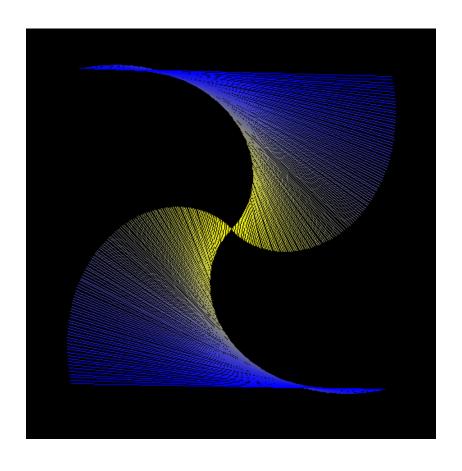
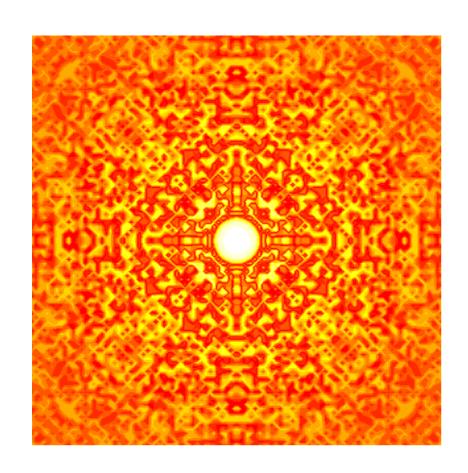
So you've got lots of zeros



Jonathan Coop
Statistics Bootcamp
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The plan and a disclaimer

- Think about why a dataset might have a lot of zeros and some different approaches to modeling with zeros.
- Analyze some of my data on tree seedling counts using generalized linear models.
- Analyze some of your data.

* I am not a statistician and everything I know is what I learned is through my own struggles with data, and lots of google searches.

Why might a dataset have lots of zeros?

Categorical (binomial vs. multinomial, ordinal (ranked) vs. nominal (unranked)), **discrete**, and **continuous** variables.

- We often use zeros vs. ones to represent two alternative outcomes of a binary outcome (e.g., 0 = absent, 1 = present). Here, a lot of zeros might be expected.
- Count data: typically, we end up zeros in our response variable when we are counting things that are not common or happen infrequently.
- Zero might be the median value of a continuous variable that spans a negative and positive range. E.g., Palmer Drought Severity, ENSO index – normal distribution?

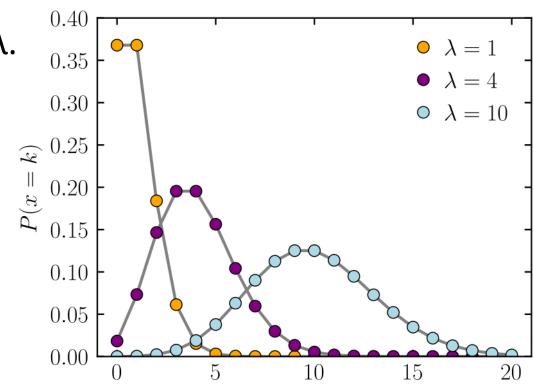
- For a range of statistical approaches, zeros can often be dealt with via non-parametric or zero-friendly alternatives (e.g., Mann-Whitney U, Wilcoxon signed rank sum, Kruskal Wallis, Fisher's exact test).
- Assuming we are interested in a linear model where y = f(x). For a normal distribution, a linear model might be y = mx + b.
- Count data are unlikely to be normally distributed, so we need to think about other types ("families") of distributions for generalized linear models.





Poisson distribution: number of events occurring within a discrete interval of time or space

- Events are independent.
- λ is expected rate of occurrence (mean)
- Variance of a Poisson distribution is also λ .

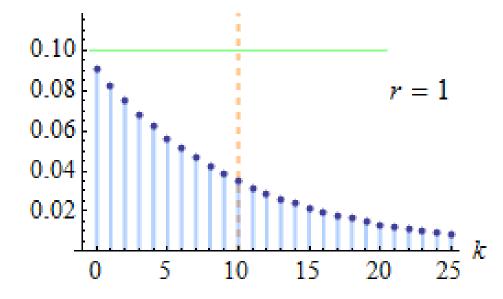


 Negative binomial distribution: number of successes in a sequence of independent and identically distributed Bernoulli trials before a specified number of failures occurs.

• Similar to Poisson, but allows for overdispersion (variance not necessarily λ) – this would be expected in a dataset with many zeros.

• Mean = μ ; variance = $\mu(1 + \mu/\Theta)$ -- overdispersion is modeled with its own

parameter θ.

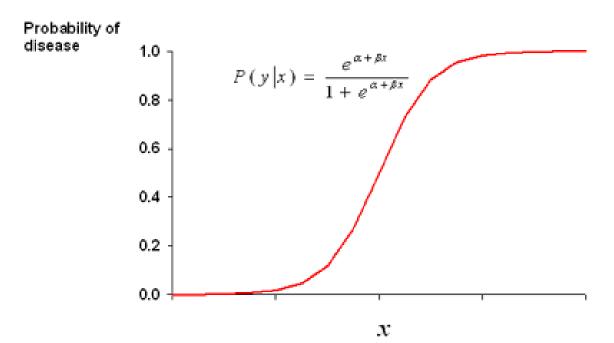


- Zero-inflated Poisson (ZIP) and Zero-inflated Negative Binomial (ZINB) models.
- For use where zero-inflated, and zero-inflated & overdispersed distributions.
- Basically employs two models at the same time:

- 1. Model zeros vs. non-zero observations.
- 2. Model non-zero observations (Poisson or NB).

What kinds of processes might give rise to zero-inflated distributions?

- Binomial logistic model two exclusive categories that can be represented as 0 or 1.
- Sometimes it is just easier to collapse a complicated distribution into a simple one, e.g. presence/absence, or occurrence > some critical minimum threshold.



Tree seedlings in post-fire landscapes

- We counted tree seedlings in 686, 100-m² plots in 12 burns in the W US.
- To what extent do fire refugia (unburned patches of forest) promote post-fire forest recovery?



esa ECOSPHERE

Contributions of fire refugia to resilient ponderosa pine and dry mixed-conifer forest landscapes

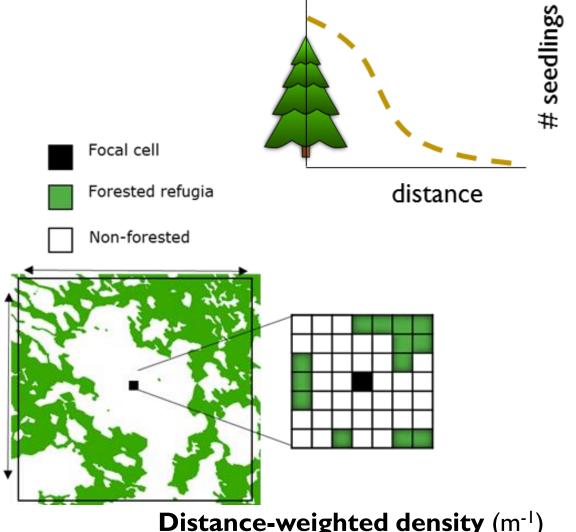
JONATHAN D. COOP, TIMOTHY J. DELORY, WILLIAM M. DOWNING, SANDRA L. HAIRE, MEG A. KRAWCHUK, CAROL MILLER, MARC-ANDRÉ PARISIEN, AND RYAN B. WALKER

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SW seedlings.csv

- Tree seedling counts in 368 plots from 8 SW burns along gradients of refugia proximity and abundance.
- Columns 1-5 are plot identifiers, coordinates.
- 6-10: elevation, topography.
- 11-15: measures of landscape pattern, burn severity. Distance is meters to surviving tree seed source. DWD is a composite measure of refugia proximity and abundance. D2WD is the same thing, but calculated with distances squared.



Distance-weighted density (m⁻¹)

$$DWD = \sum_{i=1}^{N} 1/(d_i + 1)$$

SW_seedlings.csv

- 16-18: vegetation cover
- 19-41: measures of post-fire climate from ClimateNA (http://climatena.ca)
- 42-44: synthetic measures of climate (PCA of 19-41)
- 45-49: seedling counts for ponderosa pine (PIPO), Douglas-fire (PSME), white fir (ABCO), aspen (POTR), and combined piñon and juniper (PJ).

Questions:

- What kind of distribution do seedling counts follow?
- Which is the best model: poisson, negative binomial, or zero-inflated negative binomial? With or without a random effect term?
- Which is a better predictor of PIPO seedling abundance: distance from seed source, DWD, or D2WD – or some combination?