Vector Autoregression (VAR) of Longitudinal Sleep and Self-report Mood Data

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Editor: Could use one

Abstract

Self-tracking is one of many behaviors involved in the long-term self-management of chronic illnesses. As consumer-grade wearable sensors have made the collection of health-related behaviors commonplace, the quality, volume, and availability of such data has dramatically improved. This exploratory longitudinal N-of-1 study quantitatively assesses four years of sleep data captured via the Oura Ring, a consumer-grade sleep tracking device, along with self-reported mood data logged using eMood Tracker for iOS. After assessing the data for stationarity and computing the appropriate lag-length selection, a vector autoregressive (VAR) model was fit along with Granger causality tests to assess causal mechanisms within this multivariate time series. Oura's nightly sleep quality score shown to Granger-cause self-reported presence of depressed mood using a VAR(3) model.

1 Introduction

Long-term self-management of chronic illnesses such as bipolar disorder require persistent awareness of illness state over long periods of time and at varying time scales (Murnane et al., 2016; Morton et al., 2018; Majid et al., 2022). Remaining consistently aware of key indicators signalling the onset of a chronic condition allow individuals a chance at early intervention to reduce the severity of a givene episode. For example, an individual may modify behavior, engage their health practitioners, or adjust medication dosage. However nuanced, bipolar disorder is an illness that often degrades an individual's self-awareness and capacity for self-monitoring during symptomatic periods.

In the context of this specific illness, a volume of prior work has demonstrated the vital role of sleep in order to promote mood stability and prevent symptomatic episodes (Harvey et al., 2009; Murray and Harvey, 2010; Gruber et al., 2011). Although the particulars of this topic fall beyond the scope of this paper, these nuanced relationships may in fact be self-reinforcing and bidirectional — poor sleep may lead to episodic onset, which may also lead to worsening (or shortening) sleep bouts.

Given the importance of sleep in the ongoing management of this illness, accurate consumer-grade alternatives to polysomnography (considered the gold standard of sleep tracking) have emerged over the last few years. Indeed, comparatively inexpensive sleep tracking technologies like the Oura Ring have dramatically improved the quality of information that can be used to augment and inform these self-monitoring activities. Objective sensor-based tracking technology can be complemented with subjective self-report measures in order to form a more complete picture of physical and mental health across time. Given the aforementioned interplay of sleep and mood, this combination of subjective and objective tracking creates the possibility of longitudinal analysis — and potentially deepens one's capacity for self-awareness.

Following four years of consistent sleep and mood tracking, I sought to more formally interpret the data I had collected to quantify what I had previously intuited: that certain mood states could be understood (and potentially even predicted) by recent sleep trends. Indeed, this intuition has been demonstrated quantitatively in existing literature (Bose et al., 2017; Moshe et al., 2021; Jafarlou et al., 2023). As this work also demonstrates, combining data from consumer wearable technology and subjective self-report logs allows for a more comprehensive picture of health.

2 Methods

A multivariate time series analysis was performed using a vector autoregressive (VAR) model fit using ordinary least squares. An optimal lag order was first obtained using a combination of Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC), and final prediction error (FPE). After fitting a VAR(3) model on the multiple time series data (outlined below), a Granger causality test was performed in order to assess the predictive relationships between variables. Finally, an impulse response analysis was plotted to further explore the temporal relationships between variables, specifically between sleep, heartrate variability, and self-reported mood. I will outline these analysis steps in greater detail in the sections that follow.

2.1 Dataset Description

The sleep score dataset was created using the second- and third-generation Oura Ring. As detailed in Table 1, my use of the Oura Ring was consistent across time. The proprietary Oura sleep score is on a scale of 1 to 100 and incorporates a variety of sensor-based measures (i.e., heartrate variability, resting heartrate, body temperature) across time. Although the specifics of this algorithm are not public, the Oura Ring has been found to produce accurate measures of sleep timing and heartrate variability when compared against polysomnography (de Zambotti et al., 2019). The dataset contains 1,455 nights of sleep bout data occuring between February, 2019 and March, 2023.

	Value
Total nights	1455
Missing nights	1
Mean	73.82
SD	12.36
Max	97.00
Min	30.00

Table 1: Descriptive statistics of Oura Ring sleep score data

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EMA Categories	Count
irritable	100
anxious	88
depressed	103
elevated	48

Table 2: Count of days where EMA item contains a non-zero value

2.2 Vector Autoregression

(Seabold and Perktold, 2010)

(Lütkepohl, 2005)

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2.3 Granger Causality

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2.4 Impulse Response Analysis

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3 Results

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3.1 Stationarity, Decomposition, and Autocorrelation

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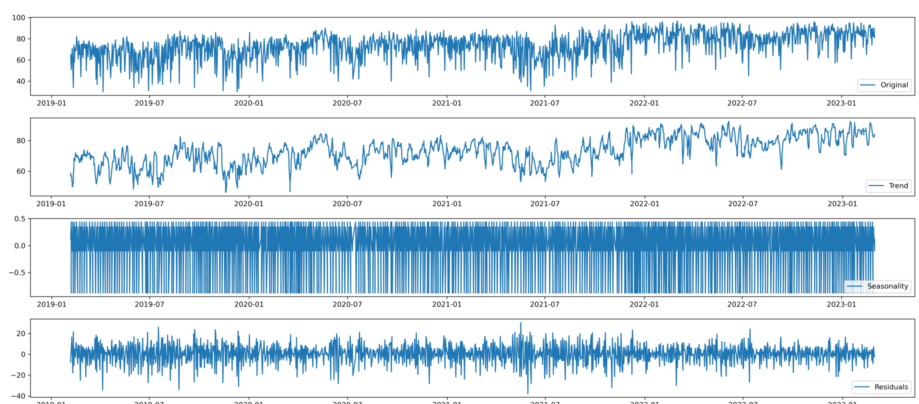

Figure 1: Decomposition of sleep time series

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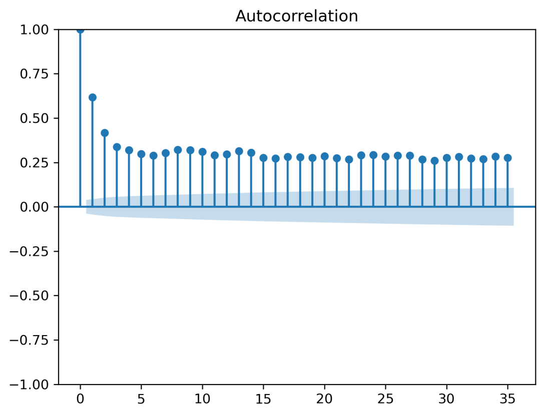

Figure 2: Autocorrelation of sleep time series

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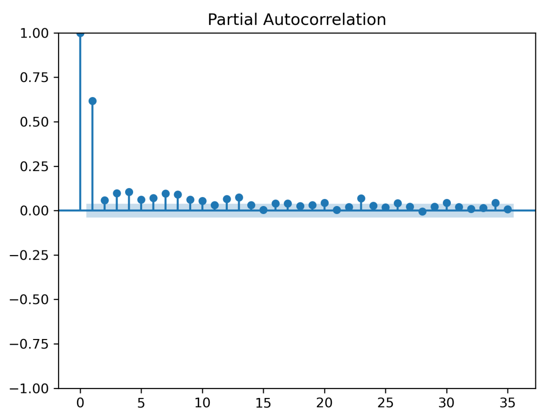

Figure 3: Partial autocorrelation of sleep time series

3.2 Lag Order Selection

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	AIC	BIC	FPE	HQIC
0	7.314	7.342	1501.	7.325
1	6.080	6.279*	436.9	6.155*
2	6.035	6.404	417.7	6.175
3	6.028*	6.568	414.9*	6.233
4	6.055	6.765	426.1	6.324
5	6.056	6.936	426.6	6.390
6	6.066	7.118	431.2	6.465
7	6.071	7.293	433.3	6.534
8	6.104	7.496	447.6	6.631
9	6.131	7.694	460.4	6.724
10	6.130	7.863	459.6	6.787
11	6.129	8.032	459.5	6.851
12	6.158	8.232	473.0	6.944
13	6.177	8.421	482.2	7.028
14	6.201	8.616	494.2	7.117
15	6.213	8.798	500.3	7.193

Table 3: VAR Order Selection (* highlights the minimum)

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3.3 Vector Autoregression Model

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	coefficient	std. error	t-stat	prob
const	33.675538	2.896460	11.626	0.000
L1.score	0.507601	0.031112	16.315	0.000
L1.average_hrv	-0.050172	0.022424	-2.237	0.025
L1.anxious	-0.078201	0.494593	-0.158	0.874
L1.depressed	0.615468	0.457538	1.345	0.179
L1.irritable	-0.015195	0.457422	-0.033	0.973
L1.elevated	-0.150473	0.729563	-0.206	0.837
L2.score	-0.020902	0.034834	-0.600	0.548
L2.average_hrv	-0.027687	0.022370	-1.238	0.216
L2.anxious	0.178654	0.540249	0.331	0.741
L2.depressed	**1.427585**	0.490653	2.910	**0.004**
L2.irritable	-0.634113	0.500474	-1.267	0.205
L2.elevated	-0.164427	0.771205	-0.213	0.831
L3.score	0.117166	0.031157	3.760	0.000
L3.average_hrv	-0.023210	0.022319	-1.040	0.298
L3.anxious	0.003463	0.492368	0.007	0.994
L3.depressed	0.152999	0.458520	0.334	0.739
L3.irritable	0.406833	0.457032	0.890	0.373
L3.elevated	-0.805440	0.732522	-1.100	0.272

Table 4: VAR results for equation score

Causal Variable	Variable	Test statistic	Critical value	p-value	df
average_hrv	depressed	1.541	2.606	0.202	(3, 6234)
average_hrv	anxious	0.3879	2.606	0.762	(3, 6234)
average_hrv	irritable	0.8046	2.606	0.491	(3, 6234)
average_hrv	elevated	0.6640	2.606	0.574	(3, 6234)
score	**depressed**	5.155	2.606	**0.001**	(3, 6234)
score	anxious	2.432	2.606	0.063	(3, 6234)
score	irritable	1.311	2.606	0.269	(3, 6234)
score	elevated	0.7891	2.606	0.500	(3, 6234)

Table 5: Granger Causality Test for HRV and Sleep Score

3.4 Granger Causality

3.5 Impulse Response Analysis

4 Discussion

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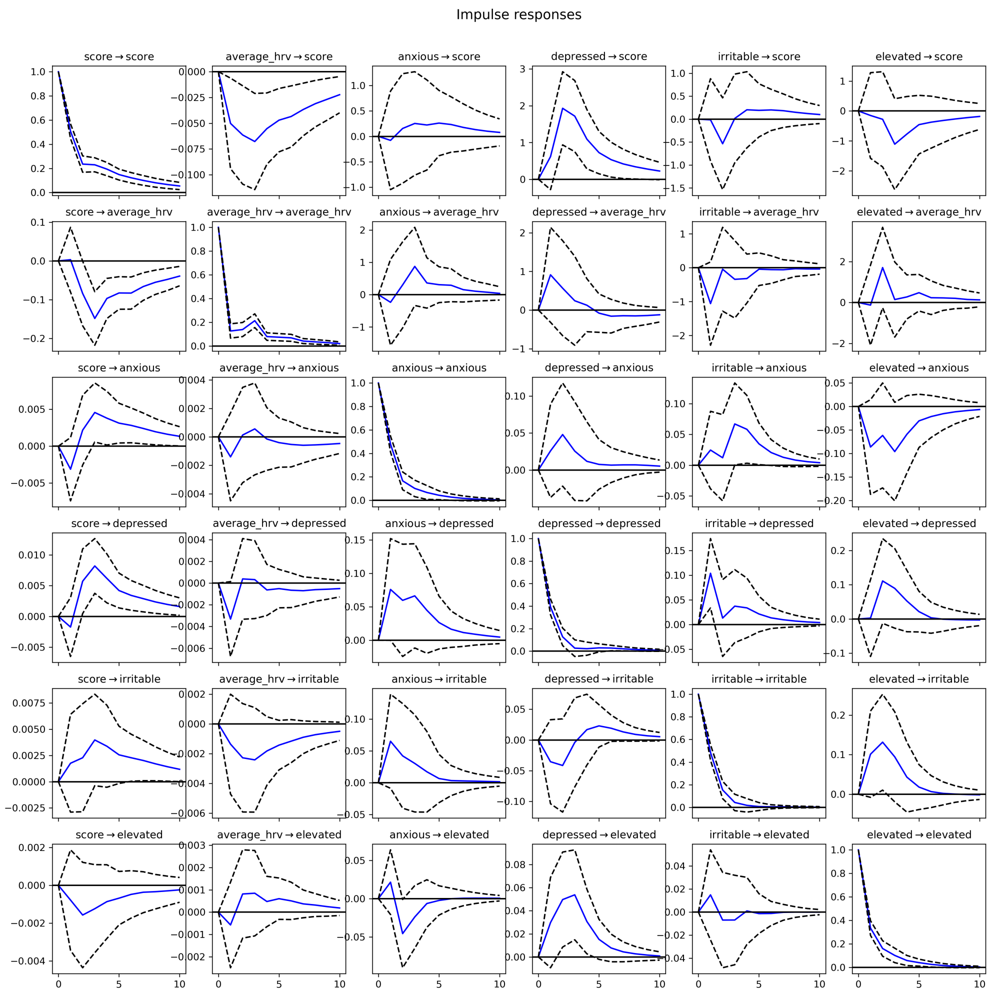

Figure 4: Plot of Impulse Response Function, Lag 0 to 10

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References

Eliezer Bose, Marilyn Hravnak, and Susan M. Sereika. Vector Autoregressive (VAR) Models and Granger Causality in Time Series Analysis in Nursing Research: Dynamic Changes Among Vital Signs Prior to Cardiorespiratory Instability Events as an Example. *Nursing research*, 66(1):12–19, 2017. ISSN 0029-6562. doi: 10.1097/NNR.0000000000000193. URL `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5161241/`.

Massimiliano de Zambotti, Leonardo Rosas, Ian M. Colrain, and Fiona C. Baker. The Sleep of the Ring: Comparison of the ŌURA Sleep Tracker Against Polysomnography. *Behavioral Sleep Medicine*, 17(2):124–136, March 2019. ISSN 1540-2002. doi: 10.1080/15402002.2017.1300587. URL `https://doi.org/10.1080/15402002.2017.1300587`. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/15402002.2017.1300587.

June Gruber, David J. Miklowitz, Allison G. Harvey, Ellen Frank, David Kupfer, Michael E. Thase, Gary S. Sachs, and Terence A. Ketter. Sleep matters: Sleep functioning and course of illness in bipolar disorder. *Journal of Affective Disorders*, 134(1):416–420, November 2011. ISSN 0165-0327. doi: 10.1016/j.jad.2011.05.016. URL `https://www.sciencedirect.com/science/article/pii/S016503271100262X`.

Allison G. Harvey, Lisa S. Talbot, and Anda Gershon. Sleep Disturbance in Bipolar Disorder Across the Lifespan. *Clinical Psychology: Science and Practice*, 16 (2):256–277, 2009. ISSN 1468-2850. doi: 10.1111/j.1468-2850.2009.01164.x. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-2850.2009.01164.x`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-2850.2009.01164.x.

Salar Jafarlou, Jocelyn Lai, Iman Azimi, Zahra Mousavi, Sina Labbaf, Ramesh C. Jain, Nikil Dutt, Jessica L. Borelli, and Amir Rahmani. Objective Prediction of Next-Day's Affect Using Multimodal Physiological and Behavioral Data: Algorithm Development and Validation Study. *JMIR Formative Research*, 7(1):e39425, March 2023. doi: 10.2196/39425. URL `https://formative.jmir.org/2023/1/e39425`. Company: JMIR Formative Research Distributor: JMIR Formative Research Institution: JMIR Formative Research Label: JMIR Formative Research Publisher: JMIR Publications Inc., Toronto, Canada.

Helmut Lütkepohl. *New introduction to multiple time series analysis*. New York : Springer, Berlin, 2005. ISBN 978-3-540-40172-8. OCLC: ocm61028971.

Shazmin Majid, Richard Morriss, Grazziela Figueredo, and Stuart Reeves. Exploring self-tracking practices for those with lived experience of bipolar disorder: Learning from combined principles of Patient and Public Involvement and HCI. In *Designing Interactive Systems Conference*, pages 1907–1920, Virtual Event Australia, June 2022. ACM. ISBN 978-1-4503-9358-4. doi: 10.1145/3532106.3533531. URL `https://dl.acm.org/doi/10.1145/3532106.3533531`.

Emma Morton, Erin E. Michalak, Rachelle Hole, Simone Buzwell, and Greg Murray. 'Taking back the reins' – A qualitative study of the meaning and experience of self-management in bipolar disorder. *Journal of Affective Disorders*, 228:160–165, March 2018. ISSN 0165-0327. doi: 10.1016/j.jad.2017.12.018. URL `https://www.sciencedirect.com/science/article/pii/S0165032717317913`.

Isaac Moshe, Yannik Terhorst, Kennedy Opoku Asare, Lasse Bosse Sander, Denzil Ferreira, Harald Baumeister, David C. Mohr, and Laura Pulkki-Råback. Predicting Symptoms of Depression and

Anxiety Using Smartphone and Wearable Data. *Frontiers in Psychiatry*, 12, 2021. ISSN 1664-0640. URL https://www.frontiersin.org/articles/10.3389/fpsyt.2021.625247.

Elizabeth L Murnane, Dan Cosley, Pamara Chang, Shion Guha, Ellen Frank, Geri Gay, and Mark Matthews. Self-monitoring practices, attitudes, and needs of individuals with bipolar disorder: implications for the design of technologies to manage mental health. *Journal of the American Medical Informatics Association*, 23(3):477–484, May 2016. ISSN 1067-5027. doi: 10.1093/jamia/ocv165. URL https://doi.org/10.1093/jamia/ocv165.

Greg Murray and Allison Harvey. Circadian rhythms and sleep in bipolar disorder. *Bipolar Disorders*, 12(5):459–472, 2010. ISSN 1399-5618. doi: 10.1111/j.1399-5618.2010.00843.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1399-5618.2010.00843.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1399-5618.2010.00843.x.

Skipper Seabold and Josef Perktold. statsmodels: Econometric and statistical modeling with python. In *9th python in science conference*, 2010.