

# Dependence modeling in General Insurance using LGC and HMMs

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# Dependence modeling-Motivation

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- Non-linear and tail dependence- an issue?





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## HMMs

- Capture complex temporal dependencies
- Handling Varying Patterns and Regimes.
- Assumes that data-generating process corresponds to a time-dependent **mixture** of conditional distributions driven by **Hidden states**





# LGC basic notation

## Define

- Let  $X = (X_1, X_2)$  2D RV with density  $f(x) = f(x_1, x_2)$  and  $\Sigma(x)$  be a Gaussian bivariate
- $\mu(x) = (\mu_1(x), \mu_2(x))$  is the local mean vector
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- Approximate  $f$  locally at each point  $x$  by  $\hat{f}_x(\cdot)$
- $\mathbf{z} = (z_1, z_2)^T$  is the running variable
- The local population parameters  $\theta(x) = (\mu(x), \Sigma(x))$  can be defined by minimizing a penalty function  $q$  measuring the difference between  $f$  and

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- Used TMB



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- LGC and HMM Illustrated using Motor LoBs and Homeowners Insurance LoBs
- For motor-15 years from July 2007 to Dec 2021 giving 756 weekly records.

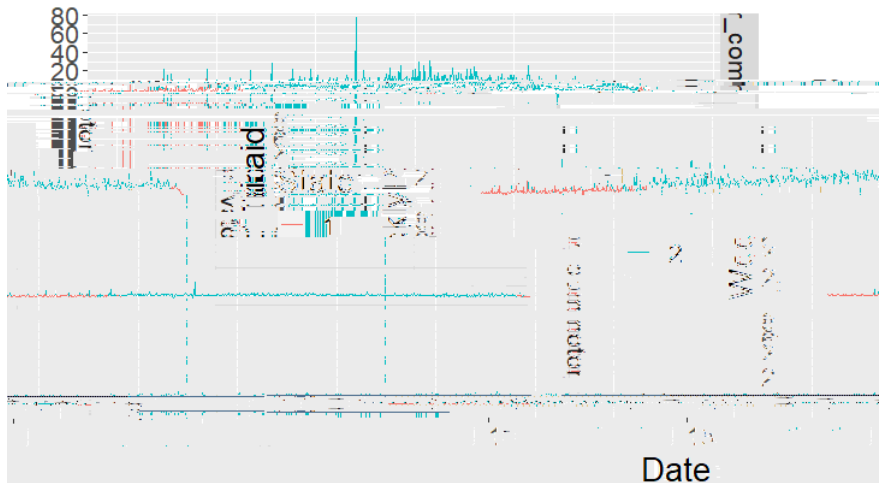






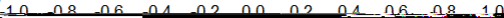
motor\_commercial vs motor\_private, rho = 0.85







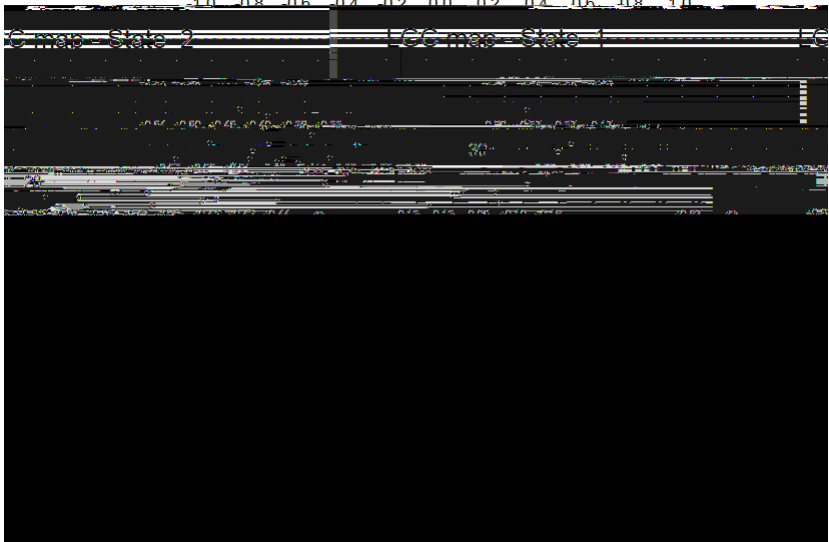
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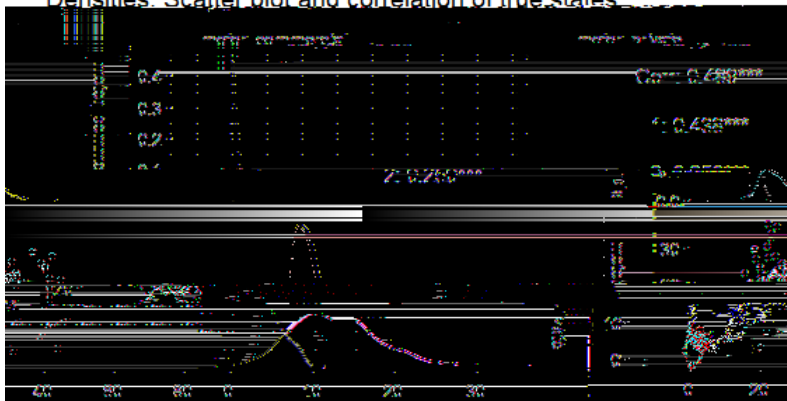
C map - State 2

LGC map - State 1

LGC



## Densities, Scatter plot and correlation of true states



# Test of asymmetric dependence between states

Hypothesis:

$$H_0 : \quad \rho_1(x_i, y_j) =$$



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- Model found time carrying dependency-financial crisis
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- This analysis enables insurers to better assess and manage their overall risk exposure across different lines of business especially during economic, political crisis periods

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- Apply to Reserving, pricing, reinsurance arrangements?

