Thesis Summary

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This thesis is dedicated to the exploration of consumption growth rate distributions using Bayesian non-parametric methods, specifically focusing on the application of the Dependent Dirichlet Process (DDP) model. The initial sections provide a comprehensive overview of Bayesian Non-Parametric methods, emphasizing key concepts like Random Probability Measure, De Finetti's theorem, and the Dirichlet Distribution.

The thesis progresses to an in-depth exploration of the Dirichlet Process, covering its fundamental attributes, including conjugacy, posterior mean, predictive distribution, and the stick-breaking construction method. Subsequently, the Dirichlet process mixture model is introduced, accompanied by an efficient inference algorithm for posterior estimation. The aim is to leverage Bayesian non-parametric methods for density estimation, addressing scenarios where traditional parametric models may fall short.

The novel approach of the Simple Dependent Dirichlet Process is proposed, balancing model complexity and computational efficiency for effective density estimation in multivariate data with dependencies across time and space. A sophisticated Gibbs sampler algorithm tailored for this model is presented, addressing challenges associated with infinite-dimensional spaces.

In the final section, the thesis applies the DDP model to measure time-varying economic tail risk, specifically focusing on macroeconomic crisis probabilities. The DDP model proves to be a powerful tool, offering flexibility and computational efficiency to capture the nuanced dynamics of consumption growth rate distributions. The model's adaptability is highlighted, seamlessly transitioning from reliance on prior information to being data-driven, accommodating evolving distributions over time.

The nonparametric nature of the DDP model sets it apart, avoiding unrealistic constraints and adapting flexibly to complex features in consumption growth rate distributions. Comparisons with Quantile Regression underscore the DDP model's strengths in accounting for spatial and temporal dependencies within the data, providing a more comprehensive understanding of how risk propagates spatially and evolves over time.

An intriguing finding from the application of the DDP model is the significant time variation observed in the left tail of the distribution, indicating varying extremes in negative outcomes over time. This underscores the importance of monitoring and understanding macroeconomic tail risk dynamically. The thesis concludes by emphasizing the DDP model's ability to navigate the complexities of economic events and its crucial role in providing a dynamic and adaptable perspective on macroeconomic tail risk.