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Preface

The 62nd International Statistical Institute World Statistics Congress (ISI WSC 2019) has a long tradition since 1887, held for the first time in Kuala Lumpur, Malaysia on 18 to 23 August 2019. ISI WSC 2019 is a global gathering of statistical practitioners, professionals and experts from industries, academia and official authorities to share insights in the development of statistical sciences.

The congress attracted an overwhelming number of participants across the regions. The scientific sessions were delivered over five days with parallel sessions and e-poster sessions running all day long. The scientific program reaches across the breadth of our discipline that comprised of Invited Paper Sessions (IPS), Special Topic Sessions (STS) and Contributed Paper Sessions (CPS). Papers presented exhibit the vitality of statistics and data science in all its manifestations.

I am very honoured to present the proceedings of ISI WSC 2019 to the authors and delegates of the congress. The proceedings contain papers presented in IPS, STS and CPS which were published in fourteen (14) volumes. Scientific papers were received from August 2018 and were carefully reviewed over few months by an external reviewer headed by Scientific Programme Committee (SPC) and Local Programme Committee (LPC). I am pleased that the papers received cover variety of topics and disciplines from across the world, representing both developed and developing nations.

My utmost gratitude and appreciation with the expertise and dedication of all the reviewers, SPC and LPC members for their contributions that helped to make the scientific programme as outstanding as it has been.

Finally, I wish to acknowledge and extend my sincere thanks to the member of National Organising Committee of ISI WSC 2019 from Department of Statistics Malaysia, Bank Negara Malaysia, Malaysia Institute of Statistics and International Statistical Institute for endless support, commitment and passion in making the ISI WSC 2019 a great success and congress to be remembered.

I hope the proceedings will furnish the statistical science community around the world with an outstanding reference guide.

Thank you.



Dr. Mohd Uzir Mahidin
Chairman
National Organising Committee
62nd ISI WSC 2019

i | ISI WSC 2019



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TABLE OF CONTENTS

Contributed Paper Session (CPS): Volume 3

Preface	i
Scientific Programme Committee	ii
Local Programme Committee	iii
CPS1923: Test for exponentiality against renewal increasing mean residual life class	1
CPS1931: Every Policy Is Connected (EPIC): A generic tool for policy-data integration	8
CPS1934: Prediction of daily respiratory tract infection episodes from prescription data	16
CPS1941: A new model selection criterion for finite mixture models	25
CPS1943: Player selection strategy: A quantitative perspective	34
CPS1944: Time-lagged variables and incidence of pneumonia in wet-dry tropical North Australia	46
CPS1946: Assessment of condominium occupancy rate in Bangkok and its vicinity from electricity meter data analytics	56
CPS1947: Semi-parametric single-index predictive regression	65
CPS1951: Comparative analysis of R&D statistical systems between China and major developed countries	72
CPS1952: A statistical modelling framework for mapping malaria seasonality	80
CPS1954: Multiclass classification of growth curves using random change point model with heterogeneity in the random effects	89
CPS1955: Master's Programme in Data Analytics for Government: The UK Experience	97
CPS1956: Detecting life expectancy anomalies in England using a Bayesian Hierarchical Model	104
CPS1965: The modified Lee-Carter model with linearized cubic spline parameter approximation for Malaysian mortality data	111
CPS1970: The Lee-Carter Model: Extensions and applications to Malaysian mortality data	118

CPS1972: Multi-Aspect permutation methods for cytomorphometric data under multivariate directional alternatives with application to comparative neuroanatomy	125
CPS1973: Structural breaks in nonparametric models via atomic pursuit methods	134
CPS1979: Investigating dissimilarity in spatial area data using Bayesian inference: The case of voter participation in the Philippine national and local elections of 2016	142
CPS1982: Traditional and newly emerging data quality problems in countries with functioning Vital Statistics: Experience of the Human Mortality Database	150
CPS1983: Data analytics for better statistics	159
CPS1985: Trusted official smart statistics - challenges for official statistics in using data sources coming from private data producers	165
CPS1988: Unreliable retrial queue with two types customers, two delays and vacations perspective	173
CPS1994: Improving energy access for Africa through regional integration	181
CPS1996: The relationship between income inequality and disparity education and effect to achieve SDGs in Egypt	190
CPS1997: Integration of Economic Establishments Data into a uniquely identified comprehensive frame in Egypt	200
CPS1999: Effect of the ocean heat content on the global sea ice extent using fuzzy logic approach	209
CPS2002: The impact of weather risk on the estimation of yield-based agricultural losses and value at risk using Copula models	216
CPS2003: Structured additive regression modeling of Pulmonary Tuberculosis infection	225
CPS2010: Spatial and temporal trends in non- monetary wealth in Latin America (1990-2010)	234
CPS2011: Using SOM-based visualization to analyse the financial performance of consumer discretionary firms	241

CPS2012: Forecasting conditional covariance matrices in high-dimensional data: A general dynamic factor approach	251
CPS2016: Spatial multivariate outlier detection in the water quality of Klang River basin, Malaysia	258
CPS2018: Using Google trend data as an initial signal Indonesia unemployment rate	266
CPS2019: Comparing rainfall curves between climatological regions using functional analysis of variance	274
CPS2025: mpcmp: Mean-Parametrized Conway- Maxwell Poisson (Com-Poisson) regression	282
CPS2026: Trends in the extremes of environments associated with severe US thunderstorms, and signals in their spatial dependence	290
CPS2037: Comparing the household final consumption expenditure in national accounts to the household budget survey - or vice versa?	299
CPS2041: Contribution and growth of selected economic activities in the non-oil real GDP in the Emirate of Abu Dhabi 2007-2018	308
CPS2045: Let the PDEs guide you to new insight into and fast inference for complex models in space and space-time	314
CPS2052: An analysis of the contribution of women in Abu Dhabi	319
CPS2054: Epidemiology of acute kidney injury in critically ill patients in a South African intensive care unit	327
CPS2060: Monitoring unit root in sequentially observed autoregressive processes against local- to-unity hypotheses	335
CPS2061: An investigation into parametric and non-parametric modelling of LGD to estimate extreme percentiles of the loss distribution with respect to defaulted loans	342
CPS2064: Experimental statistics: A hub for data innovation in official statistics?	350
CPS2071: Robust estimation of treatment effects in a latent-variable framework	359

CPS2072: A new additive index number system with maximum characteristicity for International Price Comparisons	367
CPS2074: Estimating measurement errors in mixed-mode surveys using a Multitrait-Multierror Model	374
CPS2079: Improving statistical literacy in Albania, the role of the National Statistical Institute	383
CPS2081: Composite indicator of Food insufficiency	390
CPS2082: Monitoring population strategies in GCC: opportunities and challenges	398
CPS2083: Robust estimation of multi - input transfer function model with structural change	406
CPS2085: Competing risk analysis of lifetime data using Inverse Maxwell Distribution	413
CPS2087: Outlines of SCAD's pilot test for the 2020 register based census	420
CPS2088: Advances in maintenance of critical plant machinery equipment, frequency optimization and minimization of breakdowns perspective	427
Index	434

CPS2016 Nur Fatihah Mohd A. et al.

- applications to spatial, video, and network outlier detection. *Data Mining and Knowledge Discovery*, 28(1)
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Using Google trend data as an initial signal Indonesia unemployment rate



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Abstract

Macroeconomic data are generally published with a time lag. Nowcasting uses the latest available data to provide estimates of macroeconomic variables in the short term. Surely this prediction applies until the actual estimation is generated. The ability to search data through the internet has provided a new data source for researchers who are interested in predicting macroeconomic variables in the short term. This paper trying to learn the behavior intensity of keyword from google search in order to predict unemployment growth in Indonesia. Some modeling is done to get the results of nowcasting which is quite ideal using ARIMA, BSTS without and with Google Data as an additional variable. We also conduct several treatments related to variations of keywords obtained. selection of important keywords with stepwise regression and keyword grouping using the principal component analysis method to obtain a composite keyword that can produce a better model for predicting unemployment growth rates.

Keywords

unemployment; Google trend; nowcasting; BSTS; composite

1. Introduction

The government needs various macroeconomic indicators as the basis of determination national policy strategies. They use Macroeconomic indicators that resulted by national institutions. Some indicators that are often used as a basis for policy include GDP, inflation, unemployment, exchange rates, poverty, and others. The overall indicators are obtained from the process data collection such as census/surveys. The indicator of the unemployment was conducted either by BPS Statistics of Indonesia, the Ministry of Manpower, or other agencies that conduct separate surveys regarding the labor market. Even though many parties have collected data related to employment, each of the data collection processes has limitations, especially the period of dissemination. For example, the unemployment rate produced by BPS can only be disseminated twice in a year. This certainly influences policymakers because the basis of the policy is only able based on available data which does not necessarily match with the condition at the time the policy will be made. Because often policies need to be made frequently in line with changing times.

CPS2018 Rani N. et al.

On the other hand, the development of the era has made information technology more sophisticated, from time to time the percentage of households that have computers and cell phones has increased. In sequence, they growth from 19.88 percent to 88.04 percent while households that have mobile phones have grown from 3.65 percent to 18,71 percent, during the period of 2005-2015. In line with the rapid increase in ownership and mastery of these technologies. Development of internet users is also growing rapidly. At the same period time, in Indonesia, the percentage of internet users increased from 7.4 percent to 34.9 percent. With this phenomenon, the impact of that depelovment is that people become easier to get information and also easy to give information. This has an impact on the use of search engines on the internet, more and more people are looking for information about anything through search engines that can cross between countries.

An example of a phenomenal search engine is Google Search. Google Search is commonly used to find relevant information using various keywords. The intensity of search uses various kinds of keywords that produce data that is so large (Big Data) recorded by Google. Further, the data can show the latest socio-economic conditions. Then Google began to disseminate the intensity of the search in 2009 through the Google Trend interface. Of course, this is good news for researchers. They use this data to improve the accuracy of the latest predictions. Mitra, Sanyal, and Choudhury (2017), they were nowcasting Real Estate growth in India using Google Trend Data. The availability of digital data whose time references are more up-to-date, weekly, monthly or annual, this can be supporting data for data produced by official institutions through the census/survey data collection process.

Google provides three data sources that can be useful for social science (i.e. google trend, google correlate, and google Consumer Surveys (Stephens-Davidowitz & Varian, 2015), but they claim that besides social science there are many things that can be found from Google. Koop (2013) used google data to predict macroeconomic indicators, with Google Data we can make predictions about things in the most recent period, this is called Nowcasting, so we can use Google data to support indicators related to economic or social indicators of a country. In 2009, Google began to disseminate data from Google Search, including data from 2004 to the present, covering all countries in the world.

Based on the foregoing, this study will explore Google Data in describing the conditions of economic indicators in the current period. The focus of the macroeconomic indicators that we observe is the growth rate of unemployment in Indonesia. However, in the use of Google Search Data, caution is needed in determining keywords related to the problem to be studied, the behavior of Google Search data must also be identified so that the right method can be used to produce a good prediction model. One of

the projection methods that can be used for this kind of data, internet data, is the Bayesian Structural Time Series. This paper utilizes data from the internet, Google trend (GT) data, to know the recent conditions of macroeconomic indicators in Indonesia. Then combine the GT data with another macroeconomic variable to improve short-term predictive/nowcasting capabilities model.

Google Trend Data

When we are going to use GT data, there are some things that need to be underlined. First, data of GT has the potential to predict short-term but not for the long term. Second, it is rarely used for broadening macroeconomic variables such as inflation, industrial production, etc. It is more useful for predicting certain variables related to consumption, housing or the labor market. For example, Choi and Varian (2011) succeeded in predicting motor vehicle parts and cars, initial claims for unemployment benefits and tourist arrivals in Hong Kong

In line with the development of research that utilizes GT data, we found some literature/references that conducted research using GT Data to predict macroeconomic indicators. The Google variable can be used as additional information and check whether GT involvement can improve nowcasting capabilities.

2. Methodology

2.1 Data used

The data used in this study consisted of two sources, BPS-Statistics Indonesia and Google. Macroeconomic variables, namely unemployment rate, Consumer Price Index (CPI) and inflation are obtained from BPS-Statistics Indonesia. Google trend data collected based on several keywords that are relevant to the unemployment rate of Indonesia. Unemployment rate official data of Indonesia result from survey national of labour (SAKERNAS). BPS conduct this survey twice a year, February and August. A time reference that we use in build model prediction was from February 2005 to August 2018.

2.2 Selection of Keywords

The selection of keywords has a crucial role in producing precision prediction results. It takes several stages to finally produce keywords that are closely related to the subject we tell. In the use of keywords in the early stages can refer to keywords that have been used by previous researchers who have the same concern. In addition, we can find the relevant keywords from google correlate. However, not all of the keywords produced will be relevant to the subject we are observing. Thus, we have to combine all references, all procedures, and statistic method to get the most representative keyword.

Finally, based on relevancy, the following keywords are suggested to our study (in Bahasa):

bisnis	contoh cv	karir	lowongan kerja
bisnis indonesia	contoh lamaran pekerjaan kerja		lowongan kerja di
bisnis online	employment	kerja di	lowongan kerja teknik
bursa kerja	job	kerja part time	lowongan pekerjaan
bursa lowongan	job application	lamaran kerja	lowongan teknik
career	jobsdb	lamaran pekerjaan	pekerjaan
cari duit	jobsdb.com	loker	peluang bisnis
cari kerja	jobstreet	lowongan	surat lamaran
cari uang	job vacancy	lowongan di	

The prediction of condition Unemployment rate in Indonesia will execute with only several important keywords. The selection will apply stepwise regression method to determine what keywords are most relevant to the research subject and Principal Component Analyse to combine number of variables.

2.3 ARIMA Model

An ARIMA model is a class of statistical models for analyzing and forecasting time series data. ARIMA is an acronym that stands for Auto Regressive Integrated Moving Average. It has very good accuracy for short-term forecasting. Standard notation is used of ARIMA(p,d,q) where the parameters are substituted with integer values to quickly indicate the specific ARIMA model being used. Parameter p is the number of lag observations included in the model, also called the lag order. Parameter d is the number of times that the raw observations are differenced, also called the degree of differencing. Parameter q is the size of the moving average window, also called the order of moving average.

A linear regression model is constructed including the specified number and type of terms, and the data is prepared by a degree of differencing in order to make it stationary, i.e. to remove trend and seasonal structures that negatively affect the regression model. Differencing, autoregressive, and moving average components make up a non-seasonal ARIMA. ARIMA (p,0,q) model can be written as a linear equation:

$$Y_t = c + \varphi_1 Y_{t-1} + \cdots + \varphi_p Y_{t-p} + e_t + \cdots + \theta_q e_{t-k}$$

where φ_1, φ_2 are parameters for Auto Regressive and θ_q is parameter of Moving Average. When we include either explanatory variable in to ARIMA model it is named ARIMAX model.

2.4 Bayesian Structural Time Series (BSTS) Model

One of the advantages of Bayesian modeling is to account for the uncertainty associated with parameter estimates and provide exact measures of uncertainty on the posterior distributions of these parameters, which is traditionally ignored in classical estimation models. In addition, Bayesian

estimation and inference provide confidence intervals on parameters and probability values on hypotheses that are more in line with commonsense interpretations (Congdon, 2003).

BSTS combines the two approaches of Bayesian inference and structural time series. The second component, time series in a state space form, can be described with an observation and a transition equation given by

$$\mathbf{y}_t = Z_t^T \boldsymbol{\alpha}_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \quad (1)$$

$$\boldsymbol{\alpha}_{t+1} = T_t \boldsymbol{\alpha}_t + R_t \boldsymbol{\eta}_t \quad \boldsymbol{\eta}_t \sim N(0, Q_t) \quad (2)$$

With random Gaussian noise ε_t and $\boldsymbol{\eta}_t$ with variance σ_ε^2 and Q_t respectively. Equation (1) provides information regarding the relation between the observed variables \mathbf{y}_t and the latent state variables $\boldsymbol{\alpha}_t$. Equation (2) describes the transition behavior of the latent state variables over time. The model matrix Z_t , T_t , R_t typically contain a mix of known values (often 0 and 1), and unknown parameters. Notation in the form of a state space model is convenient because one can effortlessly add further components to the state vector, such as seasonality and trend. A Model can be obtained by adding a regression component to the popular "basic structural model." This model can be written

$$\mathbf{y}_t = \mu_t + \tau_t \boldsymbol{\beta}^T \mathbf{X}_t + \varepsilon_t \quad (3)$$

Where \mathbf{y}_t , μ_t , τ_t , ω_t , ξ_t and ε_t representing target time series, local linier trend component, seasonal component, regression component and observation error terms respectively.

$$\mu_t = \mu_{t-1} + \delta_{t-1} + \mu_t \quad u_t \sim N(0, \sigma_u^2)$$

$$\tau_t = \sum_{s=1}^{S-1} \tau_{t-s} + w_t \quad w_t \sim N(0, \sigma_\tau^2)$$

$$\delta_t = \delta_{t-1} + v_t \quad v_t \sim N(0, \sigma_v^2)$$

S represent the number of season for y and τ_t denotes their join contribution to the observed target time series \mathbf{y}_t . As is typical in Bayesian data analysis, forecasts from our model are based on the posterior predictive distribution. It is trivial to simulate from the posterior predictive distribution given draws of model parameter and state from their posterior distribution. Let \tilde{y} denote the set of values to be forecast. The posterior predictive distribution of \tilde{y} is

$$p(\tilde{y}|y) = \int p(\tilde{y}|\phi)p(\phi|y)d\phi$$

3. Result

The unemployment rate in Indonesia, based on SAKERNAS data, continued to decline from 10.26 in February 2005 to 5.3 in August 2018. This make conclusion that open employment opportunities has been increased. But in particularly point of period, the unemployment rate does not always decrease,

CPS2018 Rani N. et al.

at certain times the unemployment rate higher than the previous time. For example, the unemployment rate on February 2018 higher than rate on August 2018. It was increased from 5.1 to 5.3. This happened because of the influence of seasonal factors and other influences such as depreciation of the rupiah

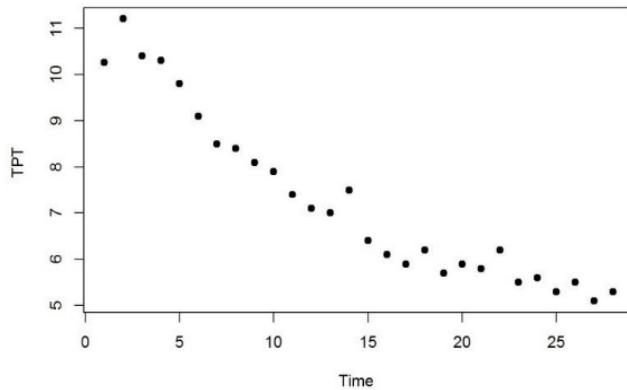


Figure 1. Unemployment Rate in Indonesia for the period 2005-2018

To predict the pattern of unemployment rates for the next recent period, GT data will be used based on 35 keywords that are relevant to Indonesia's unemployment rate. Based on 35 keywords, the most important keywords were selected using the stepwise regression method. Finally, four words are obtained, namely "bisnis indonesia", "loker", "bursa kerja", and "job". The macroeconomic variables that used in predicting unemployment rate are CPI and inflation rate. The interesting one that we can see from figure 2 is the correlation between Unemployment with "loker". They have high negative correlation. The more people who search for this keyword then the unemployment rate will decrease.

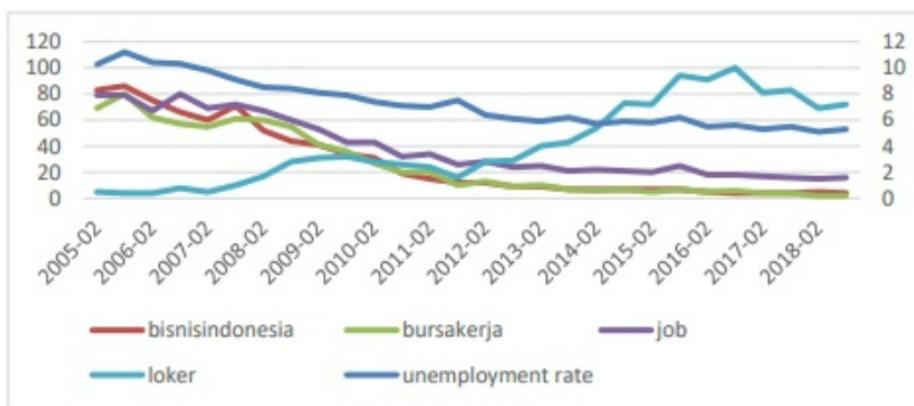


Figure 2. Inter-sample variation in keywords intensity

Based on plotting cumulative absolute error (fig 3), The performance of the prediction model with the ARIMA and Bayesian Time Series (BSTS) methods shows that the BSTS is able to produce better projection models than ARIMA. So the projection of the unemployment rate is continued with the BSTS method in several modeling scenarios. The first model, predicting

unemployment rate using official data only. the second model, adding the 5 most important keywords into the first model. The other model, adding the other macroeconomic variables such as CPI or inflation into model 1 and model 2. The complete scenario model can be seen in figure 3.

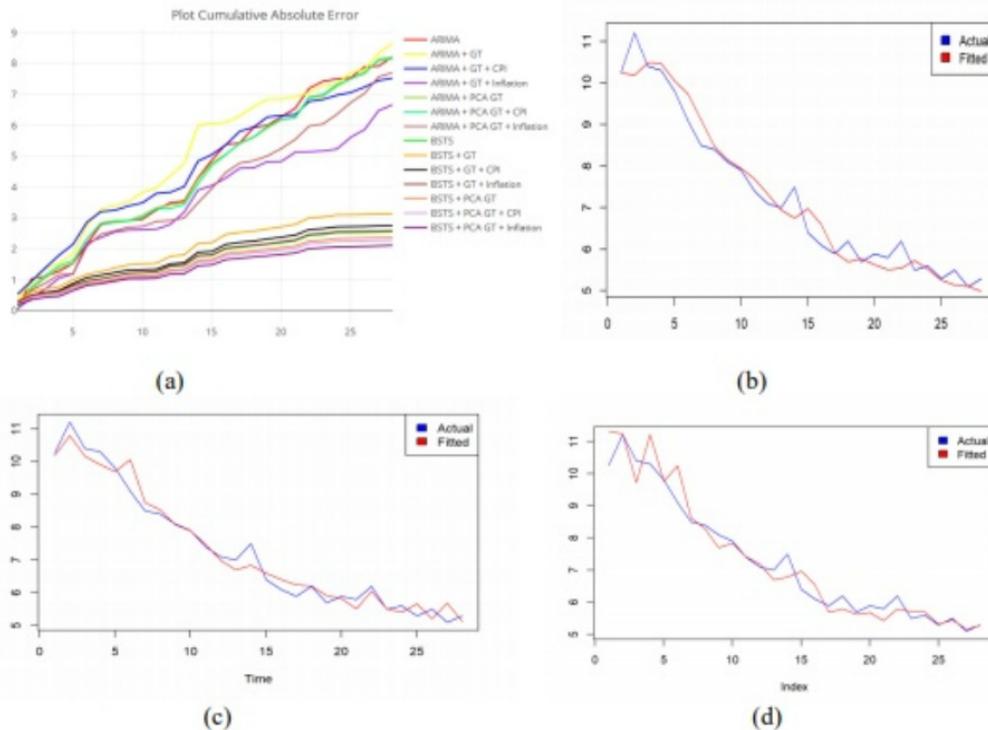


Figure 3. Plot (a) Cumulative Absolute Error for each scenario model, (b) ARIMA, (c) ARIMA+GT+Inflasi, (d) BSTS+PCA GT+Inflasi

The results of the unemployment projection using the ARIMA, ARIMAX and BSTS methods can be seen in figure 4. Projections with the BSTS method are more volatile and more relevant to official data than the ARIMA/ARIMAX method (figure 3). Based on the model BSTS and ARIMA, conditions of Unemployment Rate in February 2019 will be decreased than August 2018.

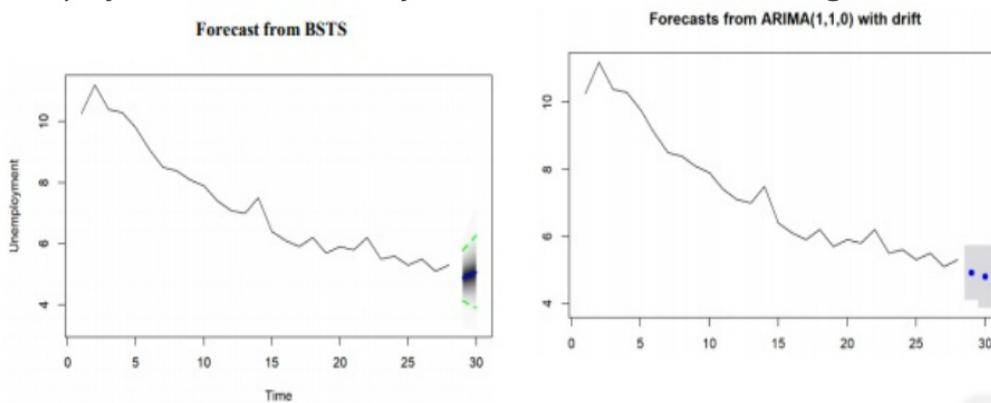


Figure 4. The Forecast plot with BSTS and ARIMA method

4. Discussion and Conclusion

The unemployment rate in Indonesia is predicted to fluctuate, this is due to seasonal influences. With Indonesia's background as an agrarian country, the dominance of sectors that absorb the most labor force in agricultural sector so that the harvest or non-harvest periods greatly affect the amount of unemployment. In addition, the stability of the rupiah value also affected fluctuations of the unemployment rate. Thus government efforts are needed to further open and enlarge employment opportunities for the Indonesian workforce as they reduce the effects of seasonal factors.

Based on the absolute error value, nowcasting the unemployment rate is better produced by BSTS than ARIMA method. the projection of BSTS can show seasonal effects such as the actual phenomenon of unemployment condition in Indonesia. While ARIMA was projecting the unemployment rate will decrease in time by the time. The use of Google Trend data as an additional information in projecting unemployment can improve nowcasting performance. Likewise, when combined with other macroeconomic variables, the involvement of Google trend data can improve the performance of the unemployment nowcasting model. Thus the role of Google trend data can increase the performance of the projection macroeconomic indicators.

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CPS2088 Rahul C.

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Index

A

- Adhitya Ronnie Effendhie, 216
 Aisha Turki, 419
 Akram Musallam Alshawawreh, 308
 Alan Huang, 282
 Alban Cela, 382
 Alexandru Cernat, 374
 Ali Hebishi Kamel Abdelhamid, 190, 200
 Ali Sulaiman Al Flaiti, 397
 Amal Mansouri, 389
 Ana Costa-Veiga, 225
 Angelita P. Tobias, 405
 Anisha P, 1
 Anthony Davison, 290
 Antonella Peruffo, 125
 Areti Boulieri, 104
 Arman Bidarbakhtnia, 8
 Atikur R. Khan, 16
 Atina Ahdika, 216
 Aya Alwan, 282

B

- Benjamin Ng, 159
 Bruno Cozzi, 125
 Bruno de Sousa, 225

C

- Carla Nunes, 225
 Carlos Pires, 225
 Carlos Trucíos, 251
 Chang Xie, 367
 Chin Tsung Rern, 111
 Chong Ning, 159
 Christopher Ryan, 8

D

- Damon Eisen, 46
 Daniel J. Weiss, 80
 Daniel Kilchmann, 350
 David Harris, 65
 David Johnson, 97
 Dedi Rosadi, 216
 Deemat C Mathew, 1
 Dharini Pathmanathan, 111, 118
 Dmitri Jdanov, 150
 Domantas Jasilionis, 150
 Dulce Gomes, 225

E

- Elizabeth van der Merwe, 327
 Emma McBryde, 46
 Enrico Grisan, 125
 Erniel B. Barrios, 405
 Erwan Koc, 290

Ewan Cameron, 80

F

Francisco N. de los Reyes, 142

G

Gary Sharp, 327
 Gerrit Grobler, 342
 Gunardi, 216

H

Haakon Bakka, 314
 Harry S. Gibson, 80
 Havard Rue, 314
 Hsein Kew, 65

I

Ibrahim Mohamed, 118, 258
 Ivan Mizera, 134

J

Jamaludin Suhaila, 274
 Janette Larney, 342
 Jang Schiltz, 25
 Jarod Y. L. Lee, 89
 Jean-Marie Graïc, 125
 Jennifer Rozier, 80
 Jeremy Heng, 159
 Jiefei Yang, 209
 Jiti Gao, 65
 Jittima Dummee, 56
 João Mazzeu, 251
 Jonathan Koh, 290
 Joseph Ryan G. Lansangan, 405
 Joseph W. Sakshaug, 374
 Justin Wishart, 282

K

K. Hitomi², J. Tao, 335
 K. Nagai, 335
 Katherine E. Battle, 80
 Katri Soinne, 299
 Khaddouj Abu Baker Abdulla, 319
 Klajd Shuka, 382
 Kuntip Trongthamakit, 56

L

Lach Lachemot Tassadit, 173
 Liu Huifeng, 72
 Livio Corain, 125
 Louise M. Ryan, 89
 Ludovica Montanucci, 125
 Luigi Salmaso, 125
 Luiz Hotta, 251

M

M S Panwar, 412
 M. Towhidul Islam, 16
 Marc Hallin, 251

Index

- Markus Zwick, 165
 Marta Blangiardo, 104
 Matúš Maciak, 134
 Mauricette Andriamananjara Nambinisoa,
 80
 Maurício Zevallos, 251
 Michele Nguyen, 80
 Mikhail Zhelonkin, 359
 Muhammad Fauzee Hamdan, 274
- N**
- Nandish Chattopadhyay, 34
 Nugroho Puspito Yudho, 266
 Nur Fatihah Mohd Ali, 258
 Nurmitra Sari Purba, 266
 Nurul Aityqah Yaacob, 111, 118
- O**
- Ourbih Tari Megdouda, 173
 Oyelola Adegbeye, 46
- P**
- Patrícia Filipe, 225
 Pedro Valls, 251
 Peter W. Gething, 80
 Prajamitra Bhuyan, 34
 Pranesh Kumar, 209
 Prasada Rao, 367
- R**
- Rahul Chattopadhyay, 426
 Rani Nooraeni, 266
 Rawia Wagih Abd ElMagid ElSayed Ragab,
 190, 200
 Robert Kohn, 89
 Rodrigo Lovatón, 234
 Rosalind E. Howes, 80
 Rossita Mohamad Yunus, 258
 Ruben Carvajal-Schiaffino, 125
- S**
- Sadeg Ines Ines, 173
 Saggou Hafida Hafida, 173
 Salah Qudairi, Badreyya Al Shehhi, 419
 Saleh Almansouri, 319
 Saleheen Khan, 16
 Scott A. Sisson, 89
 Shafiqah Azman, 111
 Sharita Serrao, 8
 Sisa Pazi, 327
 Siti Haslinda Mohd Din, 118
 Solange Correa Onel, 97
 Sudheesh K Kattumannil, 1
 Sula Sarkar, 234
 Sun Yunjie, 72
 Suzanne Keddie, 80
- T**
- Tabin Hasan, 16
 Thomas Fung, 282
 Thumna Al Rashedi, 319
 Thumna Alrashdi, 419
 Timothy C. D. Lucas, 80
- V**
- Vincent Chin, 89
- W**
- Wadeema Mohamed Alkhoori, 308
 Weilun Zhou, 65
 Wu Da, 72
- X**
- Xuan Che, 181
- Y**
- Y. Nishiyama, 335
- Z**
- Zhongshan Yang, 367
 Zhu Yingchun, 72



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