Geo-spatial Analysis with Generalized Additive Models

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Agenda

Spline Regression Recap

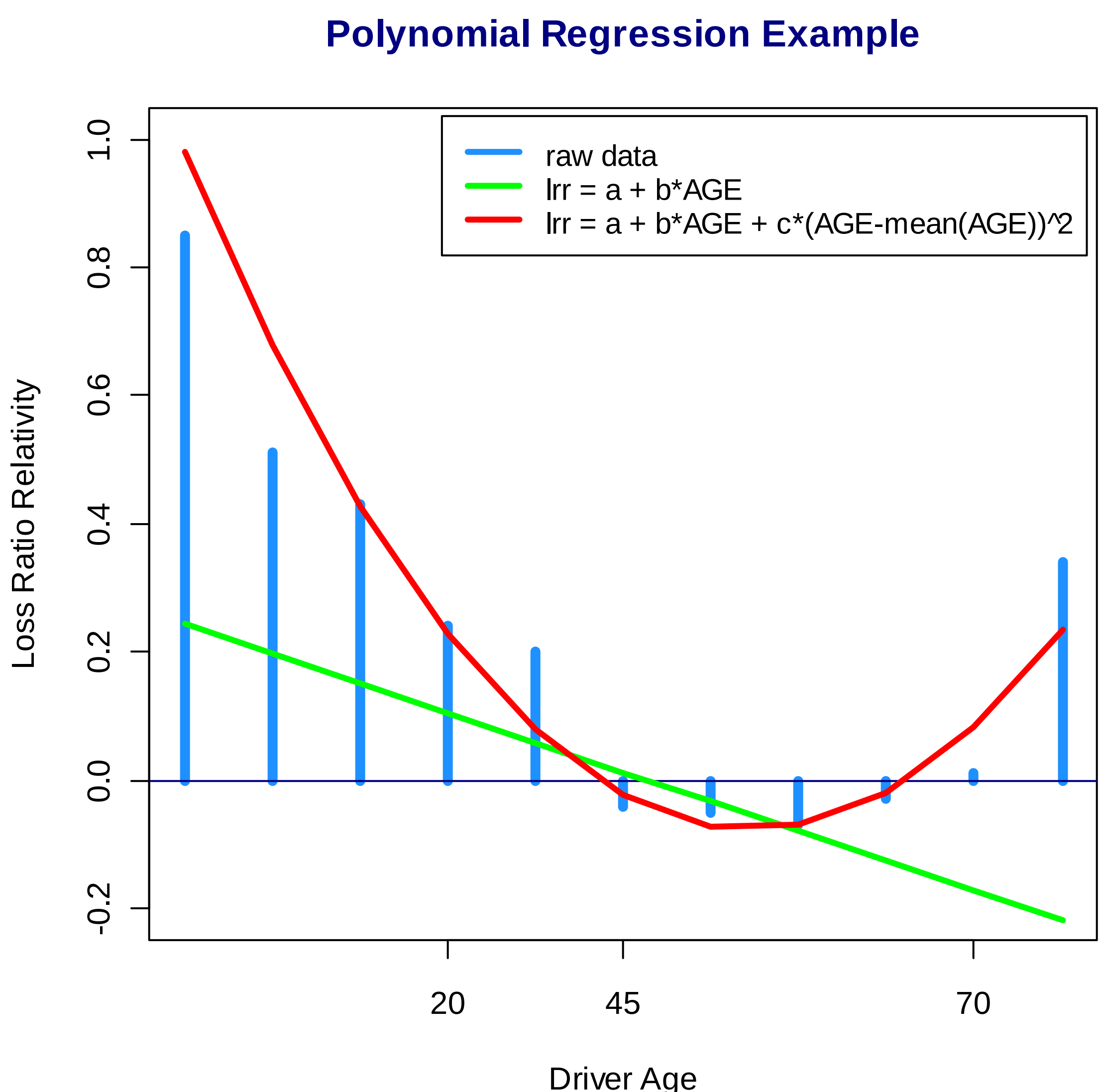
Generalized Additive Modeling Theory

Geo-spatial GAM example

Spline Regression

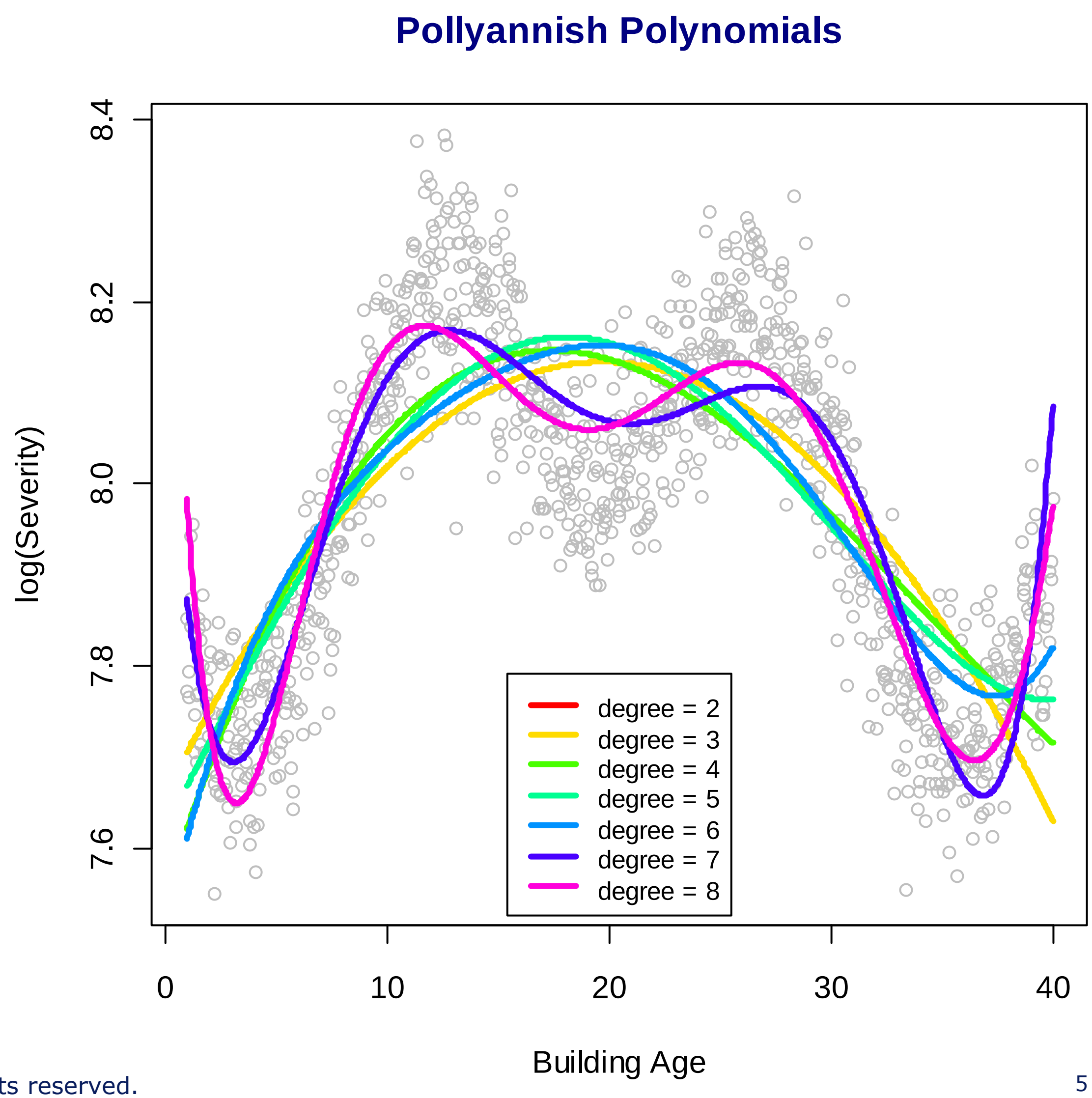
Modeling Non-Linear Patterns

- Linear models only have to be linear in the parameters.
- By cleverly transforming our variables we can model just about any non-linear relationship.
- Often in practice, adding a quadratic and maybe cubic terms will suffice.
- Here, adding a quadratic term results in a reasonable fit.



The Limits of Polynomial Regression

- In more complex cases, adding polynomial terms is not enough.
- This (exaggerated) example illustrates the limitations of polynomial regression.
- Adding quadratic and cubic terms is better than nothing, but doesn't fully capture the pattern.
- Even an 8^{th} degree polynomial regression provides only a rough approximation.

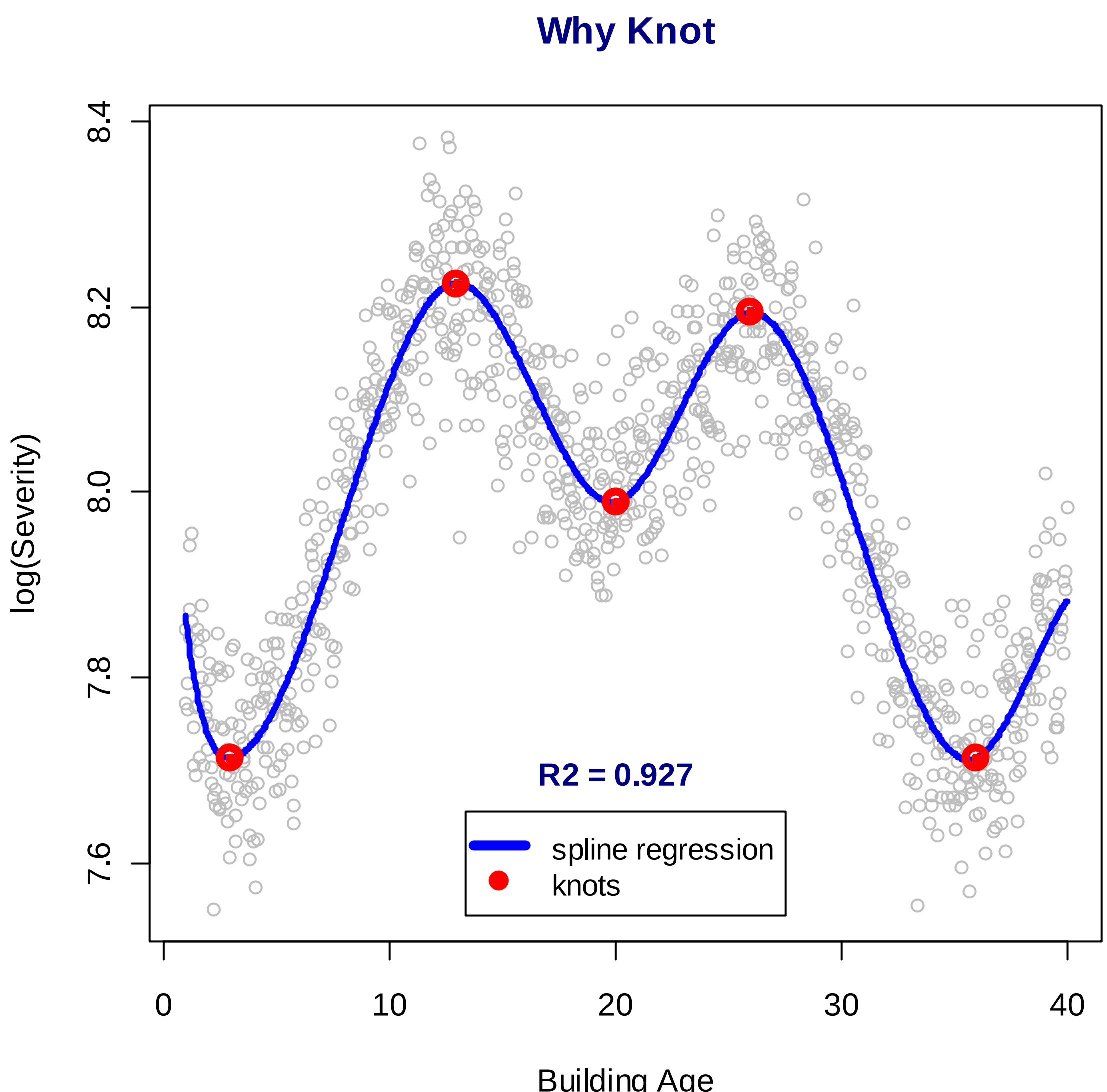


Cubic Spline Regression

- In more complex cases such as this, cubic spline regression is an excellent alternative.

- Here we have a series of cubic polynomials joined at a series of manually selected knots.
    - The model is “smooth” in the sense that it has continuous 1st and 2nd derivatives at each knot.

- In this case, a cubic spline regression with 5 knots achieves an excellent fit (R^2=0.93).



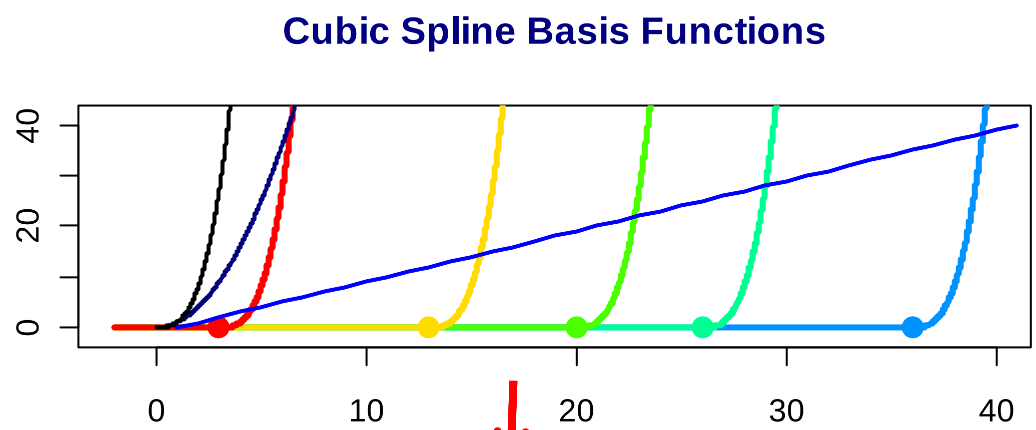
Basis Basics

- The basic trick is to identify a collection of **basis functions** $\{b_i(x)\}$ that can approximate any functional form.

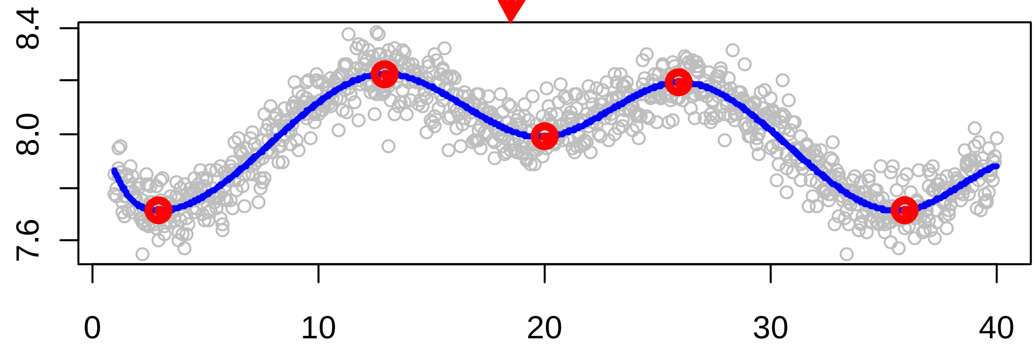
- In addition to polynomial terms, our spline regression includes a linear combination of these basis functions of building age:

$$b_{k[i]}(x) = \begin{cases} (x-k)^3 & x > k \\ 0 & x <= k \end{cases}$$

  - Aside: the "hockey stick functions" used in the MARS algorithm are the lower-degree analog of these basis functions.

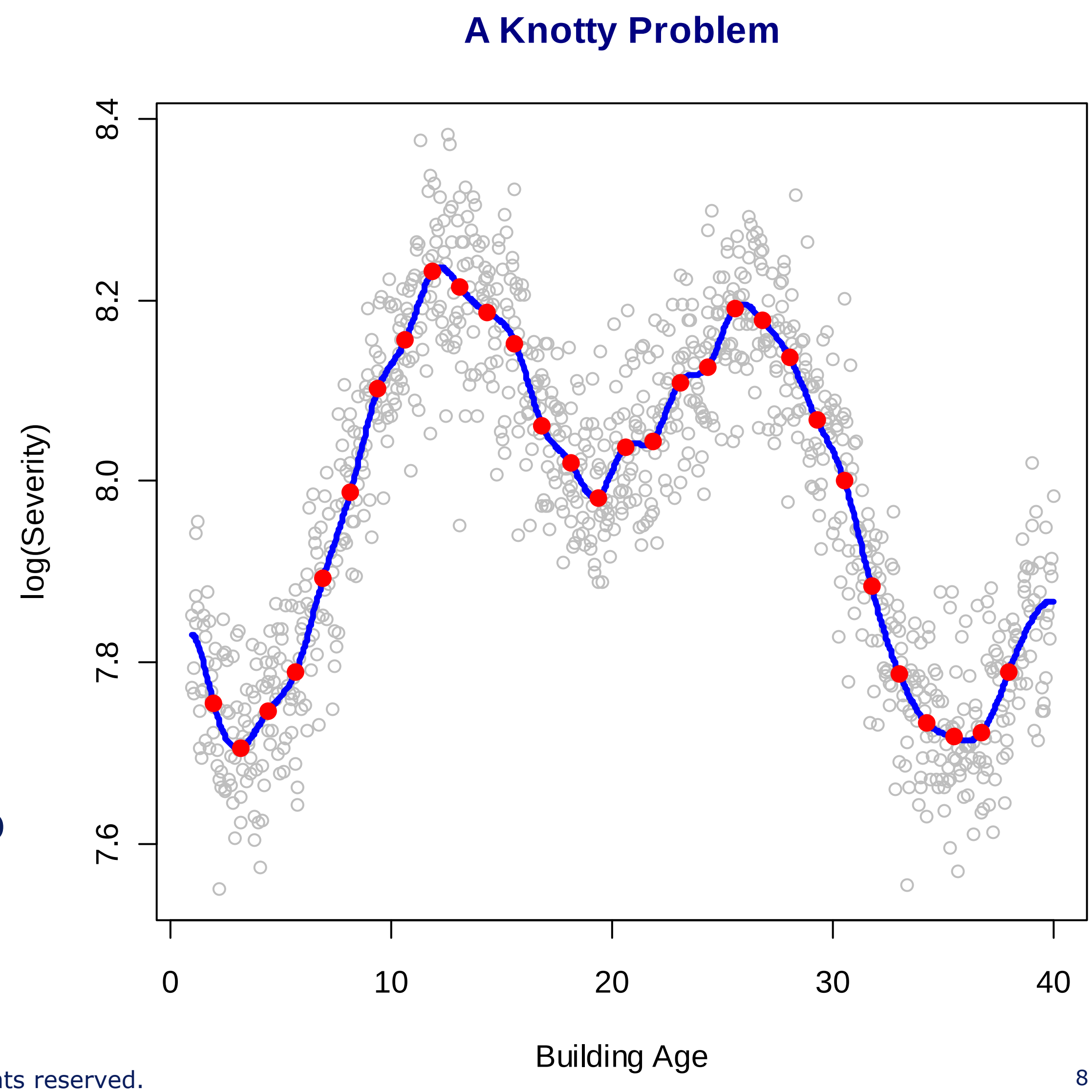


$$f(x) = \alpha + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \sum_{i=1}^{k} \gamma_i * b_i(x)$$



Overly Caffeinated Spline Regression

- Spline regression is great, but we must be careful when selecting the knots.
- Too few knots ➔ not all of the patterns will be reflected in the model.
- Too many knots ➔ our model will fit random noise in the data.
- Capturing too much random noise can lead to a model that performs poorly out-of-sample.
  - We'll come back to this point.



Generalized Additive Models

Generalized Additive Models

- Recall the basic ideas of Generalized Linear Models:
  1. $g(\mu) \equiv g(E[Y]) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_N X_N$
  2. $Y|\{X\} \sim$ exponential family

- Generalized <u>Linear</u> Models: $g(\mu)$ = linear combination of predictors

- Generalized <u>Additive</u> Models: the linear predictor can also contain one or more *smooth functions* of covariates.

$$g(\mu) = \beta \cdot \boldsymbol{X} + f_1(X_1) + f_2(X_2) + f_3(X_3, X_4) + \ldots$$

- Note that some of the *f* can be functions of more than one predictor.

- This brings us a lot of flexibility… but we need to figure out how to represent the functions $\{f\}$.

Generalized Additive Models

- GAM form:

$$g(\mu) = \beta \cdot \boldsymbol{X} + f_1(X_1) + f_2(X_2) + f_3(X_3, X_4) + \ldots$$

- How do we represent the functions $\{f\}$?
- Cubic splines offer an obvious answer.
- But recall that we had to choose the knot placements manually.
- This isn't good enough: we need a principled (and fairly automatic) way to specify a model that:
    - Fits the "true" linear and non-linear patterns in the data
    - But does not "over-fit" the data

Intuitively, it might seem that we need a way to determine the optimal placement of knots.

Fitting Signal, Not Noise

- **Alternate idea:** rather than worrying about which basis functions we need, we can fix the knots and basis functions ahead of time… but control the smoothness through <u>penalized least squares</u>.

- Rather than minimize SSE: $\sum_i \left(y_i - \sum_j \beta_j X_{ij} \right)^2$

- We can minimize ***penalized* SSE**: $\sum_i \left(y_i - \sum_j \beta_j X_{ij} \right)^2 + \lambda \cdot \int \left[f''(x) \right]^2 dx$

- The integral is a measure of the complexity of *f*(x).
  - Recall that our basis functions have continuous 2nd derivatives.

- The λ "smoothness" parameter determines how much we should penalize the complexity introduced by our cubic spline basis functions.
  - As $\lambda \rightarrow 0$, the GAM approaches an un-penalized regression spline
  - As $\lambda \rightarrow \infty$, the GAM approaches linearity

Penalized Least Squares

- The penalized SSE formula reflects a fundamental tradeoff.

$$\sum_i \left(y_i - \sum_j \beta_j X_{ij}\right)^2 + \lambda \cdot \int \left[f''(x)\right]^2 dx$$

More Basis Functions
Lower bias: Our spline model fits the data better ➔ 1st term is smaller.

Fewer Basis Functions
Higher bias: Our spline model fits the data worse ➔ 1st term is larger.

More Basis Functions
Higher Variance: there is a greater chance that the model will perform poorly out-of-sample ➔ 2nd term is larger.

Fewer Basis Functions
Lower Variance: there is a smaller chance that the model will perform poorly out-of-sample ➔ 2nd term is smaller.

- **This logic is sound… but we must determine the appropriate value of λ.**

Choosing λ

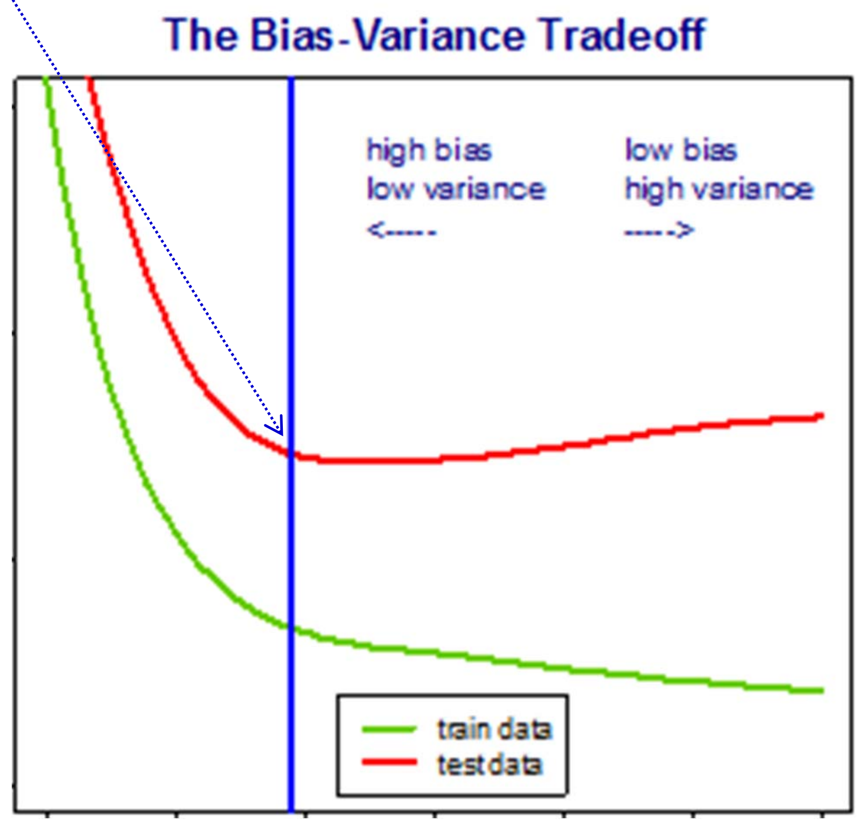
- We need a principles way to select λ before solving for the {β} parameters that minimize penalized SSE:

$$\sum_i \left(y_i - \sum_j \beta_j X_{ij}\right)^2 + \lambda \cdot \int \left[f''(x)\right]^2 dx$$

- We use **cross-validation** to do this.

- Select λ that minimizes SSE calculated using leave-one-out cross-validation.

- Conceptually the same idea used to determine the appropriate cost-complexity parameter in the CART algorithm.



To Summarize

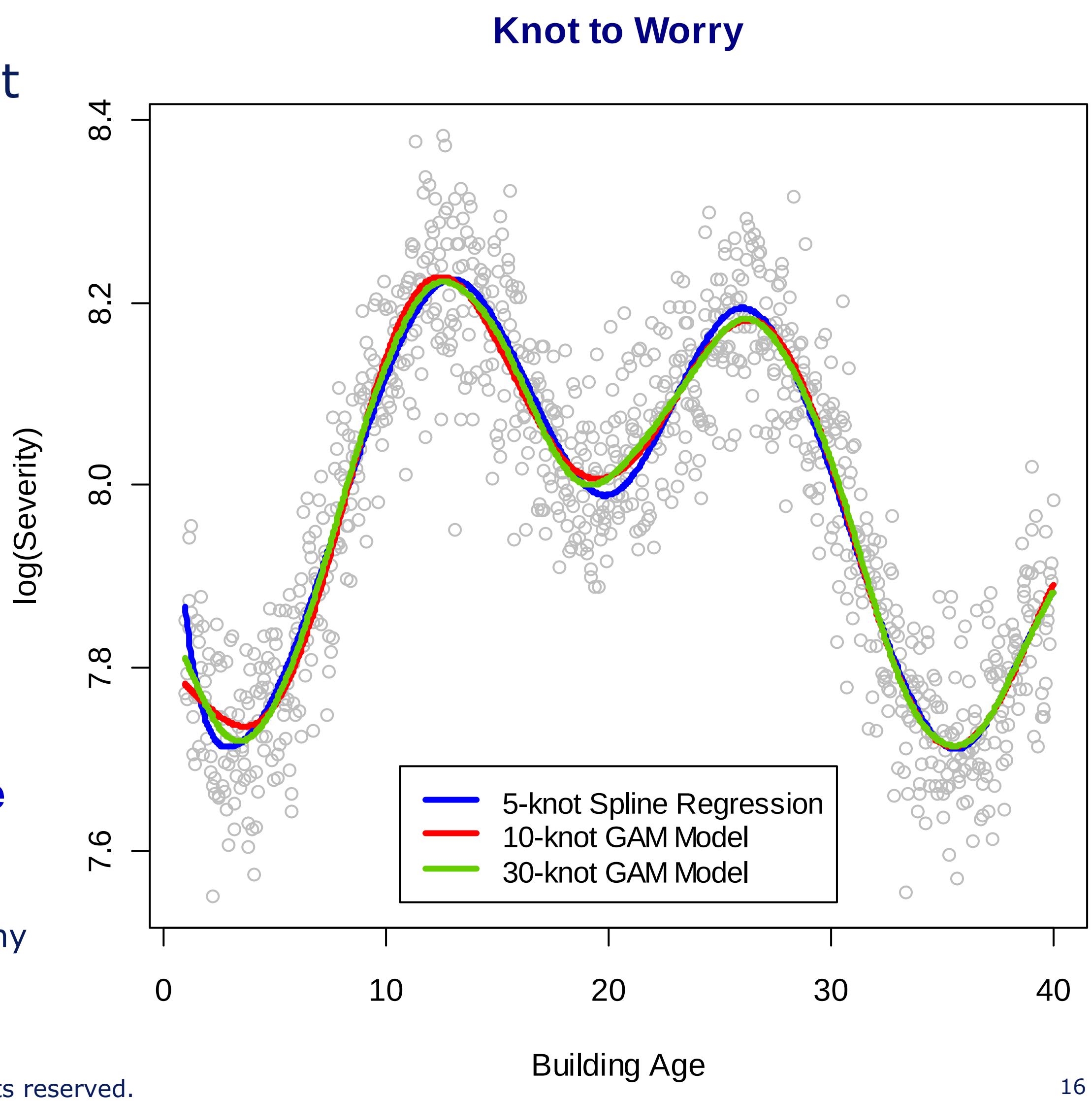
- Rather than manually select "just the right set" of knots and basis functions…
- We scatter the knots somewhat liberally…
- But add a 'wiggliness' penalty to the objective function used to estimate {β}:

$$\sum_i \left(y_i - \sum_j \beta_j X_{ij}\right)^2 + \lambda \cdot \int \left[f''(x)\right]^2 dx$$

- The penalty term removes the pressure to choose just the right set of knots.
- In case you're skeptical, let's try it.

Back to Our Example

- With "manual" spline regression we were judicious in our placement of knots.
- With GAM, we can err on the side of liberalism.
- **A 30-knot GAM slightly outperforms both a 10-knot GAM and our 5-knot spline regression.**
- **A 100-knot GAM is virtually indistinguishable from the 30-knot GAM!**
  - Run time is the primary disadvantage of choosing too many knots.



Generalized Additive Models for Geo-Spatial Analysis

Background – Territorial Ratemaking

- Common techniques for reflecting geography in insurance models:
    - Credibility models
    - Adding geo-demographic, crime, weather, traffic … variables to models
    - Spatial smoothing concepts

- Generalized Additive Models are a practical way to incorporate spatial smoothing in one's model.

- Some advantages:
    - Familiar paradigm: GAM is a generalization of GLM
    - Latitude and longitude can be used as model inputs
    - Lat/long can be incorporated alongside demographic variables
    - Use of offsets enables "modular" approach

Standard references:

- *Generalized Additive Models* by Hastie and Tibshirani (not tied to spline regression)
- *Generalized Additive Models* by Simon Wood (**paradigm followed here**)

California House Value Data

- One record per California block group.
- Target:
  - median house value
- Predictors:
  - Median income
  - Median house age
  - Average # bedrooms
  - Latitude
  - Longitude
- Let's fit a traditional GLM model on the first 3 predictors, and then bring in lat/long.

```
> ca.houses[1:10,]
    value income age  bedrooms   lat    long
1  452600 8.3252  41 0.4006211 37.88 -122.23
2  358500 8.3014  21 0.4606414 37.86 -122.22
3  352100 7.2574  52 0.3830645 37.85 -122.24
4  341300 5.6431  52 0.4211470 37.85 -122.25
5  342200 3.8462  52 0.4955752 37.85 -122.25
6  269700 4.0368  52 0.5157385 37.85 -122.25
7  299200 3.6591  52 0.4469835 37.84 -122.25
8  241400 3.1200  52 0.5937770 37.84 -122.25
9  226700 2.0804  42 0.5514096 37.84 -122.26
10 261100 3.6912  52 0.4558349 37.84 -122.25
>
>
> round(cor(ca.houses),2)
         value income   age bedrooms   lat  long
value     1.00   0.70  0.11     0.20 -0.14 -0.05
income    0.70   1.00 -0.12    -0.07 -0.08 -0.02
age       0.11  -0.12  1.00    -0.03  0.01 -0.11
bedrooms  0.20  -0.07 -0.03     1.00  0.16 -0.13
lat      -0.14  -0.08  0.01     0.16  1.00 -0.92
long     -0.05  -0.02 -0.11    -0.13 -0.92  1.00
```

The GAM is Afoot

Methodology:

1. Fit Gamma **GLM** to model house value as a linear combination of:
   - Income
   - Age
   - # Bedrooms

$$\log(VALUE) = \alpha + \beta_1 INCOME + \beta_2 AGE + \beta_3 ROOMS$$

2. Calculate the linear predictor for each data point: $\eta \equiv \beta \cdot X$

$$\eta \equiv \hat{\alpha} + \hat{\beta}_1 INCOME + \hat{\beta}_2 AGE + \hat{\beta}_3 ROOMS$$

3. Fit a Gamma **GAM** on *f*(lat,long) using η as an offset.

$$\log(VALUE) = \eta + f(lat, long)$$

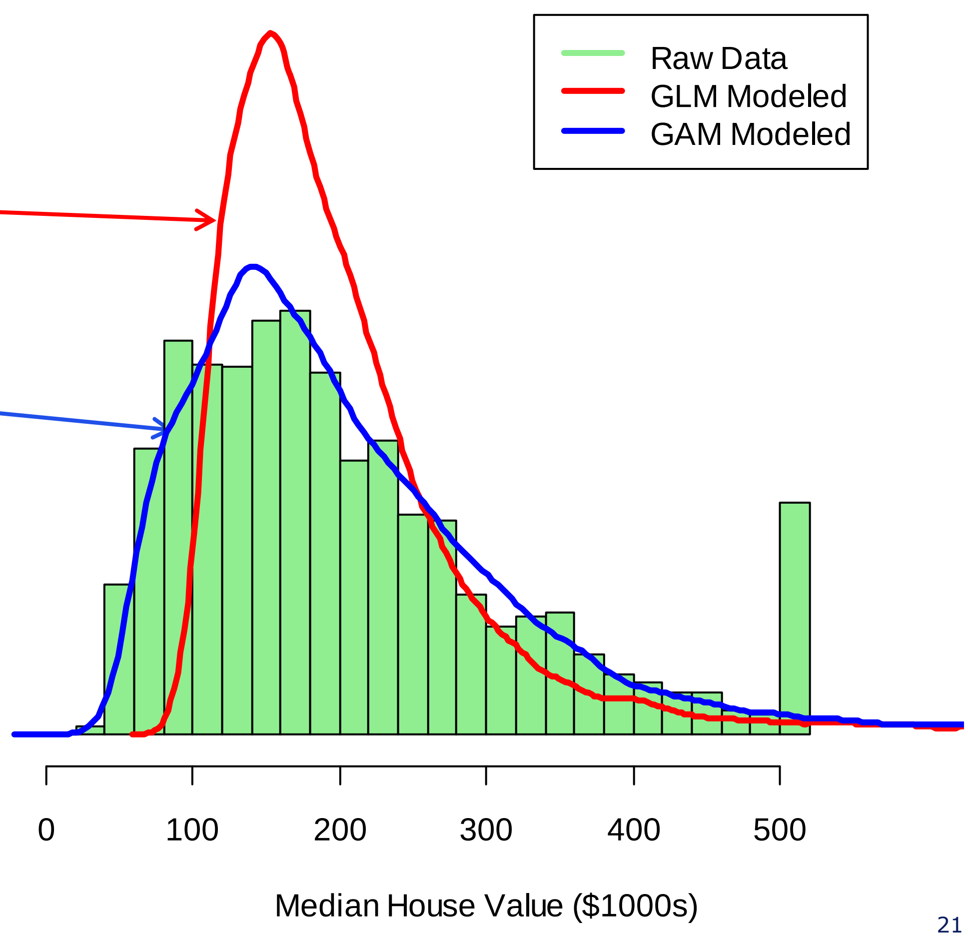
   - Note: For this illustration, tensor product basis functions with 400 knots were used.

Score Distributions

$$\log(VALUE) = \alpha + \beta_1 INCOME + \beta_2 AGE + \beta_3 ROOMS + f(lat, long)$$

- The 3-factor GLM doesn't come close to capturing all of the variation in house values.
- Adding *f*(location) helps.

California Median House Values (Block Group-Level)

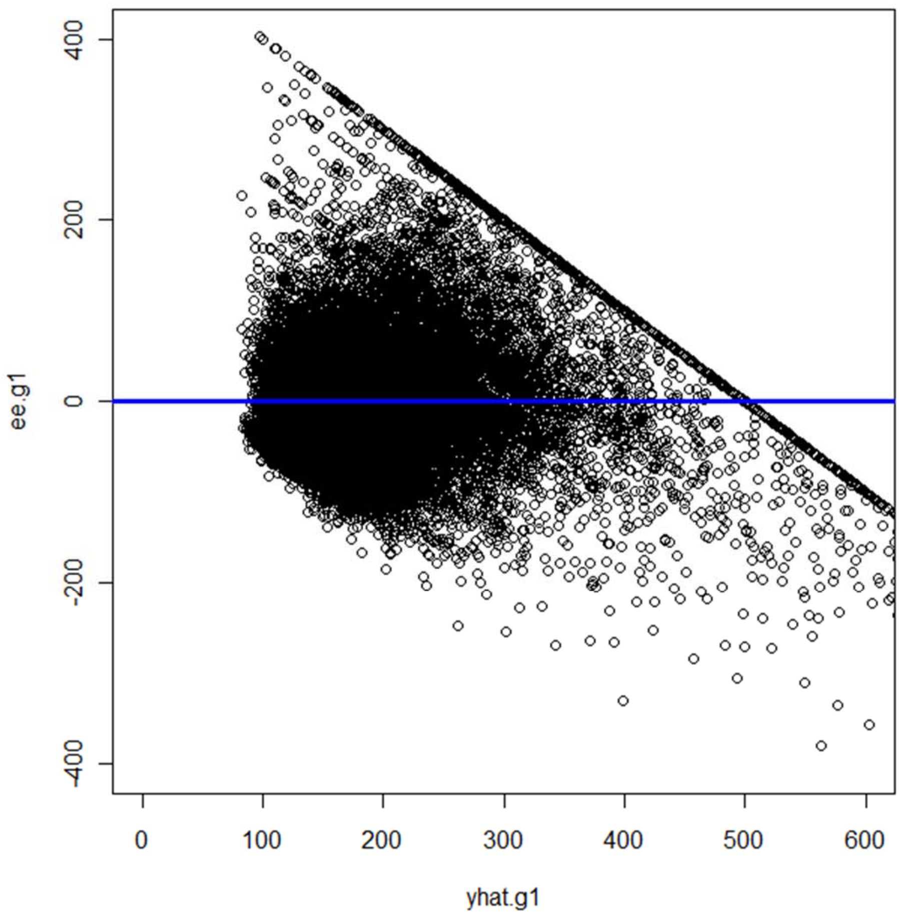


Error Diagnostics

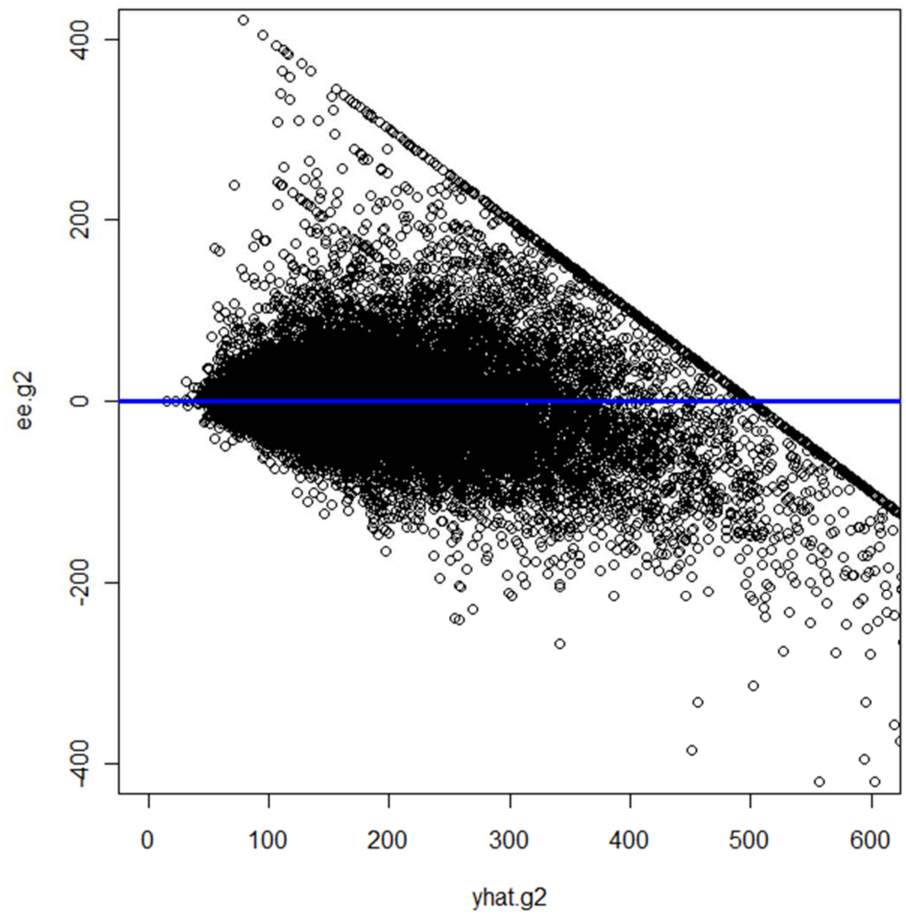
- The GAM model clearly explains more of the variation in house values.
  - R^2 GLM: 0.54
  - R^2 GAM: 0.67

Note: Raw Data capped at $500K – accounts for unusual residual pattern.

GLM Model (g1)

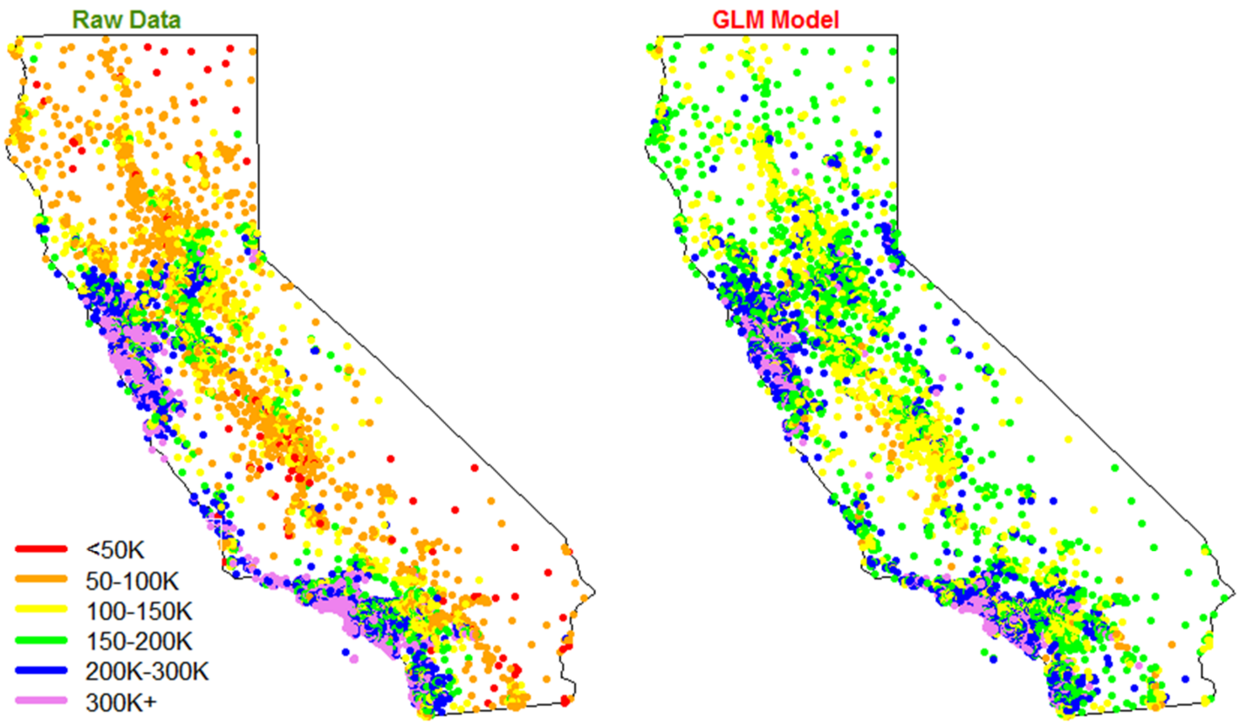


GAM Model (g2)



Geo-Spatial Diagnostics of the GLM Model

- The 3-factor GLM gets things directionally right:
  - Inland house values are lower than coastal house values
  - High values clustered around the major cities

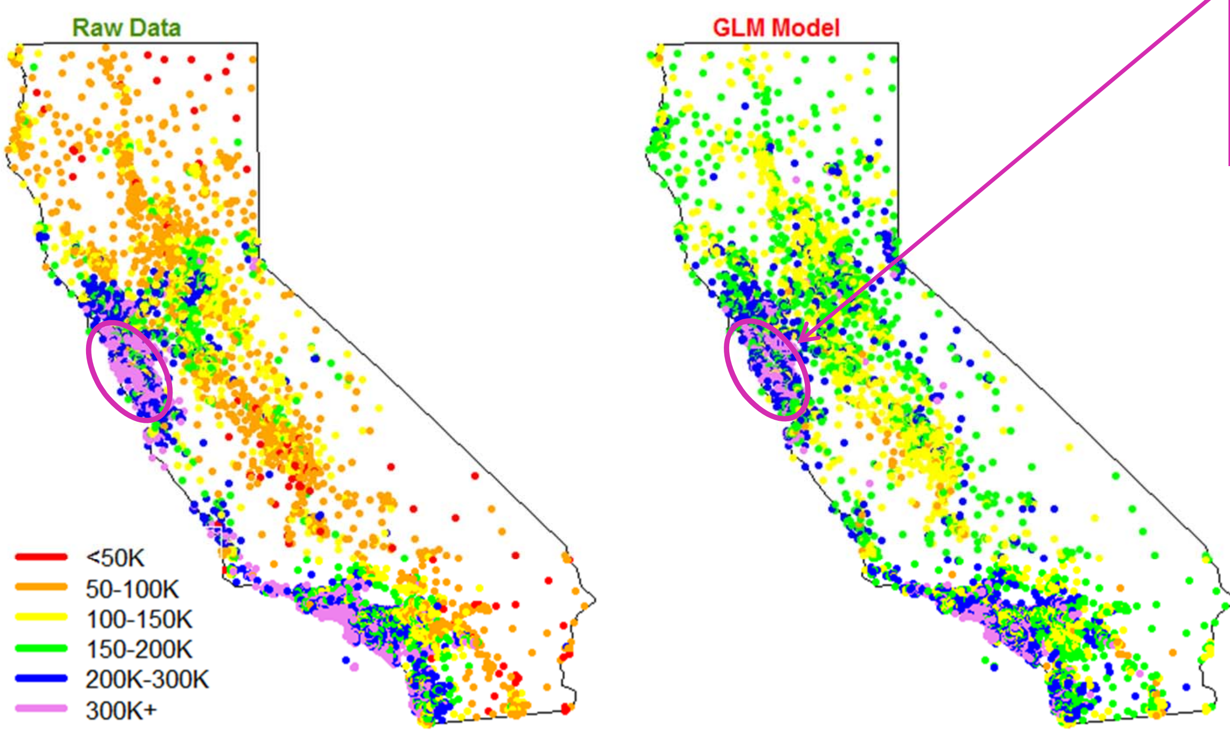


$$\log(VALUE) = \alpha + \beta_1 INCOME + \beta_2 AGE + \beta_3 ROOMS$$

Geo-Spatial Diagnostics of the GLM Model

- But the GLM model generally:
  - Over-estimates house values in the central valley
  - Under-estimates house values in along the coast

The 3-factor GLM model generally <u>under</u>-estimates the coastal enclaves of expensive houses.



Geo-Spatial Diagnostics of the GLM Model

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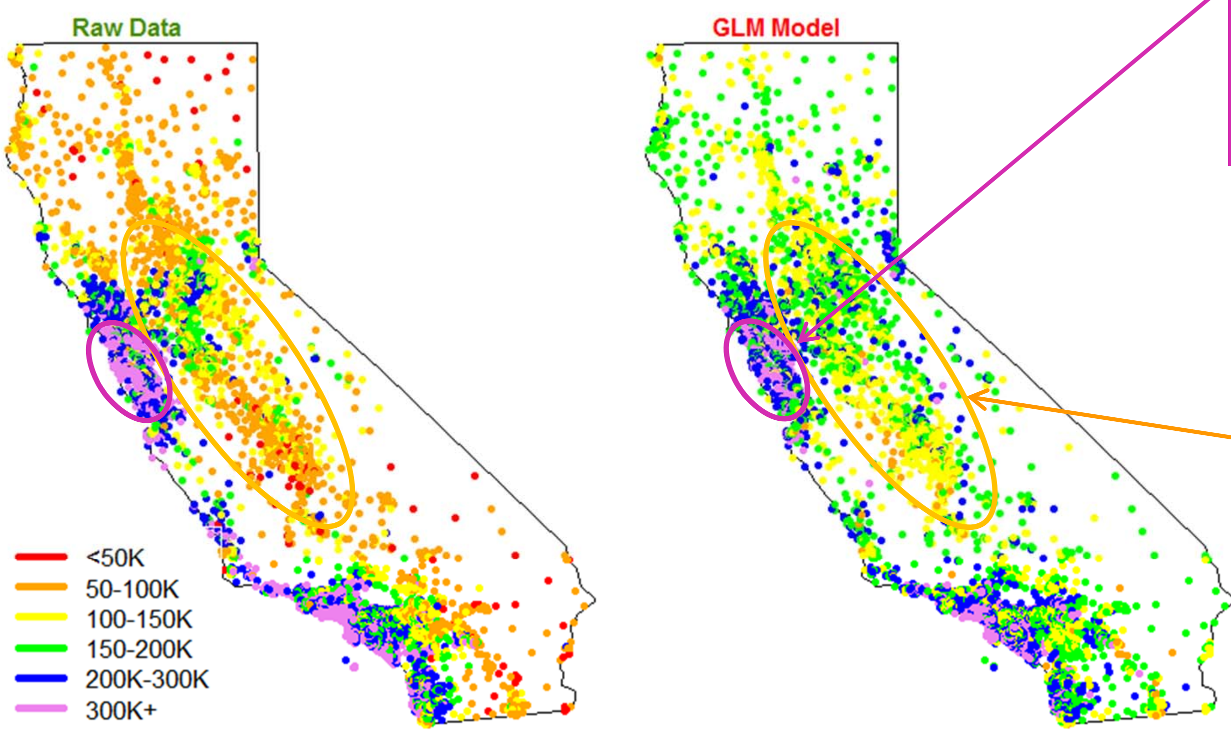
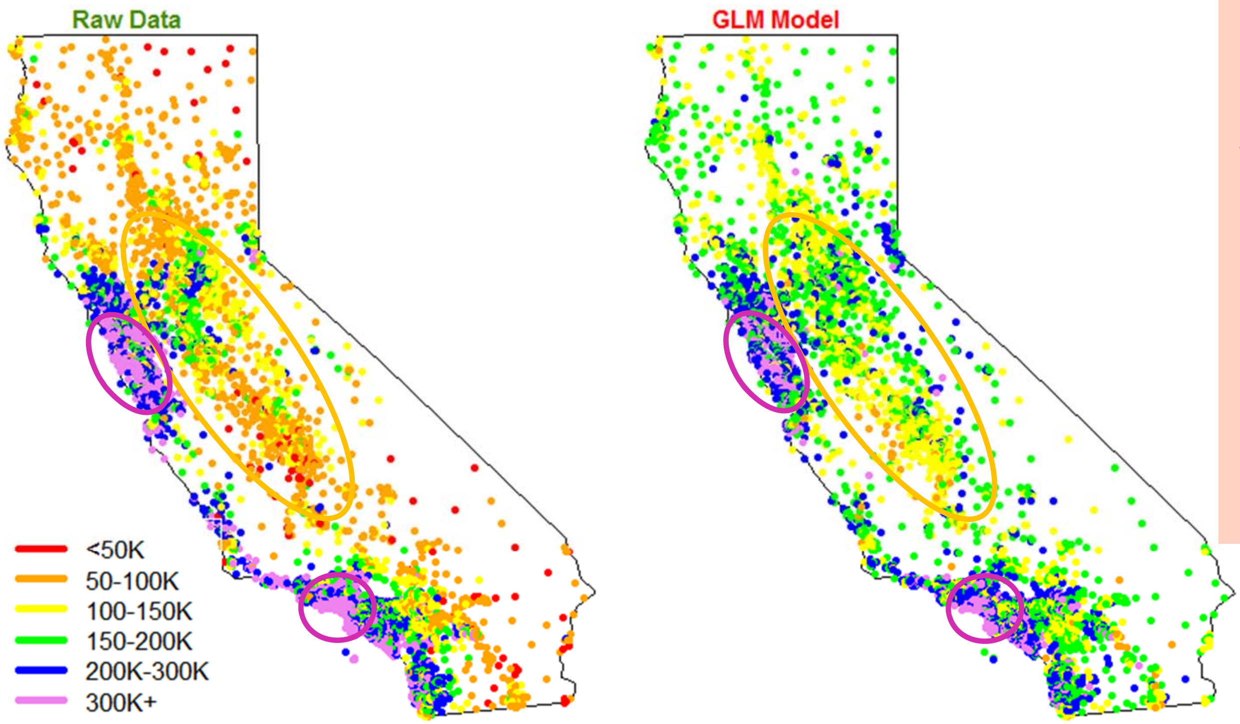


The 3-factor GLM model generally <u>under</u>-estimates the coastal enclaves of expensive houses.

At the same time, it <u>over</u>-estimates house values in the central valley

Location, Location, Location

- Implication: "Location matters."
- The GLM model shoves geo-spatial variation into the error term.



All else equal, houses in coastal / urban areas are worth more than houses in rural / inland areas.

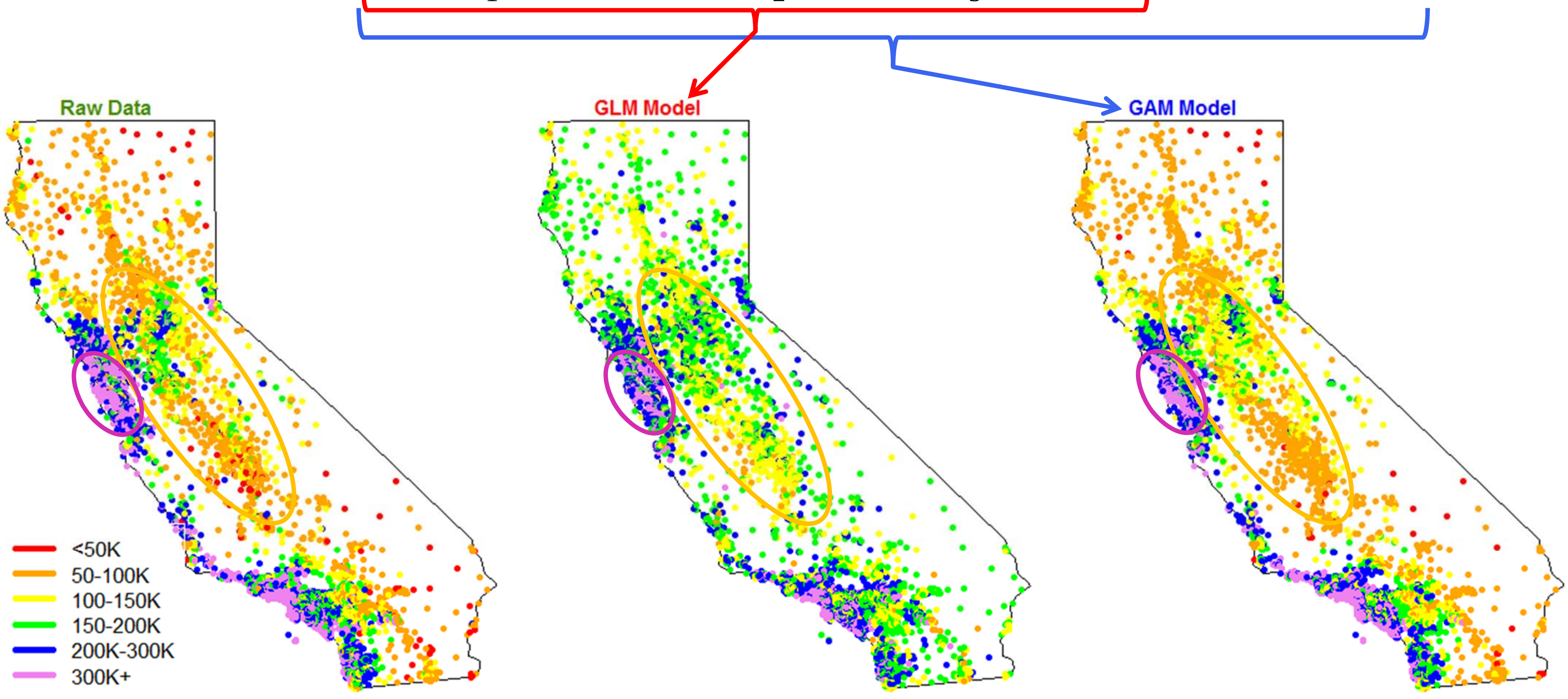
Adding further demographic predictors will help, but not eliminate the need to include location in the model.

-- miles from the coast
-- population density
-- education
-- neighborhood amenities
-- ...

GAM Diagnostics

The GAM model is still not perfect, but a big improvement over the 3-factor GLM model.

$$\log(VALUE) = \alpha + \beta_1 INCOME + \beta_2 AGE + \beta_3 ROOMS + f(lat, long)$$



Further improvements could result from superimposing one or more local GAM models built for specific metropolitan areas.