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Probabilistic Methods for Enhancing Foreground Segmentation of Various Data Model using Big Data Model

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Abstract: *Some indicators of social and economic health, especially those pertaining to developing countries, can swing wildly. A country's economy might take a hit if major economic indices like commodity prices, unemployment, currency exchange rates, etc., experience significant volatility. Instability in commodity prices is bad for economic development, financial reserves, and income distribution, and it may exacerbate poverty rather than alleviate it. Exports from various countries, including India, are dominated by commodities. The volatility of currency exchange rates has a ripple effect on commodity prices. Economic growth and stability require constant attention to these socioeconomic factors and an awareness of their inherent instability. Decades of research haven't shed any light on the reasons for a socioeconomic index's anticipated time and place fluctuations or the relationships between several indices. Economists can understand and foresee the volatility of social and economic indices with the use of predefined economic models. Traditionally, computational modelling has been the primary method of analysis for computer scientists when dealing with structured time series data. A rare opportunity to examine socioeconomic fluctuations has arisen because to the rapid expansion of unstructured data streams on the web and the development of cutting-edge computational linguistics algorithms during the past decade.*

Keywords: Probabilistic Methods

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