The Cost of Living: A Zillow Housing Forecast

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Math 404 Data Project Presentation

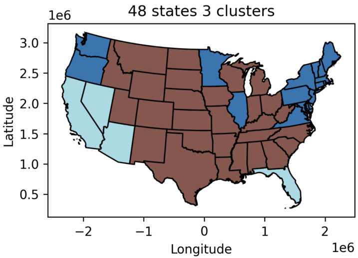
Motivation & Goals

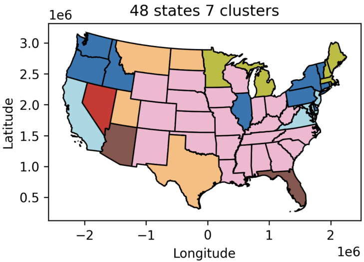
- Housing prices shape wealth, policy, and investment.
- We aim to:
  - Identify similar housing markets (clustering).
  - Forecast housing prices using multiple models.
  - Identify correlations between housing markets and demographic features.
- Focus on interpretable and regional trends.

Data Overview

- **Zillow HPI:** State-level median home prices (monthly, 2000–2020).
- **CPS/IPUMS:** Demographics, income, and tax (annual, interpolated).
- Filtered to pre-COVID period.

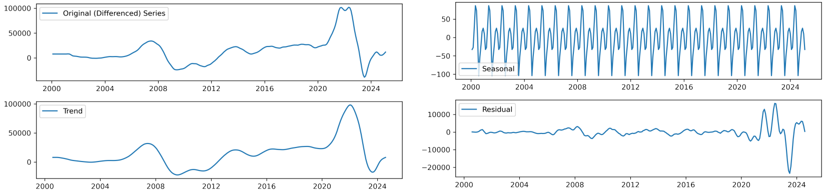
Clustering States by Price Trends





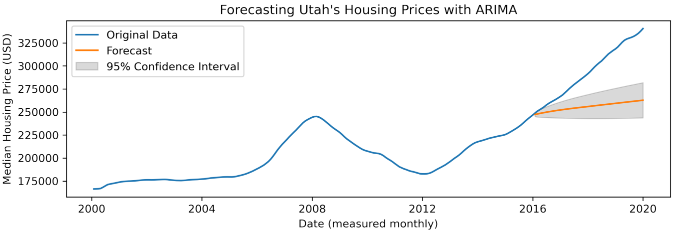
- K-means on housing price changes ⇒ groups with similar growth.
- Coastal states form distinct clusters.

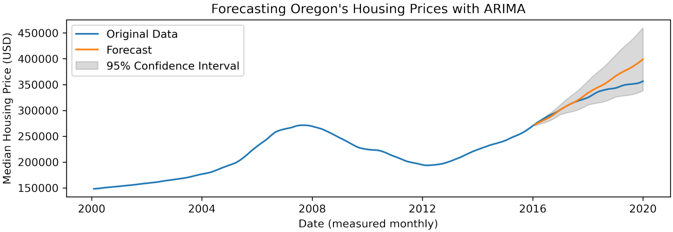
Classical Decomposition of Housing Prices



- Classical decomposition ⇒ double-peaked seasonal trends.
- Residuals spike after 2020 ⇒ excluded post-2020.

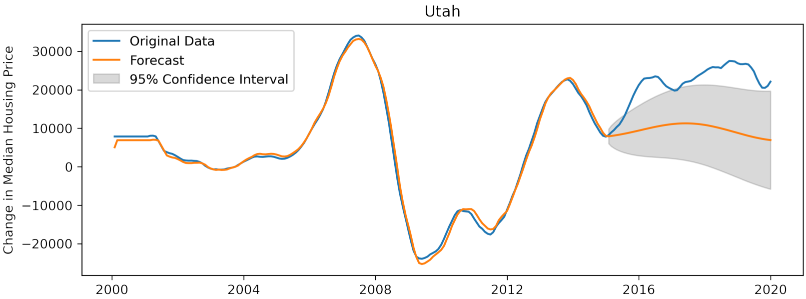
Univariate ARIMA Forecasting





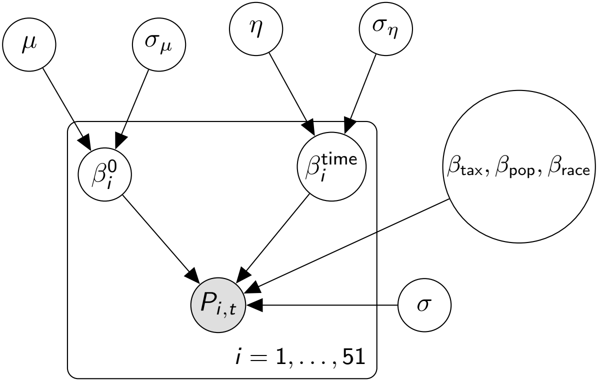
- Best ARIMA model: (4,1,0) – approximately linear forecasts
- Limited accuracy: large confidence intervals, sensitivity to shocks

VARMAX Forecasting



- Cluster-based VARMAX $\Rightarrow$ improved trend modeling
- Not applicable to states in singleton clusters
- Using demographic data led to convergence issues

Bayesian Hierarchical Model Diagram



Bayesian Hierarchical Model Setup

Model Equation

$$P_{i,t} = \beta_i^0 + \beta_i^{\text{time}} t + \beta_{tax}\,\text{tax}_i + \beta_{pop}\,\text{pop}_i + \beta_{native}\,\alpha_{native,i} + \beta_{asian}\,\alpha_{asian,i} + \beta_{black}\,\alpha_{black,i} + \beta_{white}\,\alpha_{white,i} + \epsilon$$

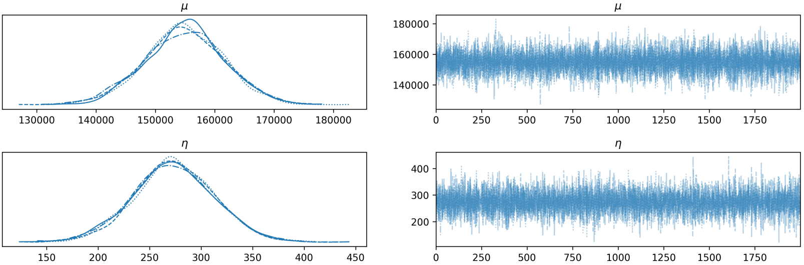
- Captures variation across states via hierarchical priors.
- Standardized predictors allow coefficient comparisons.
- Fit using NUTS algorithm (via PyMC3).

Bayesian Hierarchical Prior Distributions

$$\beta_i^0 \sim \mathcal{N}(\mu, \sigma_\mu)$$
$$\mu \sim \mathcal{N}(200000, 100000)$$
$$\sigma_\mu \sim \text{Exp}\left(\frac{1}{50000}\right)$$
$$\beta_{tax} \sim \mathcal{N}(0, 20)$$
$$\beta_{race} \sim \mathcal{N}(0, 10000)$$
$$\sigma \sim \text{HalfCauchy}(100)$$

$$\beta_i^t \sim \mathcal{N}(\eta, \sigma_\eta)$$
$$\eta \sim \mathcal{N}(1000, 1000)$$
$$\sigma_\eta \sim \text{Exp}\left(\frac{1}{5000}\right)$$
$$\beta_{pop} \sim \mathcal{N}(0, 1)$$
$$\epsilon \sim \mathcal{N}(0, \sigma)$$

Bayesian Hierarchical Modeling



- State-level intercepts/slopes + global covariates.
- Accounts for uncertainty and data imbalance.

Key Findings

- Central states show more homogeneous trends.
- ARIMA and VARMAX useful, but limited by volatility.
- Bayesian model provides interpretable insights:
  - Native/Asian/White proportion $\Rightarrow$ lower prices.
  - Black proportion $\Rightarrow$ rising prices.

Ethical Considerations

- Demographics **should not** guide individual decisions.
- Models risk perpetuating bias.
- Better use: *Policy insights and funding allocation*.

Conclusion

- Forecasting housing prices is difficult due to shocks.
- Combined methods yield the best insights.
- Future work: Combine Bayesian models with ARIMA/Kalman filters, use more robust economic models.

Resources

- GitHub Repo: github.com/jpatrickb/vol3_housing_project
- Data from Zillow + IPUMS/CPS

Questions?

Thank you!