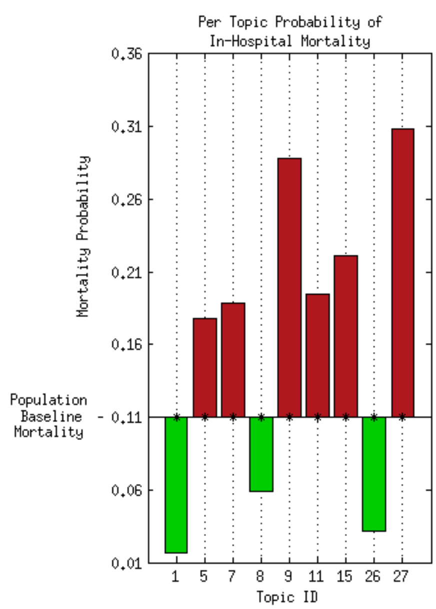

Figure 3: The likelihood of in-hospital mortality for each topic. Bars are shown as above (in red) or below (in green) the baseline in-hospital mortality based on the value of ϕ_k for each topic k.

Table 1: Top five words in chosen topics (enriched for in-hospital mortality/survival).

	Topic	**Top Ten Words**	**Possible Topic**
In-hospital Mortality	5	liver, renal, hepatic, ascites, dialysis, failure, flow, transplant, portal, ultrasound	Renal Failure
	7	thick, secretions, vent, trach, resp, tf, tube, coarse, cont, suctioned	Respiratory infection
	9	remains family gtt line map cont levophed cvp bp levo	Systematic organ failure
	11	increased temp hr pt cc ativan cont mg continues am decreased	Multiple physiological changes
	15	intubated, vent, ett, secretions, propofol, abg, respiratory, resp, care, sedated	Respiratory failure
	27	name, family, neuro, care, noted, status, plan, stitle, dr, remains	Discussion of end-of-life care
Hospital Survival	1	cabg, pain, ct, artery, coronary, valve, post, wires, chest, sp	Cardiovascular surgery
	8	chest, pneumothorax, tube, reason, clip, sp, ap, left, portable, ptx,	
	26	pain co denies oriented neuro plan diet po pt floor	Responsive patient

Table 2: Top ten most probable words for all topics.

Topic Number	Top Ten Words
1	cabg, pain, ct, artery, coronary, valve, post, wires, chest, sp
2	ccu, cath, mg, am, sp, groin, bp, cardiac, hr, cont
3	picc, line, name, procedure, catheter, vein, tip, placement, clip, access
4	biliary, mass, duct, metastatic, bile, cancer, left, ca, tumor, clip
5	liver, renal, hepatic, ascites, dialysis, failure, flow, transplant, portal, ultrasound
6	ct, contrast, pelvis, abdomen, fluid, bowel, clip, free, wcontrast, iv
7	thick, secretions, vent, trach, resp, tf, tube, coarse, cont, suctioned
8	chest, pneumothorax, tube, reason, clip, sp, ap, left, portable, ptx
9	remains, family, gtt, line, map, cont, levophed, cvp, bp, levo
10	name, neo, gtt, stitle, dr, sbp, resp, cont, wean, aware
11	remains, increased, temp, hr, pt, cc, ativan, cont, mg, continues
12	micu, code, stool, hr, bp, social, note, id, received, cchr
13	chest, pulmonary, bilateral, edema, portable, clip, reason, ap, pleural, effusions
14	resp, cough, sats, mask, sob, wheezes, nc, status, mg, neb
15	intubated, vent, ett, secretions, propofol, abg, respiratory, resp, care, sedated
16	gtt, insulin, bs, lasix, endo, monitor, mg, am, plan, iv
17	drainage, pain, abd, fluid, draining, drain, incision, sp, intact, pt
18	heparin, afib, ptt, am, gtt, mg, rate, hr, pvcs, iv
19	name, pacer, namepattern, placement, heart, pacemaker, ventricular, av, rate, chest
20	left, lung, effusion, lobe, pleural, lower, chest, upper, ct, opacity
21	skin, noted, care, left, applied, changed, draining, coccyx, wound, edema
22	tube, placement, tip, line, portable, ap, reason, position, chest, ng
23	noted, shift, name, pt, patent, patient, foley, agitated, soft, mg
24	hct, pt, gi, blood, bleeding, am, stable, unit, bleed, noted
25	name, am, mg, able, bp, time, night, times, doctor, confused
26	pain, co, denies, oriented, neuro, plan, diet, po, pt, floor
27	name, family, neuro, care, noted, status, plan, stitle, dr, remains
28	clip, reason, ro, medical, examination, evidence, impression, underlying, condition, normal
29	neuro, sbp, bp, commands, iv, cough, soft, status, lopressor, swallow
30	skin, stable, social, family, intact, tsicu, id, note, support, endo
31	woman, female, husband, name, pain, patient, pm, am, hospital, noted
32	diagnosis, admitting, name, reason, please, examination, yearold, eval, findings, underlying
33	name, neck, soft, patient, noted, anterior, epidural, level, posterior, namepattern
34	ct, contrast, chest, lymph, optiray, images, lesions, iv, nodes, lobe
35	left, stenosis, disease, clip, reason, carotid, severe, report, radiology, final
36	femoral, foot, left, leg, iliac, groin, lower, patent, graft, extremity
37	acute, reason, head, clip, evidence, eval, name, wo, status, ct
38	aortic, aorta, cta, wwo, dissection, recons, contrast, left, aneurysm, chest
39	left, ivc, filter, vein, pulmonary, veins, dvt, clip, inferior, upper
40	left, fracture, ap, views, reason, clip, hip, distal, lat, report
41	spine, cervical, spinal, clip, thoracic, fall, lumbar, vertebral, contrast, reason
42	hemorrhage, head, ct, left, frontal, contrast, subdural, hematoma, clip, bleed
43	ct, trauma, contrast, injury, fracture, fractures, pelvis, clip, wcontrast, sp
44	contrast, brain, head, left, mri, images, mra, stroke, clip, cerebral
45	catheter, name, procedure, contrast, wire, french, placed, needle, advanced, clip
46	artery, left, common, distal, catheter, internal, branches, flow, name, middle
47	vein, stent, catheter, name, mm, portal, tips, balloon, venous, sheath
48	service, distinct, procedural, artery, sel, carotid, left, cath, name, clip
49	catheter, name, performed, embolization, contrast, bleeding, procedure, mesenteric, extravasation, clip
50	artery, carotid, left, aneurysm, injection, vertebral, internal, evidence, clip, cerebral