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Linear non-Gaussian causal discovery from a composite set of major US macroeconomic factors

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ABSTRACT

In this paper, we develop an effective approach to model linear non-Gaussian causal relationships among a composite set of major US macroeconomic factors. The proposed approach first models the linear relationships of the factors using the Vector Autoregression (VAR) model, then the casual relationships are discovered using the linear non-Gaussian Structural Equation Modeling (SEM) method. One advantage of our hybrid approach is that the contemporaneous causal order of macroeconomic variables which is important for VAR practitioners is obtained naturally as a result of the computation. Applying our approach to 11 major US macroeconomic factors reveals that the federal funds rate has the dominating power in the set. This outcome purely based on the underlying data without any prior knowledge is in line with previous studies using other empirical approaches where prior knowledge is often essential. We also provide a global picture depicting the interaction among all the macroeconomic factors of concern, which are often approached individually or in small grouping in the economic research literature in the past and not studied in a unified view as in our approach.

1. Introduction

The complicated macroeconomic causal relationships have been attracting increasing interests in recent years (Boyacioglu & Avci, 2010; Breitung & Candelon, 2006; Caporale, Hassapis, & Pittis, 1998; Celik & Karatepe, 2007; Dufour & Taamouti, 2010). Conventionally, economists only had to be concerned with specific pairwise or serial causal relationships. For instance, the causality between monetary policy and the inflation or bank loans (Drake & Fleissig, 2010; Sun, Ford, & Dickinson, 2010), and the causality between stock market index and the real output (Fama & Schwert, 1977). With the growing number of the macroeconomic factors brought into the analysis, however, it becomes more and more difficult to obtain an overall causal picture of a large set of macroeconomic factors.

Previously, economists model the causality between macroeconomic factors qualitatively. Simon (1953) developed the causal ordering theory, which uses graphs composed of variable nodes and relationship edges to identify the causal dependencies among the studied variables. Iwasaki (1988) extended Simon's theory to include dynamic models. Berndsen (1995) used a CAUSOR method (Gilli, 1984) to analyze the cause and effect in public finances qualitatively using the causal sequence diagram. In order to derive the cause and effect diagram, the expert knowledge is required to predefine the relationships among many variables, and those assumptions are usually subjective.

Later, the main stream line of thought shifted towards empirical methods to discern the dynamic causality in macroeconomic activities, the representatives of which are the Vector Autoregression (VAR) approach and the Vector Error Correction (VEC) Model. Since the introduction of the VAR by Sims (1980), there have been many works using the VAR model to evaluate the properties of macroeconomic systems. Through these studies, researchers have tried to find the causal relationships among stock returns and macroeconomic factors (Cheung & Ng, 1998; Chung & Lee, 1998; Fama, 1990; Gjerde & Saettem, 1999; Hess & Lee, 1999). The VAR has also been used to analyze other interesting problems, e.g., the monetary transmission (Barth & Ramey, 2001; Peersam & Smets, 2002). The VEC model (Engle & Granger, 1987; Granger, 1983), which is a variation of the VAR model, is an effective way to examine the relationship among macroeconomic variables under the long-term equilibrium situation (Gali, Gerlach, Rotemberg, Uhlig, & Woodford, 2004; Lenza, 2006; Masih & Masih, 1996). However, one of the major deficiencies of the VAR model is that the contemporaneous causality cannot be obtained directly. Although the structural VAR can model the structural relationships between variables to some extent, for many important economic problems, the method appears to be weak and models arrived at by the method often

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lacks sufficient explanatory power (Hoover, Demiralp, & Perez, 2009).

In this paper, we develop a hybrid approach that automatically identifies the causal structure from the data records of macroeconomic factors by combining the VAR with the newly developed linear non-Gaussian Structural Equation Modeling method (Sogawa, Shimizu, Kawahara, & Washio, 2010) The proposed approach first models the linear relationships of the factors using the VAR model, then the casual relationships are discovered using the linear non-Gaussian Structural Equation Modeling method. The discovered causal relationships not only capture the contemporaneous causal order, but also depict the global causal picture among the macroeconomic factors. This purely data-driven approach does not assume any prior knowledge as often was the case in the previous methods.

Empirically, the relationships among the US monetary policy, monetary transmission, GDP, equity market, and mortgage activity are studied by applying our approach. The global picture of 11 macroeconomic factors interactions is obtained, which clearly illustrate some well-known interactions (Andersena, Bollerslevb, Dieboldc, & Vegad, 2007; Ben & Alan, 1992; Boyd, Hu, & Jaganathan, 2005; Litterman & Weiss, 1985), as well as some new findings of relationships. For example, the federal funds rate is the dominate factor in the whole structure and industrial production is the direct cause of stock market return.

The rest of the paper is organized as follows. In Section 2, we formulate the problem of causal discovery among macroeconomic factors. In Section 3, the solution taking the advantage of both VAR model and the linear non-Gaussian Structural Equation Modeling method to find the causality among macroeconomic factors is proposed. Empirical results based on time-series data of a set of 11 US major macroeconomic factors are in Section 4. Finally, some conclusions are drawn in Section 5.

2. Problem formulation

Conceptually, the problem of causal discovery from macroeconomic factors can be formulated as a 3-step process. First, select those macroeconomic factors that will be used in a model for a pre-determined objective of an analysis. For instance, factors are often selected along the lines of monetary transmission, core CPI inflation, real GDP, equity market, mortgage activity, monetary policy if the interest is in understanding the overall causality graph of a macroeconomic system. Second, apply an appropriate modeling method which can capture the causality among the selected factors using collected data samples of these factors. The set of the data samples can either be panel data or time-series data. Generally, causal discovery using panel data set or time-series data set will yield different results. Third, analyze and interpret the obtained model (in the form of causal relationship graph as in our case) to arrive at the properties and characteristics of the underlying macroeconomic system. In the above formulation, we also assume that there is no limitation in terms of a number of factors to be considered in one causal discovery along any particular line of interest, nor any prior knowledge of any kind exists for such a causal discovery, and there is a general availability of sufficient sample data. Therefore, the underlying idea of this problem formulation is that the problem has to be solved with a composite, or otherwise, large set of factors and purely based on given sample data. This idea, hence, the formulation itself necessarily requires that we must develop an effective modeling approach to be able to do so both effectively and efficiently.

In considering the number of factors that have to be considered simultaneously, the following assumption lays a foundation for an educated choice.

Assumption 1. Each macroeconomic factor is affected by a limited number of other factors, either endogenous or exogenous factors. The relationship can be described by linear equations.

This assumption is the main stream thinking in the macroeconomic area. For instance, Duffie and Singleton (1993) indicated that when a set of factors is small, selecting a non-linear model can obtain a more significant result; conversely, for a large set of factors, a linear model can be more significantly effective. It is easy to understand that a non-linear model is often too complex to compute and the results obtained may be less accurate. On the other hand, a linear model can lead to simpler and more effective computation with more accurate results. Therefore, linear model is naturally a popular choice for analysis and research in the macroeconomic community. We follow the same line of thought in approaching the causal discovery among a set of macroeconomic factors using the linear modeling methodology.

With all the above considerations, the problem of discovering the causality from macroeconomic factors can be vigorously put as follows:

Given a set of n macroeconomic factors, $\mathbf{F} = \{f_1, f_2, \ldots, f_n\}$, we try to find a set of simultaneous linear equations representing the causal relationships in $\mathbf{F}$.

In order to study the causal relationships, we assume there is a well-established data sample matrix $\mathbf{S} = [s_1, s_2, \ldots, s_n]^T$ for $\mathbf{F}$, where $s_i (1 \leqslant i \leqslant n)$ is a $1 \times$ m vector and m is the number of the samples. In particular, data samples can be either panel data or time-series data.

3. Solution methodology

In this section, a linear non-Gaussian causal discovery method is fully developed with the following three key steps. First, a novel method for VAR modeling residuals extraction is proposed. Then an appropriate causal discovery method is fully developed into a solution algorithm that can come up with an initial causality graph represented by a full directed acyclic graph. Lastly, a resultant causality graph of macroeconomic factors is obtained after we prune redundant directed edges in the initial causality graph.

3.1. VAR modeling for extracting residuals

For causal discovery, the main stream method at present is to first analyze the relationship between macroeconomic variables via VAR model, then use impulse response functions and variance decomposition approach to examine the predictive relationship among variables. However, the empirical analysis shows that the explanatory power of VAR model is limited. Although the Structural Vector Autoregression (SVAR) model has provided some economics theoretical support, such a support often appears too weak to be accepted as playing a dominant role in the main-stream economics theories (Gilbert, 1986; Mizon, 1995).

Moreover, when we use the impulse response functions and the variance decomposition approach to test the causal relationship among variables, the Cholesky decomposition, which is a widely adopted technique to find an orthogonal impulse response function, is very sensitive to the order of the variables in the VAR model. In other words, there is no mechanism that can systematically provide the contemporaneous causal order of VAR variables, which is a very important step for causality discovery. VAR practitioners always choose an order arbitrarily, thereby introducing uncertainty into the computation. This leads to our belief that there are some fundamental aspects of the variables that the VAR model as it is now is not able to capture. In other words, the residuals of a VAR model appear to still contain valid information that needs to be extracted further to improve its explanatory power.

In what follows, we propose a novel method to perform such an extraction. Our method is based on a simple idea: After a regression process with lagged variables, the residuals of the VAR model imply the contemporaneous causal order of the macroeconomic variables involved.

In general, the VAR model can be written as:

$$Y_t = a + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \tag{1}$$

where Y_t is the vector of response time series variables at time t. Y_t has n elements. a is a constant offset vector of size n. A_i is a n-by-n matrix for each i. $\{A_i\}$ are autoregressive matrices. There are p autoregressive matrices. p represents the number of lag. $\varepsilon_t \backsim N(0, Q)$ is a vector of serially uncorrelated innovations of length n. $\{\varepsilon_t\}$ are multivariate normal random vectors with a covariance matrix Q, where Q is an identity matrix, unless otherwise specified.

When Y_t is selected, the number of the lag can be determined using the Akaike Information Criterion (AIC) as in Hurvich and Tsai (1991), which is a commonly used information criterion. It follows that the formula of AIC can be written as:

$$AIC = ln|\Omega| + \frac{2pn^2}{T} \tag{2}$$

where T is the sample size, pn^2 is the total number of the coefficient in the VAR model, Ω is the variance of the residual vector.

Choosing the lag number p to allow the smallest AIC value, we can establish a VAR (p) model. With this VAR (p) model and the data samples of macroeconomic factors, we can apply the Maximum Likelihood Estimator (MLE) or the Ordinary Least Squares (OLS) method to estimate the coefficients of the VAR model. Note that the residuals of each variable in the VAR model are collected and put in Matrix **R** which is assumed to be time-independent. Consequently, the above process naturally results in the contemporaneous causal order of the selected set of macroeconomic factors.

3.2. Use the Beam-Kernel-Direct-LiNGAM method to find the causal graph of macroeconomic factors

Given **Assumption 1** and the data sample matrix **R** which collects the residuals of variables in the VAR model, we can cast our problem into the following structural equations model (SEM):

$$\mathbf{x} = \mathbf{Bx} + \mathbf{e} \tag{3}$$

where $\mathbf{x}$ is a n-dimensional vector that represents the macroeconomic factors involved and has a data sample set constituted by **R**. **B** is a $n \times n$ matrix that has the connection strength b_{ij}. It represents the relationship between variable i and j. **e** is the vector of errors. In Shimizu, Hoyer, Hyvärinen, and Kerminen (2006), it explains that comparing to Gaussianity assumption of **e**, a linear-non-Gaussian setting allows the full causal model to be estimated, with no undetermined parameters. It therefore follows that the following assumptions are reasonable:

Assumption 2. For $\mathbf{e}=[e_1,\ldots,e_n]^T$, $e_i (1 \leqslant i \leqslant n)$ are independent of each other and all with non-Gaussian distributions of non-zero variances.

We can also assume that:

Assumption 3. The observed macroeconomic factor set **F** can be arranged in a causal order.

The above assumption implies that the causality among the macroeconomic factors can be represented graphically by a directed acyclic graph (DAG) (Pearl, 2000; Spirtes, Glymour, & Scheines, 2001).

Based on these assumptions, the model is naturally named as a Linear, Non-Gaussian, Acyclic Model, abbreviated as LiNGAM (Shimizu et al., 2006).

Solving for $\mathbf{x}$ in (3) we can obtain:

$$\mathbf{x} = \mathbf{Ae} \tag{4}$$

where $A = (\mathbf{I} - \mathbf{B})^{-1}$. Independent component analysis (ICA) (Comon, 1994; Hyvärinen, Karhunen, & Oja, 2001) is a fairly standard statistical technique for identifying a linear model in Eq. (4). However, weather ICA-LiNGAM can obtain a correct solution in a finite number of steps or not mainly depends on well-thought independence assumptions of the causality graph. Moreover, a wrong causal graph is likely to emerge due to the scale-invariant property of the ICA method.

Lately, a Kernel-Direct-LiNGAM method has been proposed (Sogawa et al., 2010). This method makes good use of the kernel canonical correlation analysis (Bach & Jordan, 2003). Comparing with the ICA-LiNGAM method and Direct-LiNGAM (Shimizu, Hyvärinen, Kawahara, & Washio, 2009), this method shows higher performances in terms of accuracy, robustness to outliers and near-Gaussianity. It means that an accurate identication of the causal graph can be achieved. The updated version of Kernel-Direct-LiNGAM process (Sogawa et al., 2010) can be summarized as the following five steps:

1. Build kernel functions which can project a pair of multi-variants into a higher-dimensional feature space. These kernel functions can be denoted as:

$$k_x(\mathbf{x_i}, \mathbf{x_j}) = <\varphi_x(\mathbf{x_i}), \varphi_x(\mathbf{x_j})>, \text{ and}$$
$$k_y(\mathbf{y_i}, \mathbf{y_j}) = <\varphi_y(\mathbf{y_i}), \varphi_y(\mathbf{y_j})> .$$

Where φ_x and φ_y are mapping functions to map variable samples $\mathbf{x_i}$ and $\mathbf{y_i}$ into the higher-dimensional feature space.

2. Employ Gaussian kernel as the functions k_x and k_y, build an independent measure based on the Kernel generalized variance:

$$I(x,y) = -\frac{1}{2} log(1 - \rho^2) \tag{5}$$

Where ρ is the kernel canonical correlation.

3. Build an independence measure:

$$T_{kernel}(x_j, U) = \sum_{i \in U, i \neq j} -\frac{1}{2} log\left(1 - \rho^2_{x_j, r_i^{(j)}}\right) \tag{6}$$

where U is a set of subscripts of all $x_i \in \mathbf{X}$ and $\rho_{x_j, r_i^{(j)}}$ is the kernel canonical correlation coefficient between a variable x_j and its residuals $r_i^{(j)}$.

4. Use the independence measure (6) to find the most independent variable x_t, and update the data sample matrix **X** into the residuals after the regression process of x_t on $x_j (j \neq t)$. Repeat this process until the causal order has been determined. We can obtain a causal order of the variables **K**.
5. Construct **B** by **K**, and estimate connection strengths b_{ij} by applying a conventional estimation technique to the original data matrix **X**.

In Sogawa et al. (2010), some numerical experiments are provided which demonstrate that the variant using both kernel method and the beam search[1] often provide better performance than the previous LiNGAM methods. These improvements mainly focus on robustness to near-Gaussianity, outliers and scale-invariance. The

[1] Beam search (Sogawa et al., 2010) is an extending search algorithm for the greedy search algorithm in Shimizu et al. (2009). With the beam search, it can reduce the chance for obtain the identification of a wrong exogenous variable.

most accurate identification of the causal ordering appears to be delivered by Beam-Kernel-DirectLiNGAM, which is the reason why we apply this method to discover the casual relationship among macroeconomic factors.

We use **R** obtained from the residuals of the VAR model as input data to the Beam-Kernel-DirectLiNGAM method, we obtain a contemporaneous causal order **K** of the macroeconomic factors and a coefficient matrix **B** which have connection strength of the variables encoded.

3.3. Prune redundant directed edges in the full DAGs causal graph

Although we have already obtained the coefficient matrix **B**, it is a dense matrix representing a full DAG. We need to prune redundant directed edges in the full DAG to obtain the final causality graph desired. To do so, we only need to repeatedly apply a sparse method called Adaptive Lasso (Zou, 2006) on each variable and its potential parents.

The adaptive Lasso penalizes connection strengths b_{ij} by minimizing the objective function defined as:

$$\|x_i - \sum_{k(j)<k(i)} b_{ij}x_j\|^2 + \lambda \sum_{k(j)<k(i)} \frac{|b_{ij}|}{|\overline{b_{ij}}|^{\gamma}} \tag{7}$$

where λ and γ are tuning parameters and $\overline{b_{ij}}$ is a consistent estimate of b_{ij} as in Zou (2006). It was suggested to select the tuning parameters by fivefold cross validation and obtain $\overline{b_{ij}}$ by ordinary least squares regression.

Through this method, we can obtain a set of edges that have strong relationship in the full DAG. Moreover, we use the information theoretic measures which are widely used in AI and the economic community (Cover & Thomas, 1991; Golan & March, 2002; Zellner, 2002). For factor F_i, its entropy is defined as:

$$H(F_i) = \int p(f_i) log p(f_i) df_i$$

where $p(f_i)$ is the probability density. For each pair of factors F_i and F_j, their mutual information is defined as:

$$I(F_i, F_j) = \iint p(f_i, f_j) log \frac{p(f_i, f_j)}{p(f_i)p(f_j)} df_i f_j$$

Where $p(f_i,f_j)$ is the joint probability density and $p(f_i)$, $p(f_j)$ are the marginal probability densities.

We use the measure as the entropy reduction rate given the existence of edge c in Wang and Tan (2009):

$$\eta(F_i, F_j) = \frac{I(F_i, F_j)}{min(H(F_i), H(F_j))} \tag{8}$$

We category the edge $F_i \to F_j$ as reliable if $\eta(F_i,F_j)$ ranks top 3 in whether entropy reduction rates between F_i and each other factors or F_j and each other factors.

All the above procedures allow us to obtain a causality graph of any given macroeconomic factors. With this graph, we can study the relationship among the macroeconomic factors. In the next section, we will give the experimental results that use the real US macroeconomic data for a causality analysis.

4. Experimental results

11 macroeconomic factors are chosen from selected areas such as monetary, core CPI inflation, real GDP, equity market, mortgage activity and monetary policy. The factors and their respective short descriptions are shown in Table 1. The data set consists of eleven monthly series that run from 1990:02 to 2005:03.[2]

Table 1
The description of factors.

Index	Factor	Short description
1	COREINF	core CPI inflation
2	FF	Federal funds rate-the representation of monetary policy
3	IP	(the logarithm of) industrial production-a monthly proxy for real GDP
4	LIQDEP	(the logarithm of) Liquid deposits- an active component of M2
5	REFI	(the logarithm of) Index of mortgage refinancing
6	SP100VOL	Stock market volatility
7	SP500	(the logarithm of) Stock market index
8	M2OWN	Own rate on M2
9	MORG30	Interest rate on 30 year fixed-rate mortgages
10	SPPE	Price-earnings ratio
11	TBILL3	3-month Treasury bill rate

Table 2
Contemporaneous causal order of macroeconomic factors.

Index	Factor	Causal rank
2	FF	1
11	TBILL3	2
8	M2OWN	3
3	IP	4
1	COREINF	5
9	MORG30	6
6	SP100VOL	7
5	REFI	8
4	LIQDEP	9
7	SP500	10
10	SPPE	11

Table 3
The estimated entropy reduction rate and reliability of each edge.

Edges	Entropy reduction rate	Reliable
FF → TBILL3	0.26	√
FF → M2OWN	0.27	√
FF → COREINF	0.15	√
TBILL3 → MORG30	0.22	√
TBILL3 → LIQDEP	0.11	
M2OWN → IP	0.14	√
M2OWN → REFI	0.16	√
IP → SP100VOL	0.13	√
MORG30 → REF	0.31	√
SP100VOL → SP500	0.14	√
SP500 → SPPE	0.33	√

First, the data are scaled to the same numeric level. Then the process introduced in Section 3 is applied to the data set. A suitable lag number is computed that minimizes AIC as in Formula (2). We use Matlab to run the VAR model and collect the residual matrix **R** which is subsequently used as the input to run the Beam-Kernel-Direct-LiNGAM method to obtain a contemporaneous causal order **K** shown in Table 2 and the coefficient matrix **B**. Redundant directed edges are pruned in the full DAG by adaptive Lasso with 11 edges. We then use information theoretic measure as in formula (8) to examine reliability of the edges as shown in Table 3. Finally we obtain a causality graph of the 11 macroeconomic factors illustrated in Fig. 1.

From the causality graph shown in Fig. 1, we can find that “FF”, which represents the federal funds rate, is a dominate factor among all the factors. This observation is supported by Ben and Alan (1992) in an article published in The American Economic

[2] The data source is from Kevin Hoover’s website:http://www.econ.duke.edu/~kdh9/research.html.

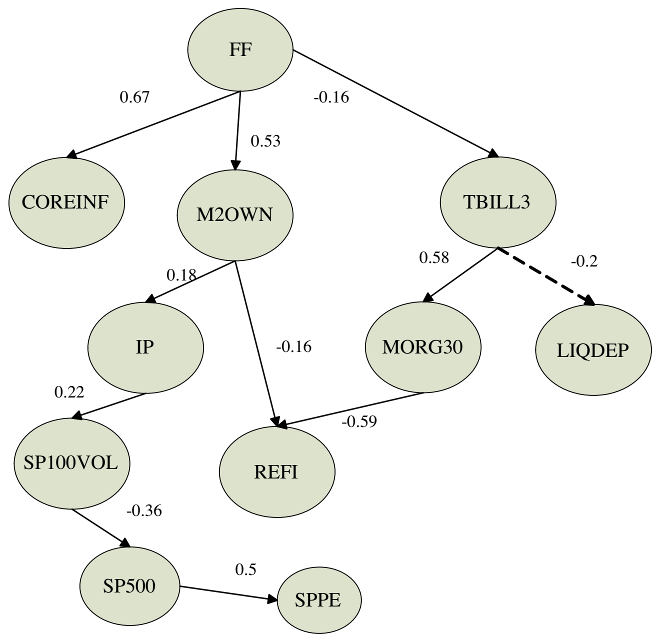

Fig. 1. The SEM causality graph for macroeconomic factors.

Review. It argued that the funds rate is probably less contaminated by endogenous responses to contemporaneous economic. Moreover, the research also found that federal funds rate dominates both money and the bill. It is because the funds rate sensitively records shocks to the supply of bank reserves. This relationship shows itself clearly in Fig. 1. Litterman and Weiss (1985) argued that bill rate dominates money, which is also found in our model. However, the edge TBILL3 → LIQDEP is unreliable after we used the information theoretic measure to examine the link.

In Fig. 1, it also shows a path of how macroeconomic factors affect the stock market. Monetary policy (FF) impacts the opportunity cost of M2 (M2OWN and TBILL3). This effect is then transmitted to the stock market over industrial production (IP). This finding is very interesting, since (Beltratti & Morana, 2006; Schwert, 1990) all argued that industrial production volatility weakly explains the volatility of stock returns. However, according to our finding, industrial production is the direct cause of changes in stock market. It affects the S&P 500 index through the volatility of stock market. This relationship indicates that when we consider a contemporaneous causal relationship between macroeconomic factors and the stock market, we should consider the volatility of stock market as the cause rather than the effect of the stock market index. This is a new point of view of casual discovering of the stock market. Meanwhile, if we consider the coefficient on the edge of Fig. 1, we can confirm the findings (Andersena et al., 2007; Boyd et al., 2005): 'bad' news about the real economy is 'good' news for the stock market.

It is important to observe that these interesting findings are obtained directly from data, taking advantages of both VAR model and AI method, without any input or interference from any human expert in economics. This pure data-driven approach deserves further in-depth analysis for its scope and explaining power.

5. Conclusions

In this paper we have developed an approach to discover the causal relationship and demonstrated its validity by applying to the analysis of some US macroeconomic factors. Being a hybrid technique, our method combines the economic model VAR and artificial intelligence methods LiNGAM together. It is able to identify the causality from the data automatically and without any prior knowledge or expert input of any kind. There are some very interesting relationships discovered by our experiment with the US macroeconomic data, which not only prove certain claims and hypothesis in some of the previous research works, but also provide a new perspective of causal relationship between macroeconomic and stock market.

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