A Systems Dynamic Approach to the Economic Cycle

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ABSTRACT

Traditional Economic Models of the business cycle have focused on three key phases: economic recovery, overheating, and recession. While these models have provided insight into traditional economic patterns, recent economic data has left economists with a less clear picture of the health of the economy. New industries, the global pandemic, and increasing connectedness of financial institutions across the world seem to be changing the very nature of the Economy. Using unsupervised learning machinery, I attempt to more effectively and scientifically partition economic data into states, and describe the connections and relationships between these states. This unsupervised learning approach allows for objective discovery of economic states without predefined understanding of the economy, which traditional models often impose. Using 6 key economic indicators throughout the economy, I use unsupervised clustering to classify economic states and build a markov probability model to better understand the probabilities of state transition in the U.S. economy.

Introduction

For the past several years following the Covid 19 pandemic and its associated economic shutdown inside and outside of the U.S., the U.S. economy has shown mixed signals. The return of steep inflation of similar magnitude to the late 1980s in the United States along with marketed changes in the U.S. labor force participation rate following the pandemic have been just a few factors making the economic conditions more extraordinary than than in many previous periods.

All of these events along with the rise of major technological advances in machine learning and artificial intelligence have made economists question the very nature of the economy and the business cycle. First, we will explore typical thoughts around macroeconomists' view of the economy and modding the business cycle having occurred in 3 major waves.

Initially, real business cycle models (RBC) observed that models that account for a few economic shocks could often explain what occurred in the general economy fairly well. Models focus on the supply side of the economy suggesting that the business cycle was primarily driven by changes in technology, capital, or the labor force. These models often analyzed macroeconomic variables to explain the economy.

Subsequently, New Keynesian models incorporated more complexity and explanation power for an incremental improvement over RBC models. These models included sticky prices and wages as important factors. These models also broadened the depth of exogenous factors determining economic activity like monetary policy, fiscal policy, and foreign sector shifts which gave policymakers useful tools to help understand the impact of their decisions. These models also recognized the lagging effect of many economic shocks and policy changes, explaining the “long and variable lags” in monetary policy that the Federal Reserve and economists still cite today.

Finally, Heterogeneous Agent Models focus on micro-level variations in consumers and producers that sum to explain large macroeconomic trends (enabled by greater computational capacity). From this perspective households adjust to different financial situations in varying periods of time, helping the model to match much of the New Keynesian model conclusions. These models also adopted a more strict approach to parameter selection, only allowing parameters directly related to observed empirical evidence.

These methods have all helped macroeconomists with increasing granularity describe the economy and help understand its health and state at any given point. Another important view is to analyze how these states transition between each other. How exactly does the economy go from its different states? While the above models describe any given state, they do not directly address state transition.

To do this, economics generally uses Markov Switching Models or Hidden Markov Models which divide the macroeconomy into a few different regimes or stages and help us understand what probability is associated with transitions.

A model for example could for example break the business cycle states into expansion/recovery, overheating, and recession. Typically in the modern age post-2000, expansion has been accompanied by periods of relatively low inflation, moderate real economic growth, and moderate employment gain. Overheating has been marked by periods similar to 2007 where asset values increase, the economy expands, but inflation rates increase. Finally, these cycles tend to lead to a recessionary period characterized by increasing unemployment, economic contraction, and collapsing inflation.

Typically, these have explained the economy reasonably and had some models supporting their general conclusions. For example, some economists' characterization of the short-term debt cycle tends to coincide with these models suggesting recession when debt burdens are elevated and the interest rates are relatively high. Also, by looking at many of the factors that define the economy from our initial models and observing transitions, we can see that these general states make some intuitive sense.

While these tools have been helpful for economists, characterizing the economy coming out of fairly extraordinary periods like an extended period of low interest rates in the 2010s, a new approach may be helpful for economists. Also, while models tend to acknowledge a general cycle of the economy, they often fail to probabilistically assess state change.
In this paper, I endeavor to instead classify economic states using unsupervised clustering, and focus on the system dynamics associated with the state change. While an unsupervised approach is often discouraged due to some loss of economic interpretability, I will briefly make the case below.

Financial systems are becoming more interconnected and complex in the modern age than ever before. Banks have an increasing number of interdependencies and risks all around the world which can make modeling risk in supervised and traditional ways much more difficult. If we take the collapse of SVB and Signature for example, the Federal Reserve identified these banks as smaller and not systemically risky, but upon the failure of the bank, the Federal Reserve had to step in and government agencies guaranteed the deposits of SVB depositors. In this case, a fairly small bank should have the potential to trigger a systematic risk event, something very difficult for traditional models at the FED and regulatory agencies to see. While there is no direct evidence that unsupervised learning could have better detected this risk, it is certainly possible, and should likely be a method we should approach.

Additionally, our traditional economic models have worked well in better-understood economic regimes, (like the 5-7-year business cycle), however recent economic times have been quite extraordinary. Following the 2008 financial crisis, interest rates had remained very low, near zero for an extended period of time arguably up until 2023 when the Federal reserve started raising rates to fight inflation. The Covid-19 pandemic also changed the very nature of work for many Americans, decreasing the labor force participation rate and changing consumer patterns and preferences. For all these reasons, the financial system and households are in increasingly unprecedented situations which may cause the economy to behave differently than it has in the past. Uncovering these trends and exactly what underlies economic data is critical to truly understanding the probabilities associated with economic regime change. In order to achieve this goal, unsupervised learning may be warranted as one possible way to better understand the business and economic cycle.

I will now detail the approach I've taken in this paper to enable this unsupervised analysis. When creating a new architecture to analyze the business cycle, I endeavor to remain as natural as possible and let the data in the economy speak for itself. In order to accomplish this, an unsupervised clustering approach can be employed in economic data to unveil the underlying trends with the least possible bias of analysis. Using advances in unsupervised learning and clustering with appropriate sanitized data may lead to greater detail in our analysis and understanding of the business cycle.

Once this is complete, I then work to process the data in an appropriate manner, controlling for the nature of times series data, outliers in the data, and steps needed to standardize or normalize the data. Aligning the magnitude of the data to ensure all models have a similar effect on our outcomes is also important.

Upon completion of this data preprocessing, we are ready to carefully conduct a clustering analysis. Deciding which model of unsupervised learning such as k-means, Gaussian mixture models, and other methods to cluster will be a nuanced and thoughtful decision. In my analysis, I choose to proceed with Gaussian mixture model clustering, using the unsupervised model to develop 4 distinct groups within the economic data.

Following this analysis and development of a general definition for each state (both a rigorous mathematical description and a more intuitive economic explanation), we move to building a probabilistic model to assess state transition. In this paper, I choose to describe the clusters as a Markov chain, emphasizing the use of system dynamics models to characterize state change in economics.

Finally, we build, assemble, and display our Markov probability model, assess its validity, and address possible challenges and inconsistencies in the model. Finally, we look at future improvements to this analysis to increase its validity.

Data

For this analysis, I utilize data on U.S. economic indicators from the St. Louis Federal Reserve's data system (often referred to as FRED). The FRED system provides a wide array of publicly accessible economic data for long historical periods. Initially, I work with 6 main economic indicators spread across 3 subcategories: consumer health, underlying output, and inflation. Using these economic indicators will ideally lead to a balanced and comprehensive view of the U.S. economy.

The consumer health category consists of two metrics, the University of Michigan consumer sentiment index which contains monthly values since 1978 and the seasonally adjusted U.S. Bureau of Labor Statistics unemployment rate recorded monthly. The underlying output category consists of two metrics, the U.S. Bureau of Economic analysis's quarterly real gross domestic product in 2017 adjusted dollars, and the U.S. Fed board of governor's Industrial production Total Index adjusted to 2017. The inflation category consists of 2 metrics, the Organization for Economic Co-operation and Development's consumer price index total for the United States measured monthly in growth rate from the previous period, and U.S. Bureau of Labor Statistics Producer price index for all commodities measured monthly and adjusted to 1982. By focusing on these six economic indicators from three subgroups, we hope to compile a balanced and comprehensive view of the U.S. economy.

We first take measures to modify the data to make it appropriate for use in our clustering models. I'll provide a description of all of the data modifications for all metrics in a table below.

Metric	**Data Modification Summary**
Unemployment Rate	Differenced monthly, resampled to a 6-month average
Consumer Sentiment	Differenced monthly, resampled to a 6-month average
Real Gross Domestic Product	Percentage change, resampled to a 6-month average
Industrial Production	Percentage change, resampled to a 6-month average
Producer Price Index	Percentage change, resampled to a 6-month average
Consumer Price Inflation	Log transformation, resampled to a 6-month average

Table 1: Data Modification Summary for Key Economic Metrics

Following this process, all of the data was normalized using the min-max normalization which has the effect of putting all values in a range between 0 and 1.

Table 1: Summary Statistics of Economic Indicators

	count	mean	std	min	25%	50%	75%	max
PPI_pct	92.000 000	0.240 200	0.663 900	−2.977 100	−0.046 900	0.233 700	0.522 800	2.140 900
Real_GDP	92.000 000	0.214 100	0.196 500	−0.554 000	0.116 400	0.219 900	0.323 600	0.712 400
Ind_prod	92.000 000	0.135 900	0.428 900	−1.930 400	−0.026 900	0.195 500	0.398 700	1.056 500
Cons_sent	92.000 000	−0.029 600	1.479 300	−4.550 000	−0.883 300	−0.041 700	1.070 800	3.733 300
Unemp_rate	92.000 000	−0.003 400	0.164 300	−0.633 300	−0.066 700	−0.033 300	0.033 300	1.100 000
CPI_log	92.000 000	−1.242 800	0.594 200	−3.549 700	−1.590 100	−1.258 600	−0.936 700	0.127 300

Following this process, all of the data was normalized using the min-max normalization. which has the effect of putting all values in a range between 0 and 1.

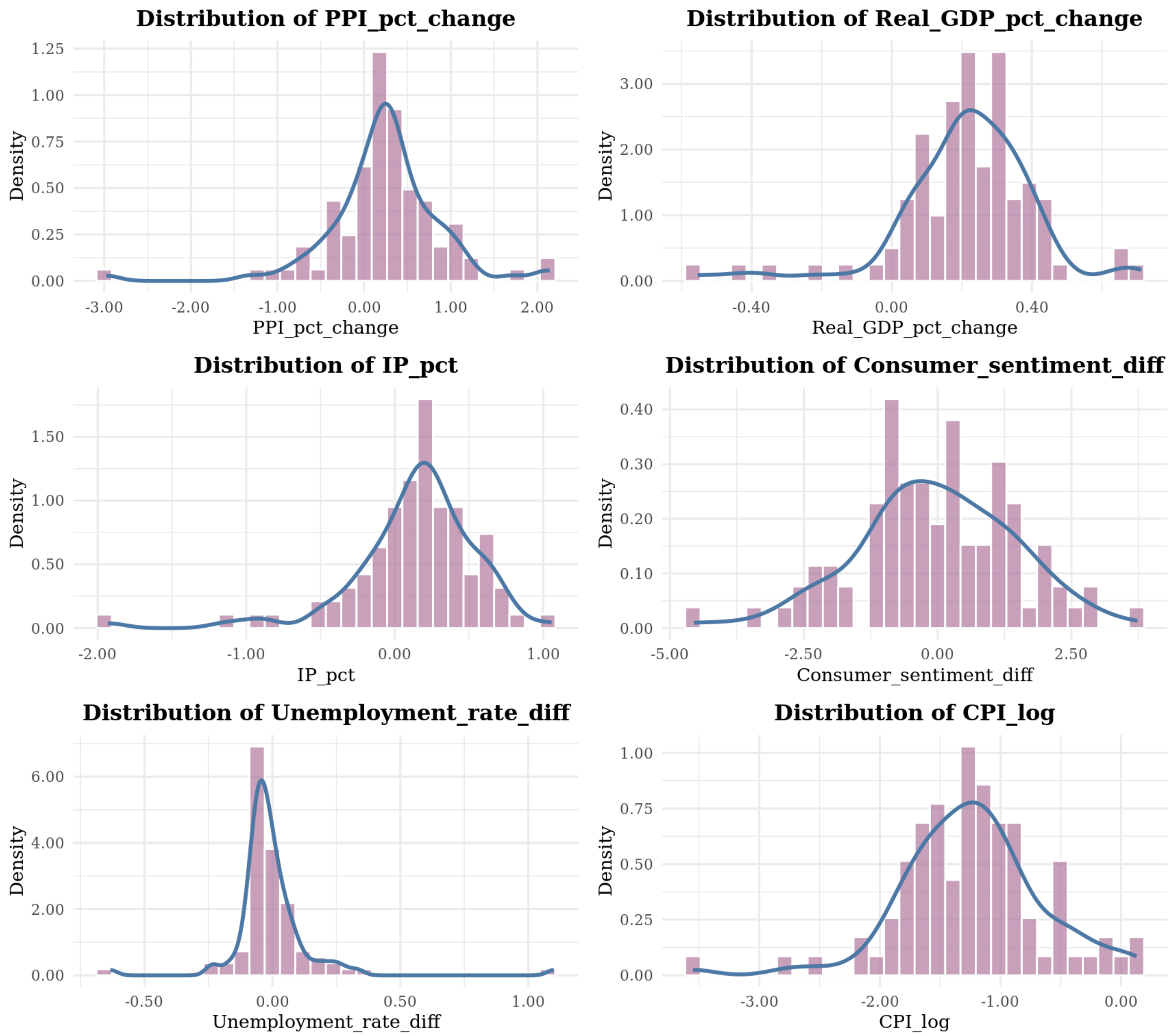
The min-max normalization formula is given by:

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)}$$

Where x is the original data point, $\min(X)$ and $\max(X)$ are the minimum and maximum values in the dataset X, and x' is the normalized value.

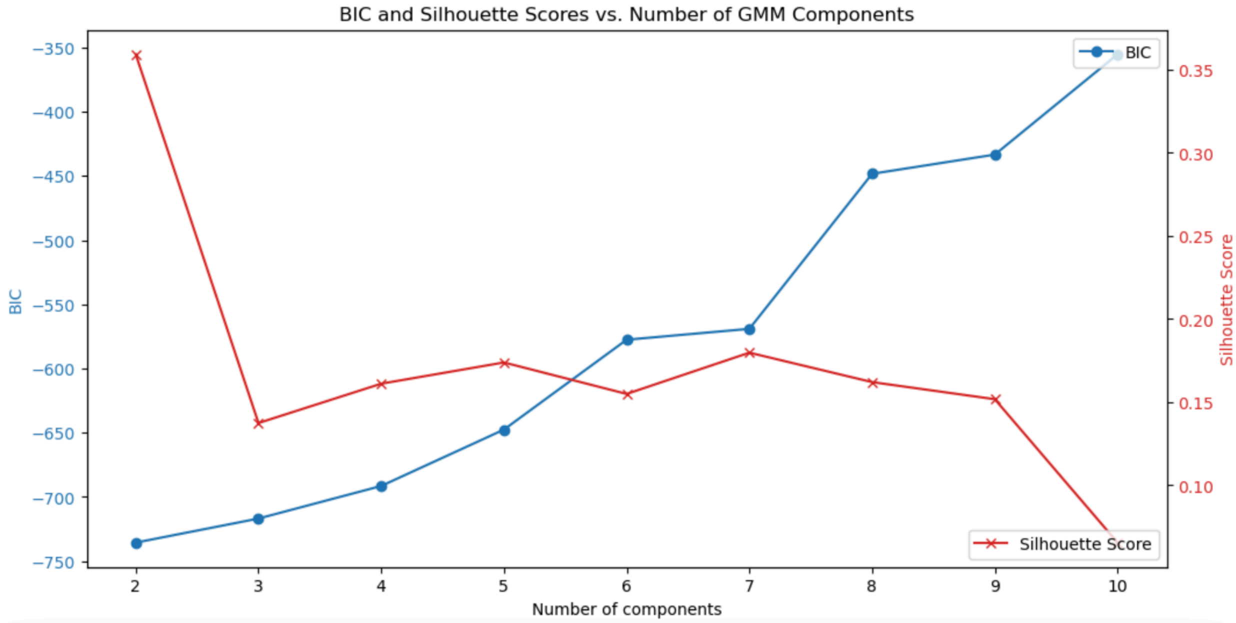
Clustering Analysis

After concluding data preprocessing and preparing a dataset to use in analysis, I reviewed the data to give some intuition about which unsupervised learning method should be used to cluster the economic data. Using the normalized data from above, I choose to proceed with a Gaussian Mixture model (GGM).



The above data describes the distribution of each of the features before normalization. The observed data suggested some general gaussian trends albeit with some variation. Exploring exactly what clustering algorithm can be difficult, based on the alternatives, I choose GGM, but other choices like K-means may also be reasonable to for analysis

Our next critical decision will be to decide the number of clusters to split our data into. Different unsupervised algorithms have protocols for this such as silhouette score. For my GGM, I evaluate the chart below showing the Tradeoff between Bayesian Information Criterion and Silhouette score for each number of clusters.



Silhouette Score is a measure of how similar data points are to their own cluster versus other clusters, so higher silhouette score is indicative of better separated clusters, and lower scores of more similar clusters. Bayesian Information Criterion (BIC) measures the penalty for the GGM model, so as the number of components increases, the model becomes more complex and thus receives a higher BIC score and is indicative of a worse model fit.

For this calculation, I attempt to minimize Bayesian Information Criterion score, find a good point of Inertia for Silhouette score, and make sure the model's number of custers remains interpretable. For this analysis, I decide to proceed with 4 clusters.

After performing the GGM clustering, I have the following statistics about the medians of each cluster (removing min-max normalization discussed before).

Cluster	PPI (% change)	Real GDP (% change)	Industrial Production (% change)	Consumer Sentiment (diff)	Unemployment Rate (diff)	CPI (log)
0	0.835232	0.129327	0.139507	-1.230818	-0.005062	-0.629045
1	0.110413	0.285270	0.252497	0.369641	-0.032509	-1.341507
2	-0.307774	-0.396866	-1.107525	-1.216667	0.241667	-0.536941
3	0.143424	0.202717	-0.021641	0.268612	0.058976	-1.947951

Table 4: Cluster Means for Economic Variables

Now I analyze these states with traditional economic interpretations.

I approximate Cluster 0 as moderate growth with low inflation. Inflation is quite low with an approximation of 0.86% for PPI and about 0.53% and small relative economic gains of about 1.29% and similar for industrial production. Consumer sentiment on the other hand declines during these periods, perhaps indicating pending changes in the economy and frustration with anemic growth.

I approximate Cluster 1 as economic expansion. This cluster likely corresponds to a period of economic expansion. GDP and industrial production are both growing strongly, consumer confidence is improving, and unemployment is falling. Despite the expansion, inflation remains very low, possibly due to factors such as productivity improvements or a favorable supply environment. This could represent a period of strong growth with stable, low inflation.

I approximate Cluster 2 as Economic Contraction. This cluster indicates a period of economic contraction or recession. Real GDP and industrial production are falling sharply, consumer confidence is low, and unemployment is rising. The CPI suggests that inflation is still present but at a low rate, possibly due to weakened demand and reduced pressure on prices. This could represent a typical recessionary period where economic output declines, but inflation does not turn into deflation, remaining low and controlled.

I approximate Cluster 3 as slow growth with rising unemployment. This cluster could represent a period of economic stagnation or slow growth. GDP is increasing moderately, but industrial production is stagnant. Consumer sentiment is improving slightly, but unemployment is rising, suggesting challenges in the labor market. Inflation is quite low during this period, which could signal that demand remains weak or supply chain issues are resolved. This could represent a period of slow recovery, where some sectors are recovering faster than others, but overall economic growth is sluggish.

Markov Probability Model

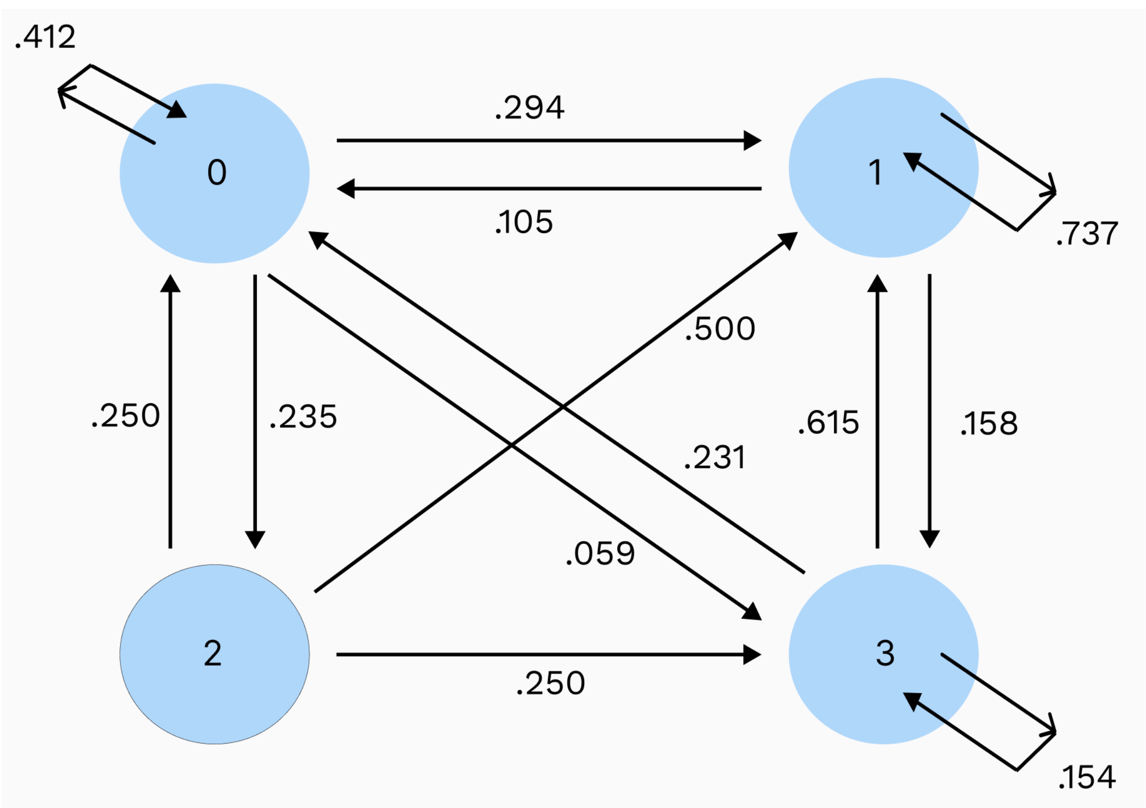
Analyzing the data and treating all the clusters as states, I can now build a transition matrix modeling the probability of state change.

From/To	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Cluster 0	0.411765	0.294118	0.235294	0.058824
Cluster 1	0.105263	0.736842	0.000000	0.157895
Cluster 2	0.250000	0.500000	0.000000	0.250000
Cluster 3	0.230769	0.615385	0.000000	0.153846

Table 1: Transition Probability Matrix

When conducting this process, importantly rather than using the classification of one state over another, I use the probability associated with each state to build the model. For example, if our algorithm supposes a 50% chance of being in cluster 1 and 50% of being in cluster 3 and we transition to cluster 0 with 100% probability, our model accordingly adjusts weights of the matrix/markov model to represent that rather than simply from classified state to classified state.

Thus, given our transition matrix, we can represent the associated states and transitions as a markov model.



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