Modeling of Temporal Data

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- What are some basic issues that may arise when inferring from temporal data?

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- Survival, time until failure / success, growth rates

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- Unevenly spaced obs

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 - ▶ Detrending, differencing, transformation, etc.

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- In words: You want to predict the position of the cat with time. How accurate will you be? Of course you will become more and more inaccurate as the position of the cat changes. At t=0 you exactly know where the cat is. Next time, it can only move to 8 squares and hence your probability dips to $\frac{1}{8}$ instead of 1 and it keeps on going down.

Random Walk Formulation

$$X(t) = X(t-1) + e(t)$$
 (1)

$$X(t) = X(0) + \sum_{l=1}^{t} e(l)$$
 (2)

$$E[X(t)] = E[X(0)] + \sum_{l=1}^{t} E[e(l)]$$
 (3)

$$= E[X(0)] \to constant \tag{4}$$

$$Var[X(t)] = Var[X(0)] + \sum_{l=1}^{t} Var[e(l)]$$
 (5)

$$= t \times Var(\mathbf{e}) \rightarrow \text{time dependent}$$
 (6)

Make it Stationary with ρ

$$X(t) = \rho X(t-1) + e(t) \tag{7}$$

$$E[X(t)] = \rho \times E[X(t-1)] \tag{8}$$

$$X(t) - X(t-1) = (\rho - 1)X(t-1) + e(t)$$
(9)

- ullet What if ho= 1? No force can pull the X down in the next step ightarrow non-stationary
- ullet We test if (
 ho-1) is significantly different than zero or not
- If the null hypothesis gets rejected, we have a stationary time series (Dickey Fuller test)

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- While very useful for prediction / forecasting, very difficult to make substantive claims (e.g., causality or unconfounded correlation)

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- More in TSCS, where it is more applicable

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 - ► Often better (though harder to convey) to use non-parametric approaches

David Carlson Temporal April 18, 2022 11 / 14

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- May wish to look at stages of growth

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- Recurring event or repeated event models relax that assumption

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