Explaining House Selling Price Variation Using Linear Regression

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Purdue University

Work Product - Insight2Profit

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What Is This Project?

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- Build a multiple linear regression model to explain house price variation based on past selling data

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- Analyze which variables contribute most to a house's selling price

- Demonstrate potential to make predictions about house prices

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- Accurate home value estimates are very profitable
  - Ad revenue
  - Real estate bots that buy/sell properties

Overview of Linear Regression

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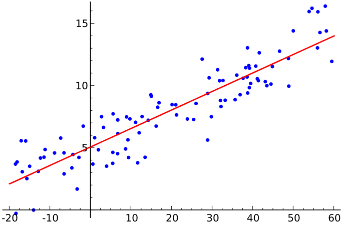

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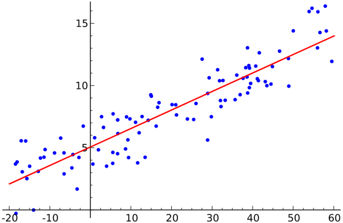

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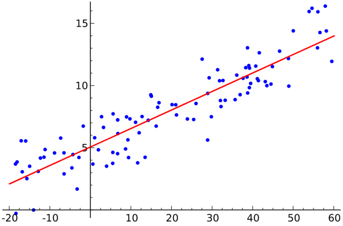

$$RSS(\beta_0, \beta_1) = \sum_{i=1}^{n} [y_i - (\beta_0 + \beta_1 x_i)]^2$$

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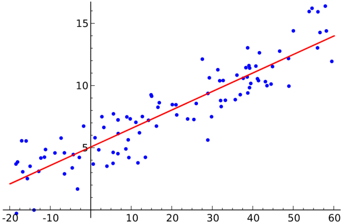

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To find β_0, take the partial with respect to β_0, set equal to 0, solve for β_0:

$$\frac{\partial}{\partial \beta_0} \left[RSS(\beta_0, \beta_1) \right] = 0$$

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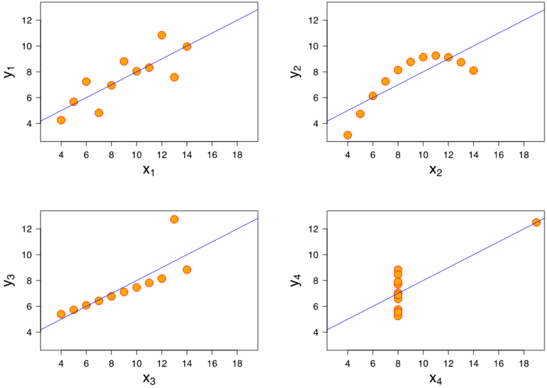

Figure: Different data, **same** model!

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- Response: Sale price of a home (`SalePrice`)
- Lots of missing values and redundant variables (`Utilities`)

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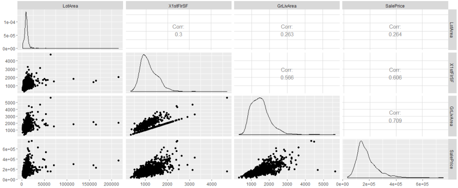

Figure: **Before** transformation

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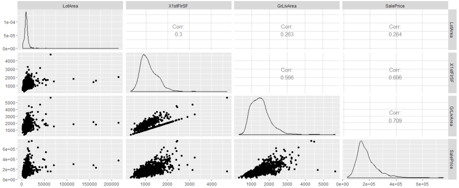

Figure: **Before** transformation

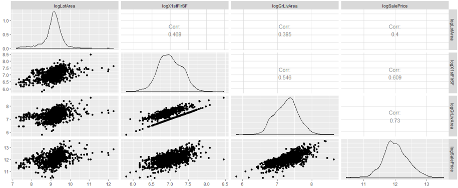

Figure: **After** transformation

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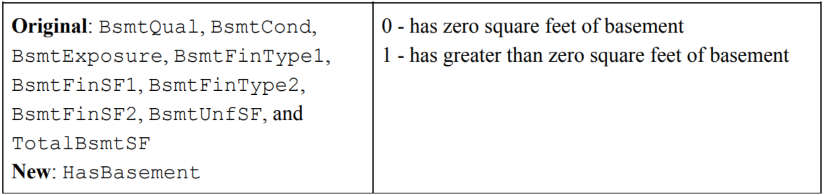

Original: BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinSF1, BsmtFinType2, BsmtFinSF2, BsmtUnfSF, and TotalBsmtSF **New**: HasBasement	0 - has zero square feet of basement 1 - has greater than zero square feet of basement

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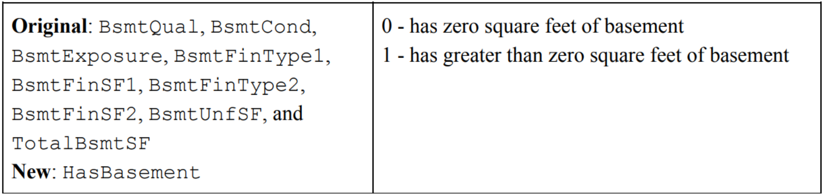

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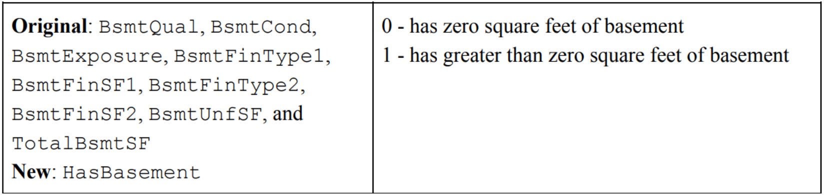

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- Selected the rest of the variables using Bayesian information criterion
- Analyzed our model using ANalysis Of VAriance (ANOVA) to remove one redundant variable, Roof Material

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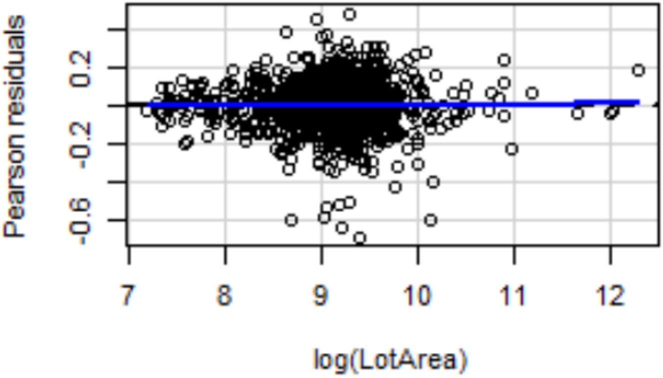

Figure: Average of the residuals is 0; constant variance; no pattern

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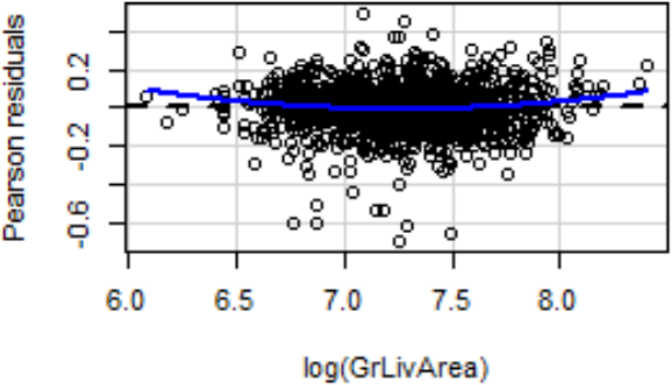

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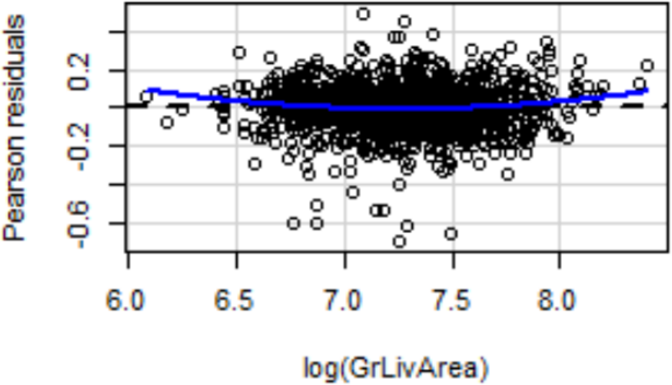

Figure: Average of the residuals is **not** 0, **nonconstant** variance

- We used methods to correct for this nonconstant variance

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- So, what variables affect a house's price?!

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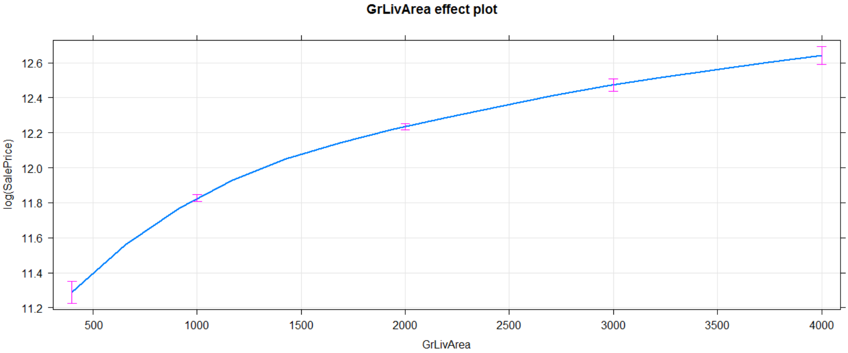

Figure: More above grade sq. ft. ⇒ higher selling price

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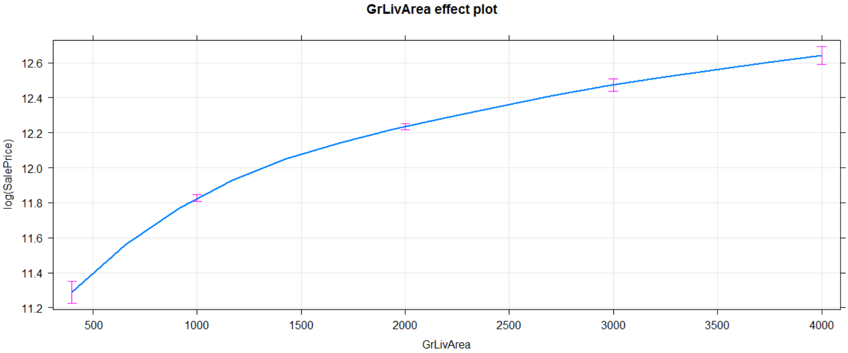

Figure: More above grade sq. ft. ⇒ higher selling price

- Linear relationship of living area vs sale price (remember we are in log scale)

Effect Size: Lot Area

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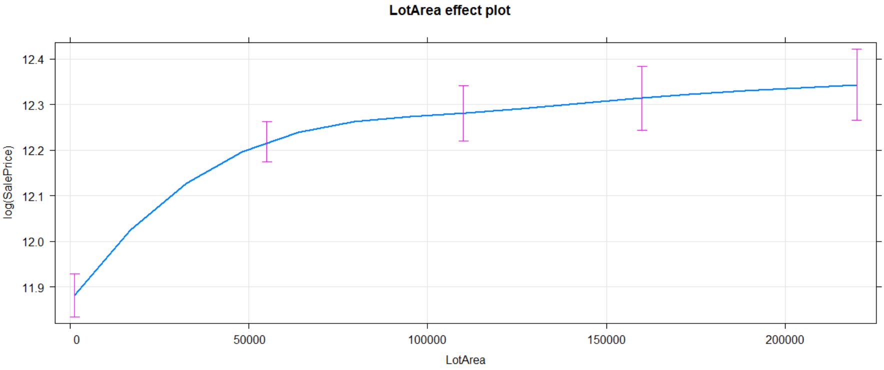

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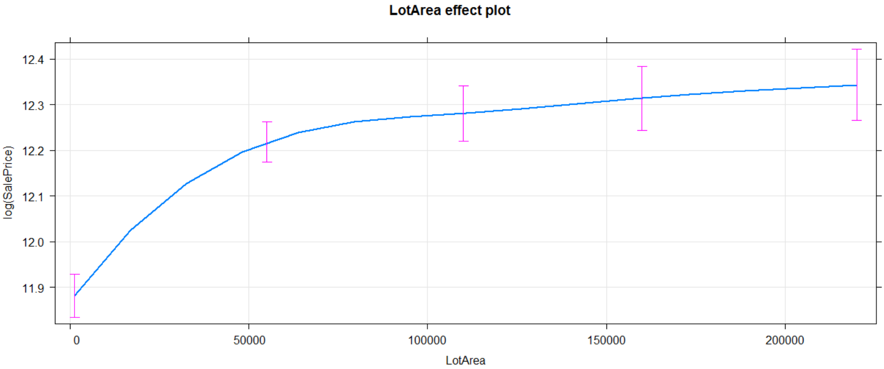

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- Again, approx. linear relationship between lot area and sale price (log scale)

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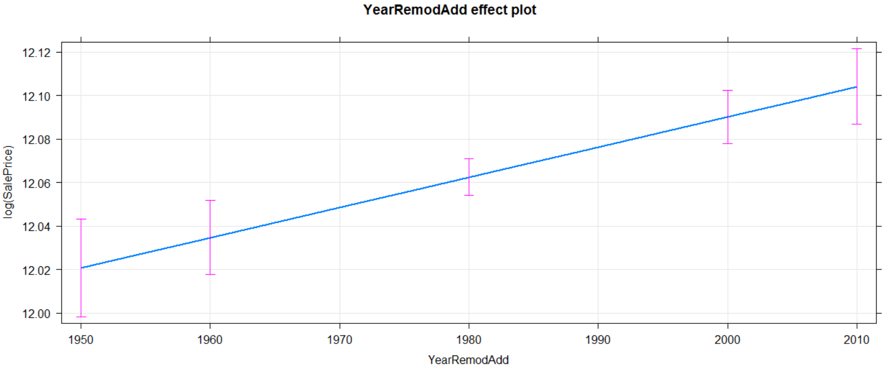

Figure: More recent remodel ⇒ higher selling price

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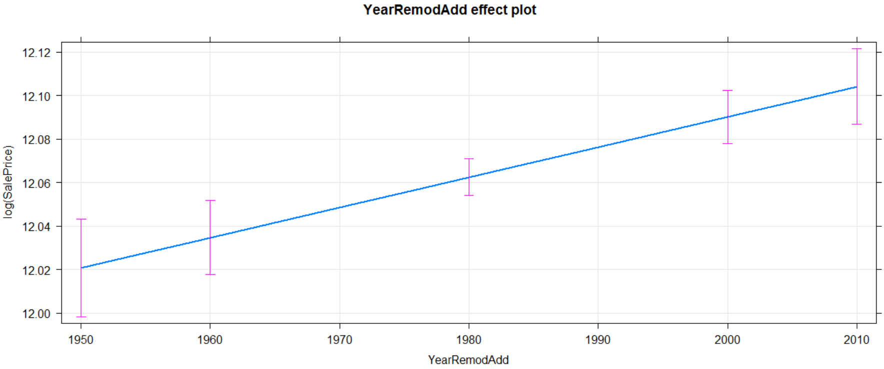

Figure: More recent remodel ⇒ higher selling price

- High variation on very old or very new remodels

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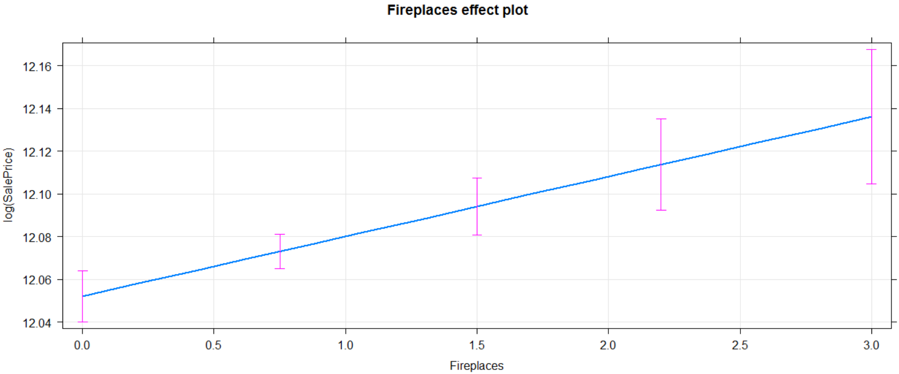

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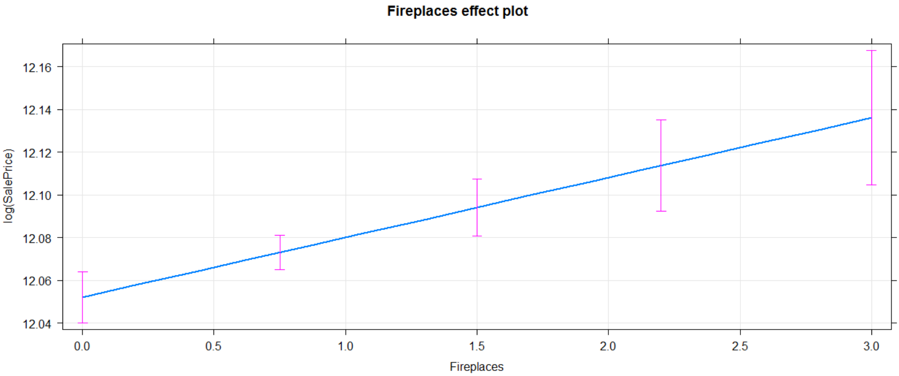

Figure: More fireplaces ⇒ higher selling price

- Increasing variation in sale price as number of fireplaces increases

Effect Size: Sale Condition

- Abnorml = trade, foreclosure, short sale
- AdjLand = Adjoining Land Purchase
- Alloca = Allocation - two linked properties with separate deeds, typically condo with a garage unit
- Family = sale between family members
- Normal = normal sale
- Partial = home was not completed when last assessed (associated with new homes)

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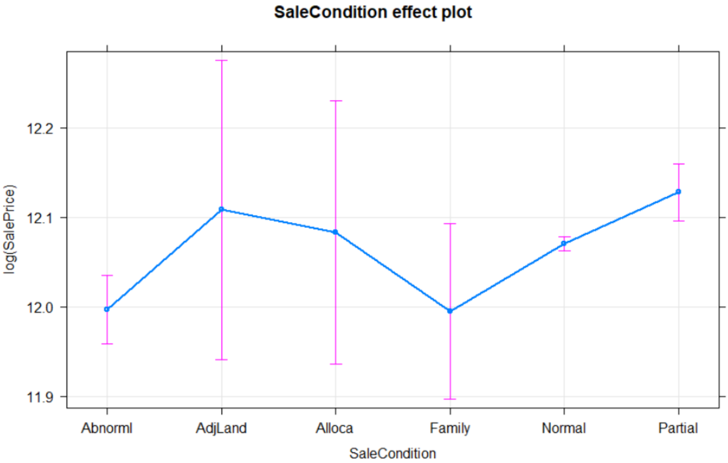

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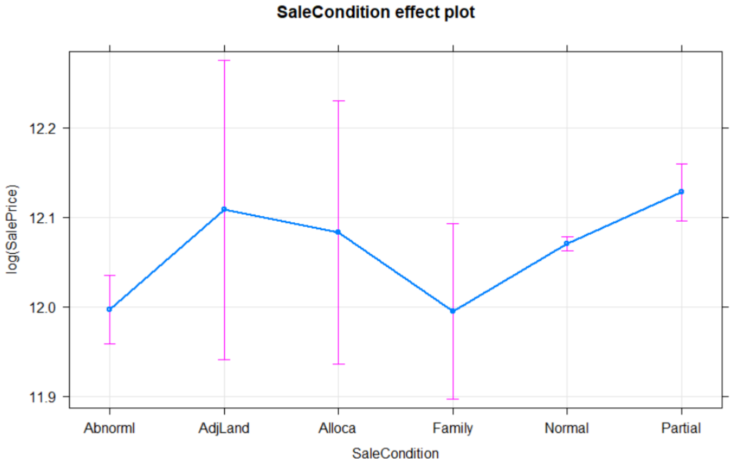

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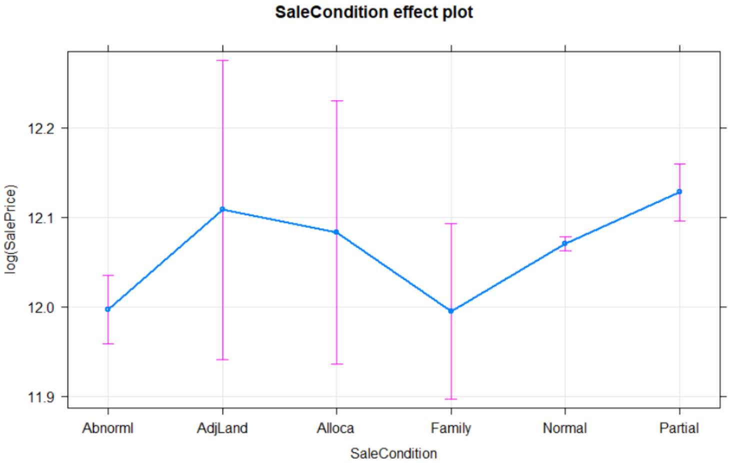

- Family lower than Normal
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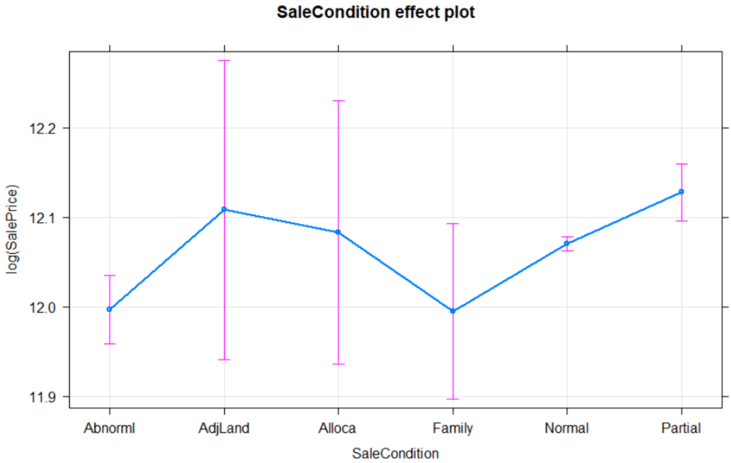

- Family lower than Normal
- Normal has very little variation
- Very high variation on allocations and adjoining land purchases!

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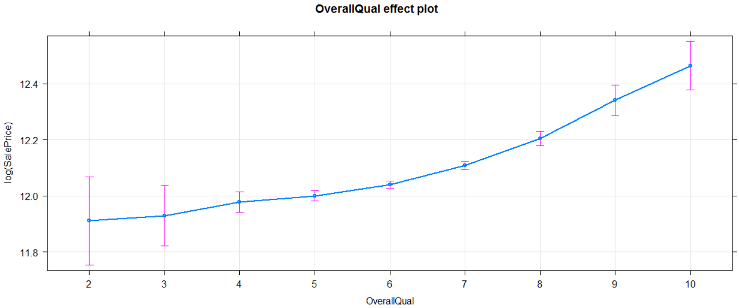

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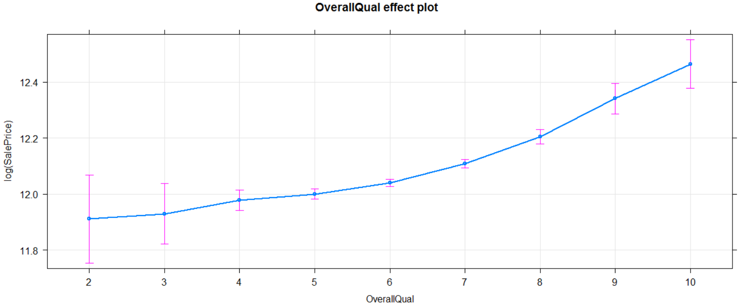

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- Subjective measure surprisingly shows clear relationship?!

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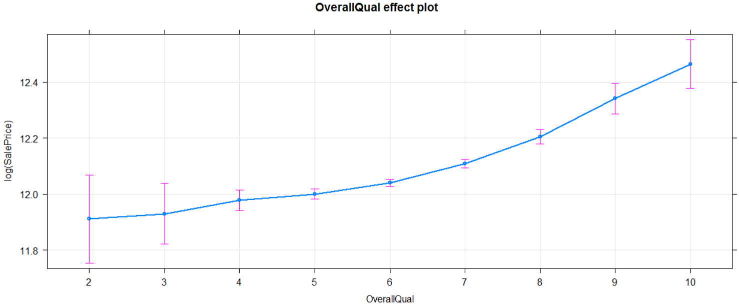

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- Subjective measure surprisingly shows clear relationship?!
- Again, higher variation in sale price in extremes

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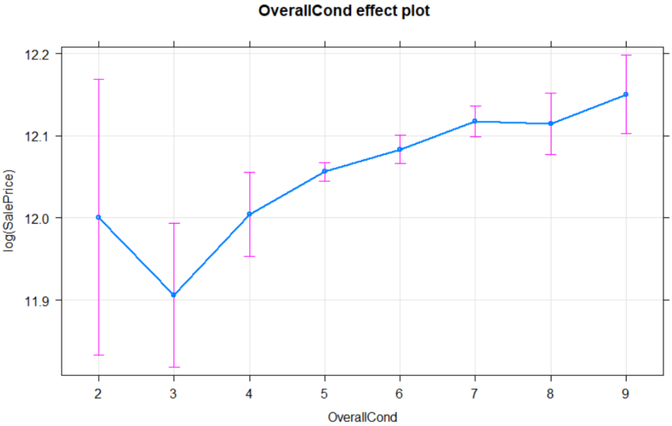

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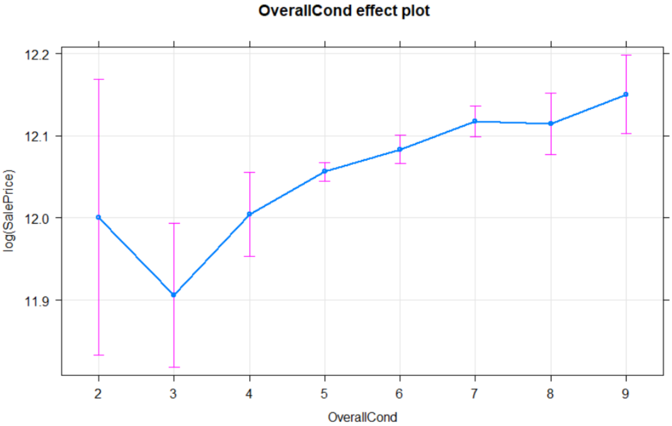

Figure: Higher overall condition ⇒ higher sale price

- This is the weird relationship expected in a subjective measure

Effect Size: Central Air

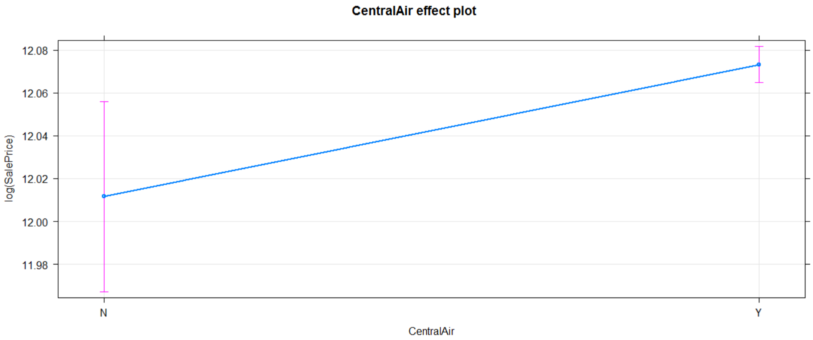

Figure: Presence of central air ⇒ higher sale price

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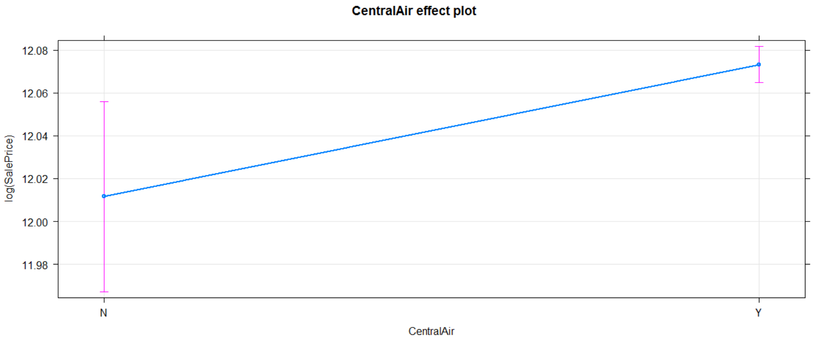

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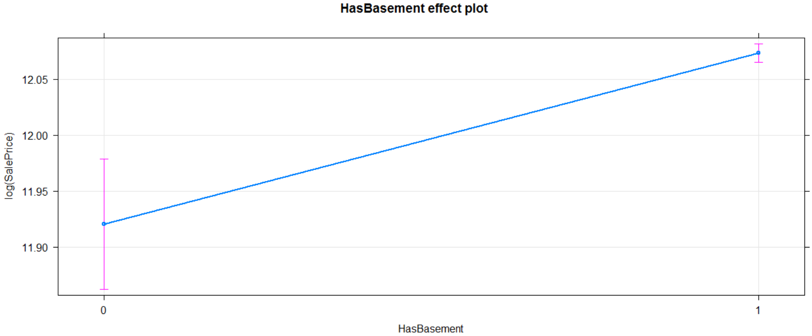

Figure: Presence of basement ⇒ higher sale price

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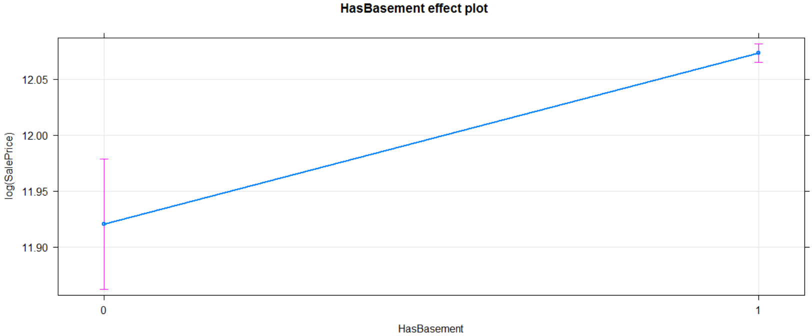

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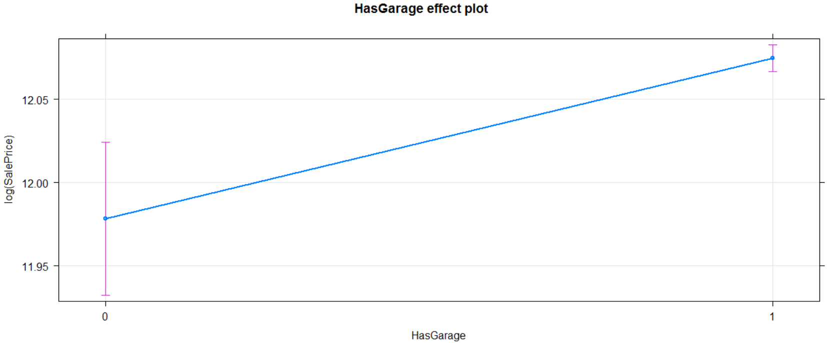

Figure: Presence of garage ⇒ higher sale price

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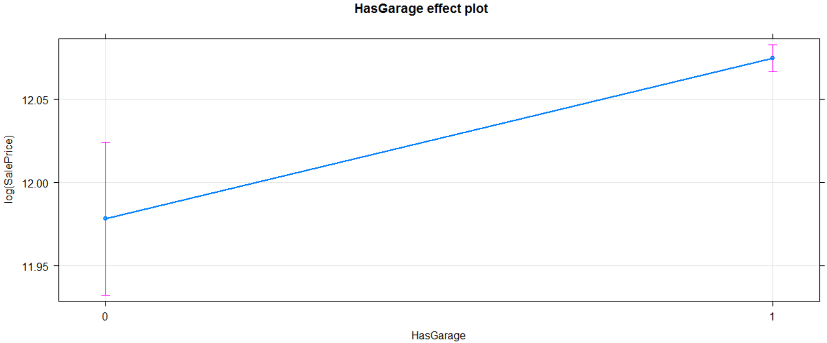

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Unexpected Relationships: Has 2nd Floor

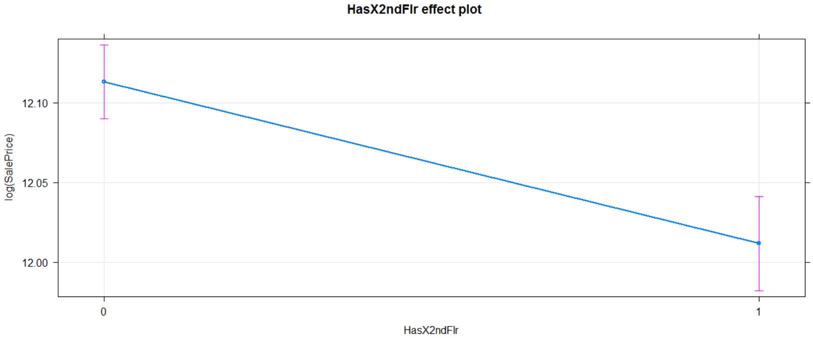

Figure: Presence of 2nd floor ⇒ lower sale price?

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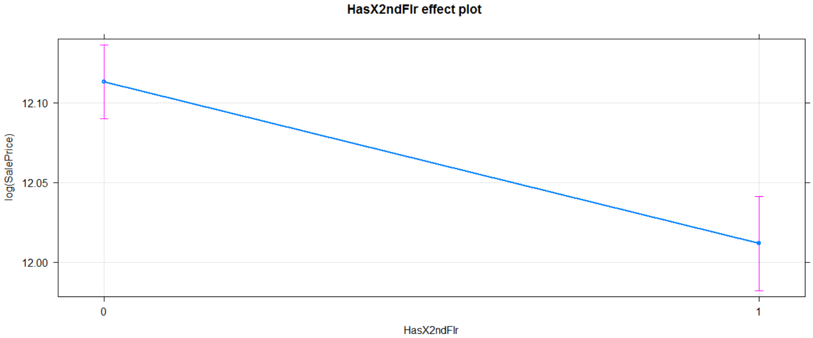

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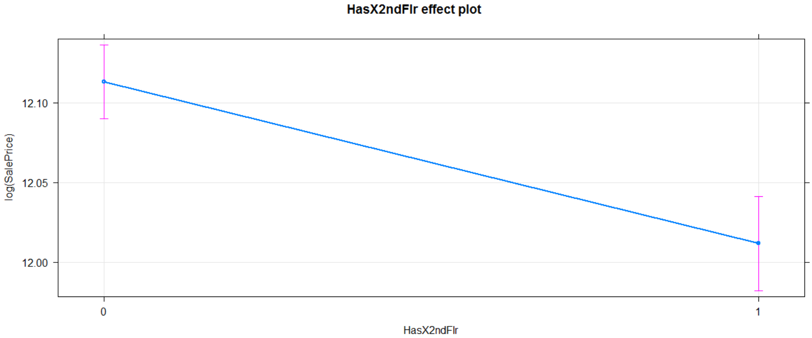

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- 2nd floor homes have a higher average sale price

Unexpected Relationships: Kitchens Above Grade

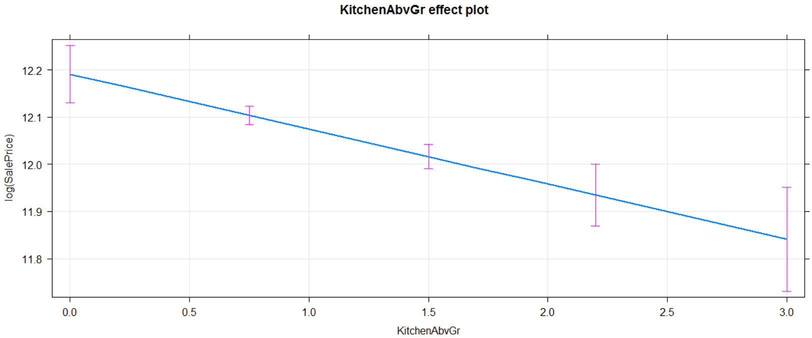

Figure: More kitchens ⇒ lower sale price?

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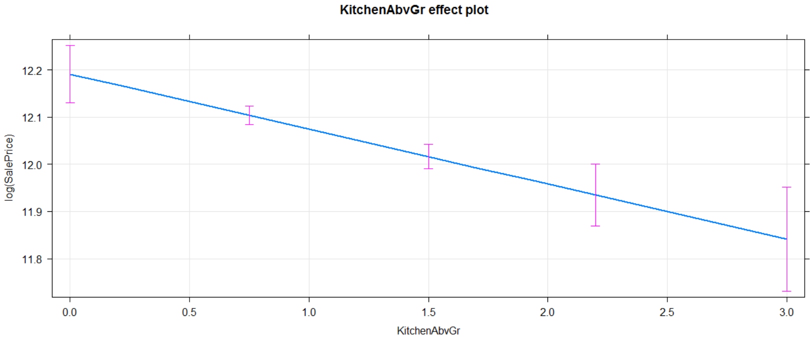

Figure: More kitchens ⇒ lower sale price?

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Effect Size: Kitchens Quality

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- TA - typical/average
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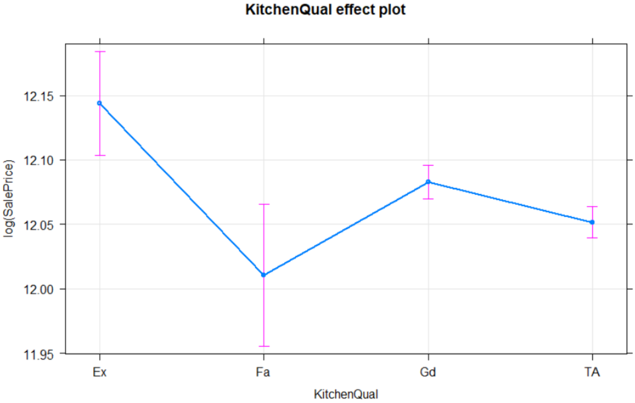

Figure: Higher quality kitchens ⇒ higher sale price

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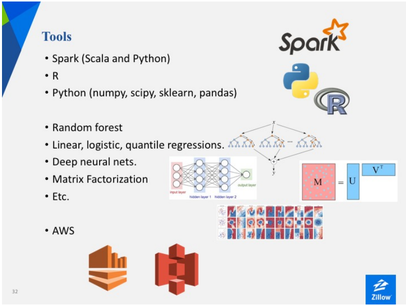
- Correlation $\neq$ Causation
- I'm not Zillow!
  - There are more accurate (and complex) methods



Tools

- Spark (Scala and Python)
- R
- Python (numpy, scipy, sklearn, pandas)

- Random forest
- Linear, logistic, quantile regressions.
- Deep neural nets.
- Matrix Factorization
- Etc.

- AWS

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Questions?