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Dependent Variable: D4LNGDP				
Method: Least Squares				
Date: 06/30/07 Time: 15:22				
Sample (adjusted): 1982Q2 2006Q4				
Included observations: 99 after adjustments				

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D1	0.023682	0.069117	0.342640	0.7327
D2	0.021555	0.069275	0.311146	0.7564
D3	0.022655	0.069099	0.327870	0.7438
D4	0.024569	0.069475	0.353632	0.7245
LNGDP(-4)	-0.001483	0.006427	-0.230790	0.8180
D4LNGDP(-1)	0.760041	0.096776	7.853634	0.0000
D4LNGDP(-2)	0.171648	0.112739	1.522527	0.1314
D4LNGDP(-3)	-0.060442	0.113433	-0.532844	0.5955
D4LNGDP(-4)	-0.579852	0.113701	-5.099803	0.0000
D4LNGDP(-5)	0.387072	0.093588	4.135898	0.0001

Statistics:			
R-squared	0.634339	Mean dependent var	0.021517
Adjusted R-squared	0.597362	S.D. dependent var	0.016270
S.E. of regression	0.010324	Akaike info criterion	-6.213125
Sum squared resid	0.009486	Schwarz criterion	-5.950991
Log likelihood	317.5497	Durbin-Watson stat	2.011525



Nonlinear time series analysis revisited*
 Journal Article
 Journal of Economic Surveys, University of Oxford, Number 20, 2006, pp. 1-50, 50 p.
 The paper reviews the literature on nonlinear time series analysis. It starts with a brief review of the linear time series models and then discusses the various forms of nonlinear models. The paper also discusses the various tests for nonlinearity and the various methods for estimating nonlinear models. The paper concludes with a discussion of the future research agenda in this area.

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A Time Series Analysis of Microarray Data

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Abstract

As the capture and analysis of single-time-point microarray expression data becomes routine, investigators are turning to time-series expression data to investigate complex gene regulation schemes and metabolic pathways. These investigations are facilitated by algorithms that can extract and cluster related behaviors from the full population of time-series behaviors observed. Although traditional clustering techniques have shown to be effective for certain types of expression analysis, they do not take the biological nature of the process into account, and therefore are clearly not optimized for this purpose. Moreover, the current approaches provide internal comparisons for the experiments utilized for clustering, but cross-comparisons between clustered results are qualitative and subjective. We present a combination of current and novel methods for the analysis of time series gene expression data. We focus on an actual study we have performed for *Haemophilus influenzae* which is a major cause of otitis media in children. We first perform a discretization of the gene expression data that takes both positive and negative correlations into consideration and then develop a clustering algorithm optimized for such data that allows elucidation and searching of time-series patterns. The resulting approach allows time-series data to be usefully compared across multiple experiments. We demonstrate the success of our algorithm by showing some of the genes that it finds to be co-regulated are not detected by current methods. As a result we are able to identify several signal pathways that initiate competence development, and to characterize the transcriptomes of wild-type and an adenylate cyclase mutant (*cyj*) strains under both nutrient-limiting and nutrient-complete growth conditions.

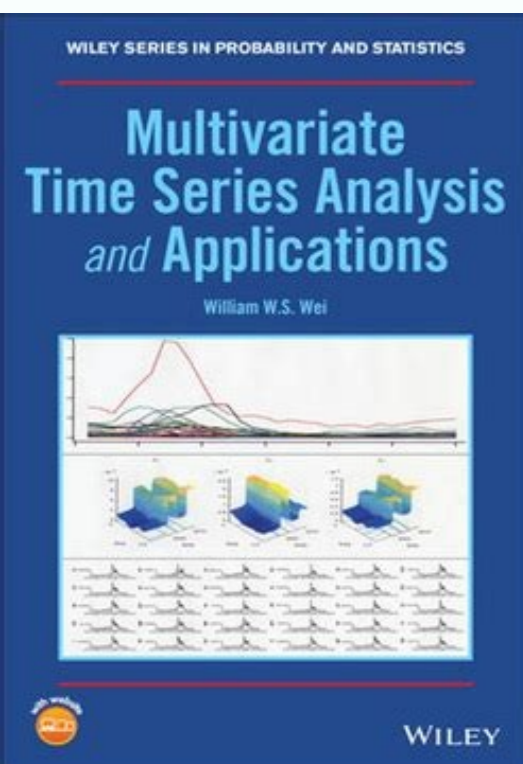
1. Introduction

Genes are the code of proteins that are fundamental components of all living cells and carry out vital organism func-

tions. Before being translated into protein, this code must be transcribed from chromosomal DNA into messenger RNA (mRNA). The rate of transcription by the cell for some genes can be varied, and therefore the amount of certain mRNAs in the cell cytoplasm is a measure of the production speed of corresponding protein in the cell. Depending on the environment of the cell (and other factors), different amounts of some proteins are required; hence different concentrations of mRNAs for different genes exist in the cell. The relationship between the amount of an mRNA observed under experimental conditions, versus the amount observed under control conditions is called the expression level. Immobilized DNA microarrays (aka. probe arrays) are a tool for high-throughput gene expression studies. In microarray studies, probes (i.e. oligonucleotide sequences) with known identity are placed on glass or nylon substrates in a grid and used to determine expression levels through hybridization to bulk unknown populations of sequences (11). In the results we see the relative expression levels of genes.

As the capture and analysis of single-time-point microarray expression data becomes routine, investigators have started examining time-series expression data to investigate complex gene regulation schemes and metabolic pathways. The current approach is basically to cluster the time-series sequences based on common methods such as k-means. These algorithms provide internal comparisons for the experiments utilized for clustering, but cross-comparisons between clustered results are qualitative and subjective. In this paper, we present a combination of current and novel methods for the analysis of time series gene expression data. We first perform a discretization of gene expression data that takes both positive and negative correlations into consideration and then develop a clustering algorithm optimized for such data that allows both elucidation and searching of time-series patterns. The resulting approach allows time-series data to be usefully compared across multiple experiments.

The proposed technique can be used as a decision support tool for a researcher who is searching for candidate



a sa rorre retemaid eht fo elpmaxe na swohs erugif gniwollof eht .seires emit a fo serusaem lacitsitats ro evitpircsed niabto ot sdohtem sisyana seires emit eht esu nac uoYÁ Á Á ç noitpircsed: swollof sa era sisyana seires emit fo sevitecbebo eht .slangis owt eht neewteb pihnoitaler eht fo erutan eht dnatsrednu uoy pleh nac hcihw, seires emit detaler a fo noitairav eht nialpxe ot seires emit a fo noitairav devresbo eht esu nac uoYÁ Á Á ç noitanalpxE .seires emit a fo selpmaxe era gnireenigne livic ro gnireenigne lacinahcem ni noitarbiv ro, ecneics lacidemoib ni erusserp doolb, ecneics lacigoloroetem ni erutarepmet ria eht, elpmaxe roF .metsys lacisyhp eht revo lortnoc evorpni ot ro, seires emit a fo segnahc eht tciderp ot, seires emit eht setareneg taht metsys lacisyhp a fo scitsiretcarahc eht revocsid OT, EMIT A MORF NOITAMROFNI TCARTXE OT TNW UOY NEHW LUFESU SI SISYLANA SEIRES EMIT SEVITCEJBO SISYLANA SEIRES EMIT.YRANOITATSNON SI SEIRES EMIT EHT EHIWREHTO EMIT EMIT A FO EDUT ilpma eht fo margotsih a enimaxe nac uoy, noitubitsid edutilpma seires-emit a fo yrtemmys eht erusaem of .seires emit a fo scitsiretcarahc, lacitsitats ro, citsahcots eht toelfer syawla seular detciderp eht os, secabrutsid fo sdink ynam yb detceffa era smetsys lacisyhp, ecitcarp ni, revewoH .rehto dna.) DSP (ytisned lartceps rewop eht gniupmoo, snotalerroe gniurofrop, sledom cimanyd gniulub, sretemarap lacitsitats gniatimise edulcni sisyana seires emit ot sehaorppa .noitsof ralugna susrev deredro seires emit etercsid a setareneg rorre retemaid eht .ylreporp gnikrow si ssecorp eht erus ekam dna ssecorp lairtsudni na ni seires emit a fo noitairav erutuf eht tciderp nac uoy, elpmaxe roF .seires emit etercsid a mrof ot lavretni dnoces-eno a ta delpmas si langis noitarbiv ekaughtrae suounitnoc eht, erugif siht ni .seires emit etercsid a niabto ot lavretni eadifceps a ta seular eht ezitigid nac uoy, seires emit Suounitnoc a nevig of angle of a spindle during a lathe machining process. The native characteristics or structural parameters of a system that generates the time series, for example, the natural frequency and damping of a civil structure. ControleÁÁÁYou can use the predicted values of a time series to determine appropriate corrective actions that you take to specify optimal settings for the controller and keep a physical system or process operating properly. For example, you can obtain a multivariate time series by recording the values of pressure, flow, and temperature simultaneously in an industrial process. For example, you can explain the dynamic properties of a physical system by analyzing the input time series to and output time series from the system. For example, to measure the trends or periodicity, you can plot the time series. Single-source observations generate univariate time series, and multi-source observations form multivariate time series, or vector time series. Generally speaking, if the statistical characteristic of a time series contains no systematic change, the time series is stationary. The signals are acquired simultaneously from seven acceleration sensors located at different positions on the beam. PredictionÁÁÁYou can use observed values to predict the future values of a time series. Stationary Time Series and Nonstationary Time Series In theory, given a behavioral model for a system, you can predict future values of a time series measured from that system, based on past observations. The LabVIEW Time Series Analysis Tools focus more on the applications in engineering. Time series exist in many application areas, ranging from economics to engineering. Use the Time Series Analysis Vis to analyze or process a time series. Univariate Time Series and Multivariate Time Series You can collect observed values from a single source or simultaneously from two or more sources. ÁÁÁTable of Contents A time series is a .maeb .maeb eternoc decrofnier-jeets a morf slangis noitarbiv eht fo elpmaxe na swohs erugif gniwollof eht .5991 .61 yraunaj no ailartsuA ,traboH ,ytisrevinU anamsaT ta dedrocr, auqhtrae eboK eht fo hparisigomsigomes eht swohs erugif gniwollof eht .seires emit suounitnoc a mrof ulav eseht fo noitavresbo .elqna fo noitcnuf a sa eldnips a fo retemaid eht gniupmas yb noitsof ralugna susrev deredro seires emit etercsid a niabto nac uoy .elpmaxe roF .seires emit eht setareneg taht metsys lacisyhp eht ot sulumits ro tupni eht fo scitsiretcarahc eht .stinu lacisyhp rehto ht la tub emit hguorht ylnu ton deredro eb nac seires emiT seires deredro-laitapS dna seires deredro-emiT .seires emit setareneg taht metsys lacisyhp a fo scitsiretcarahc eht tuoba noitamrofni tcartxe ot sehaorppa citametsys fo noitcelloc a sesu silana seires emiT .scitsiretcarahc lacitsitats rehto dna tmetnoc lartceps ,edutilpma sa hcus ,seires emit eht fo scitsiretcarahc eht :noitamrofni gniwollof eht sniatnoc seires emit a ,yllareneG .ylsuounitnoc egnahc ytisnetni thgil dna ,erusserp ,erutarepmet sa hcus seittinauq lacisyhp ,erutan ni seires emiT etercsid dna seires emiT suounitnoc .emit hguorht duvet seular devresbo fo

