Exploring Perceived/Actual Impact on Property Value after a Hurricane

•••

Robert Becotte | Drew Dellarocco | Rose Dennis

Why are we here today?

During a disaster, it is important to model and estimate the potential or forecasted effect of the event, including the projected/forecasted damage. Existing indicators of forecasted damage include number of structures within the affected area, number of people in the area, number of households, demographics of the impacted population, etc. ***This project will add an additional perspective: It will compare how hurricanes do or do not impact real estate sale prices by zip code before and after the storm.***

Problem Statement:

How do we quickly glean insights on property values before and after a hurricane through a user friendly application?

Goals:

- Provide an **initial proof of concept** for a potential web application using Flask software for Python.
- This rudimentary web app will allow the user to input a zip code and see summary statistics for how **median real estate prices were affected after a hurricane.**

Limitations:

1. We used the **top ~6000 zip codes by population**, not the ~41000 exhaustive list of zips
2. This initial proof focuses on the recent hurricanes of **Sandy, Harvey, and Dorian**
3. Our focus for this project was financial impact on zip code aggregated **median sale prices**
4. This project considers **nominal/actual sale prices**, not indirect/real economic costs

Executive Summary:

1. While hurricanes have numerous nominal and real costs on individuals, groups, property, and governments, we have found that their impact on real estate sale prices **does not necessarily follow intuitive logic (size, proximity to storm or ocean).**

2. We identified **large fluctuations in sale price** in the affected areas, even when comparing adjacent zip codes, **suggesting limited geographic relevance.**

3. Hurricane Harvey produced the highest damage count of $125B, however, the real estate prices were **virtually unaffected when compared to the national average.**

Baseline Context (U.S. Impacted Data only)

National Median Real Estate Sale Price (% Change YoY | $ in Thousands)

2012:	+8.7%	|	$244	**2016**: +3.7%	|	$305
2013:	+8.9%	|	$266	**2017**: +5.7%	|	$322
2014:	+7.3%	|	$286	**2018**: +0.9%	|	$325
2015:	+2.9%	|	$294	**2019**: -1.7%	|	$319

Proof of concept MVP for three hurricanes within different regions of U.S.

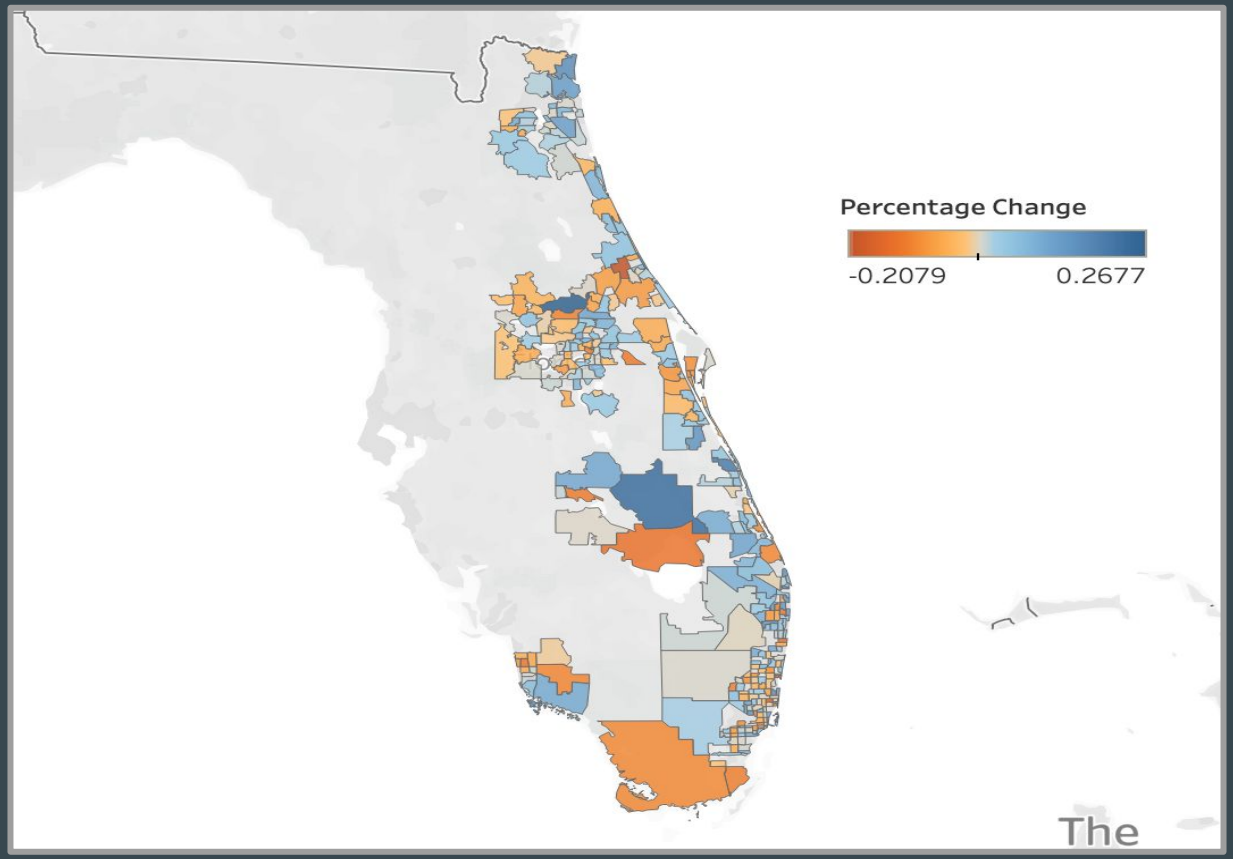
- **Sandy (Cat 1):** 2012 Northeast U.S. — **Damage Estimate: $70B, 200K Homes**
- **Harvey (Cat 4):** 2017 Gulf (TX/LA) — **Damage Estimate: $125B, 135K Homes**
- **Dorian (Cat 1):** 2019 South East — **Damage Estimate: $1.2B**

https://www.nhc.noaa.gov/news/UpdatedCostliest.pdf https://www.livescience.com/40774-hurricane-sandy-s-impact-infographic.html
https://fred.stlouisfed.org/series/MSPUS?utm_source=series_page&utm_medium=related_content&utm_term=related_resources&utm_campaign=categories#0 https://www.ncdc.noaa.gov/billions/

Acquiring the Data

- Background Research (Zillow)
- FEMA reports
- Counties/Cities → Zip codes
- Reusable Webscraper
- Worked individually on own datasets, then created the ‘master’
- Feature engineered % change affected by storm

Hurricane Dorian- August 24, 2019 - September 10, 2019

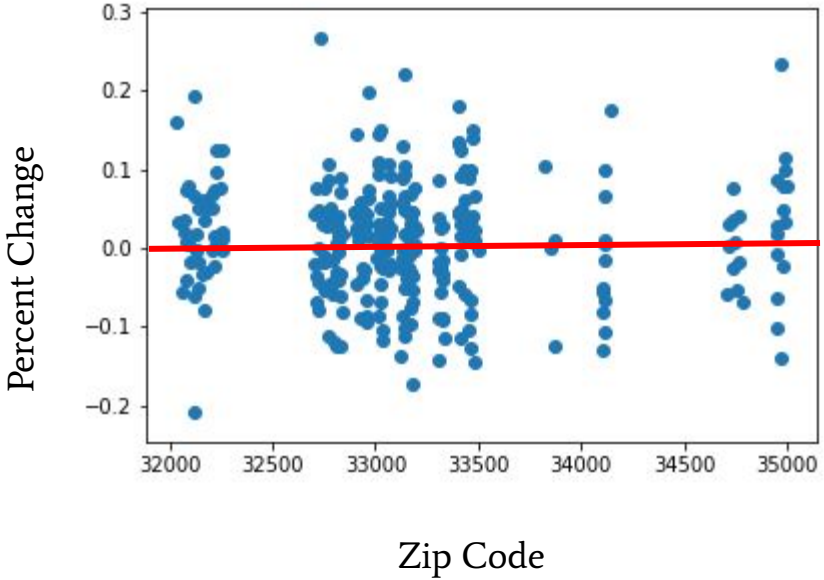


Hurricane Dorian

Takeaways:

- Mean percent change was negligible ~ 0.0099 or barely 1%
- Most positive percent change ~ 27% in city of Eustis
- Most negative percent change ~ 21% in Daytona Beach

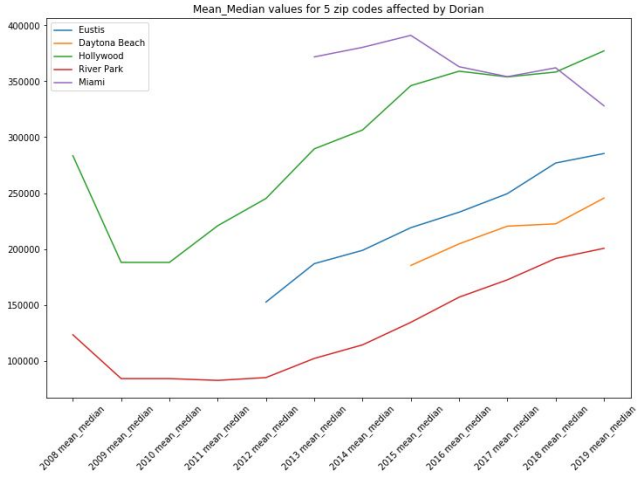
Percent Change for each zipcode from Dorian

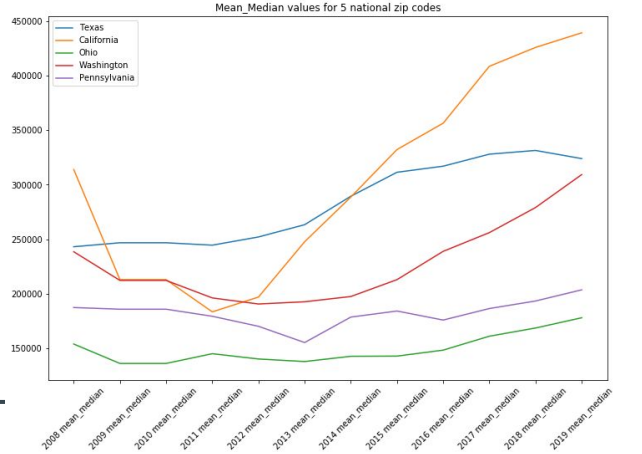


Hurricane Dorian

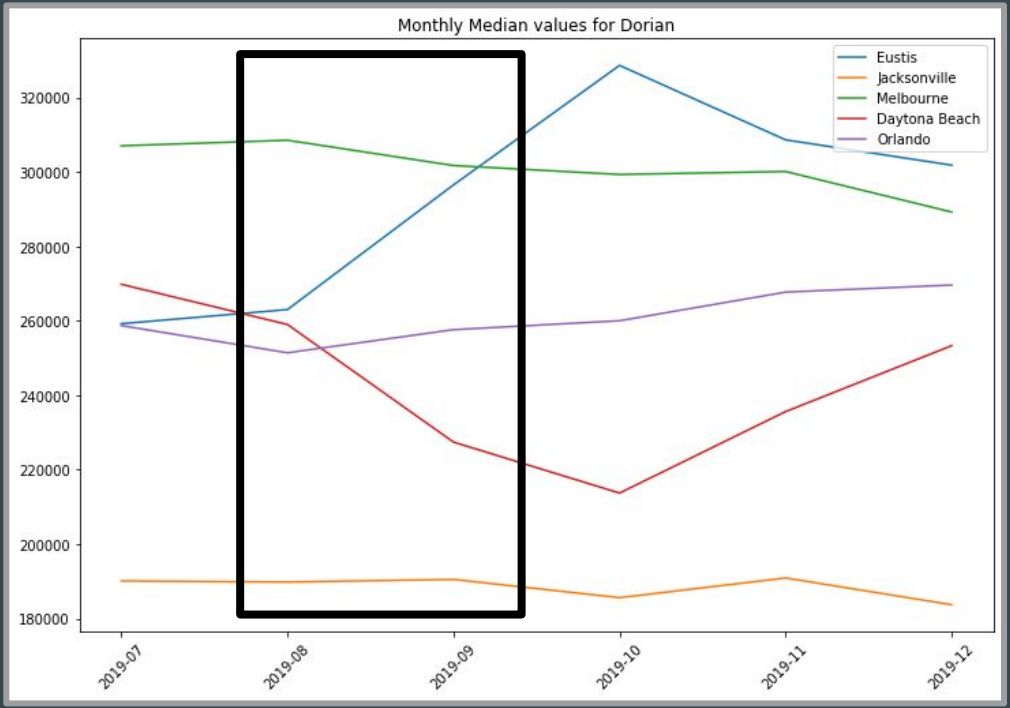
Comparing to National Trends:

- Significant number of NA values makes trend analysis harder
- Can't see the min/max % change from storm because it's within the year
- Each zip code has a certain range of median values

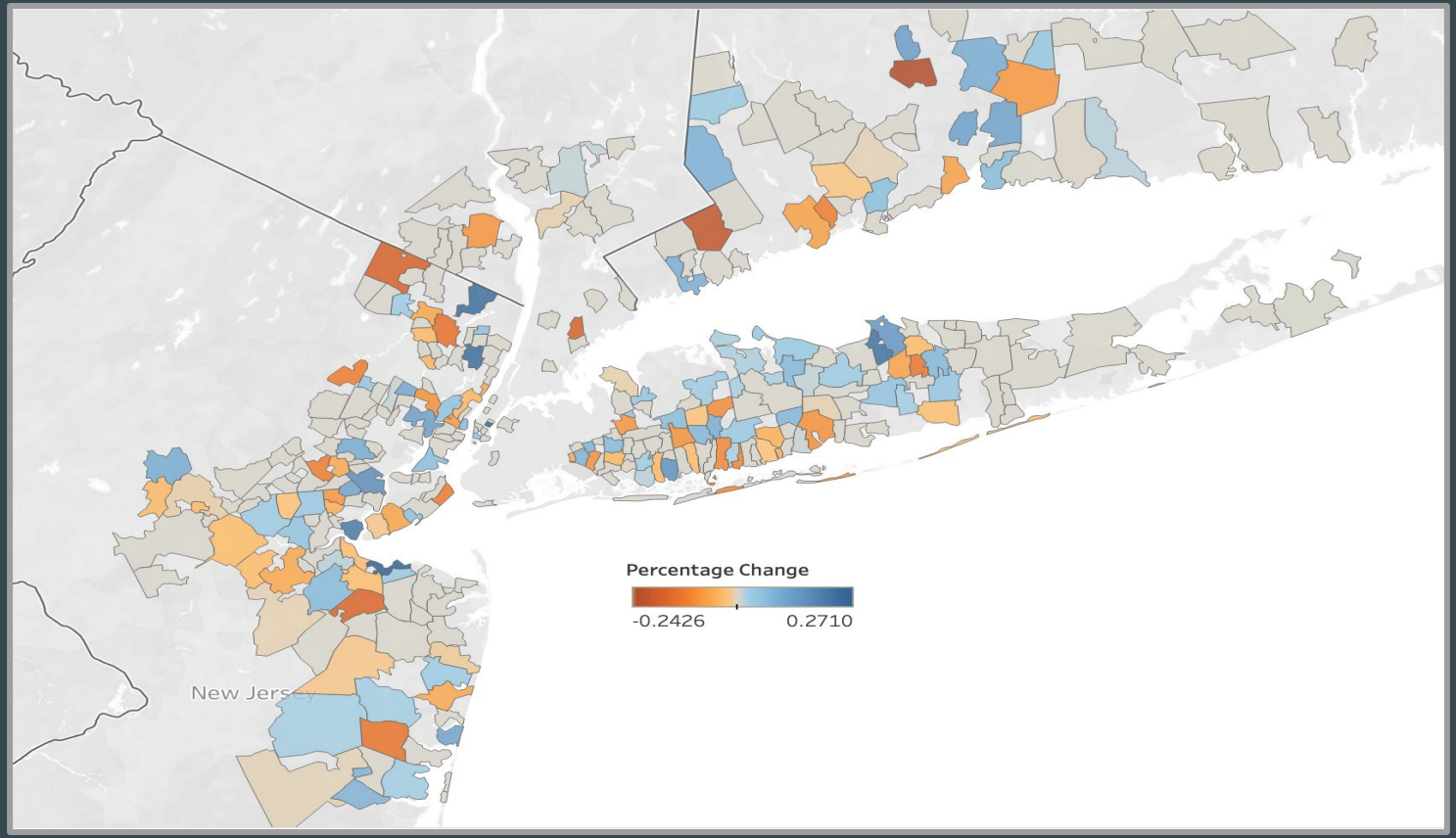




Hurricane Dorian--narrowing down to affected months



Hurricane Sandy- October 22, 2012 - November 2, 2012

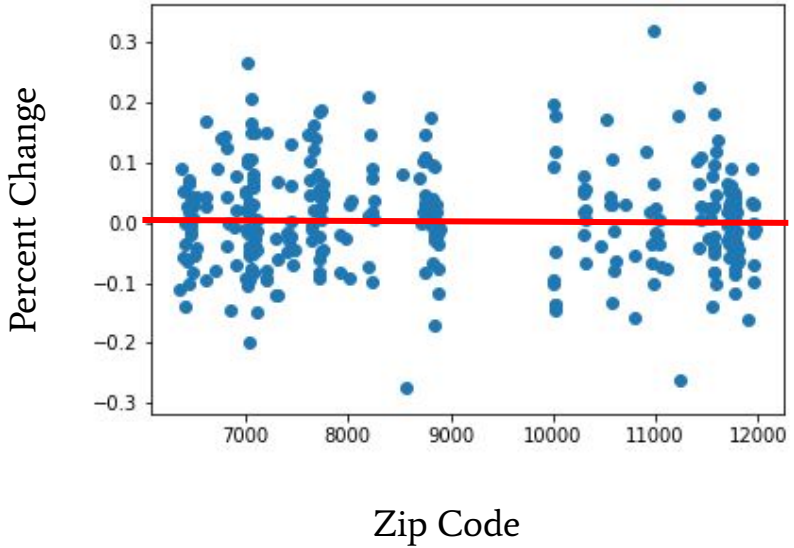


Hurricane Sandy

Takeaways:

- Mean percent change was negligible ~ 0.0076 or barely 1%
- Most positive percent change ~ 27% in city of Keyport, NJ
- Most negative percent change ~ 24% in Middlebury, CT

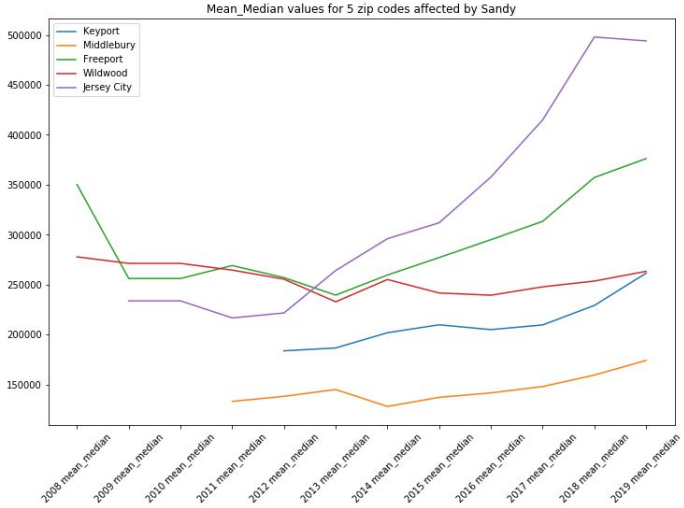
Percent Change for each zipcode from Sandy

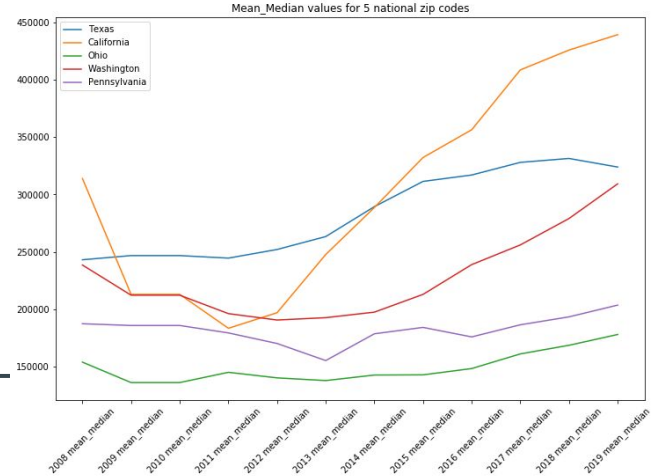


Hurricane Sandy

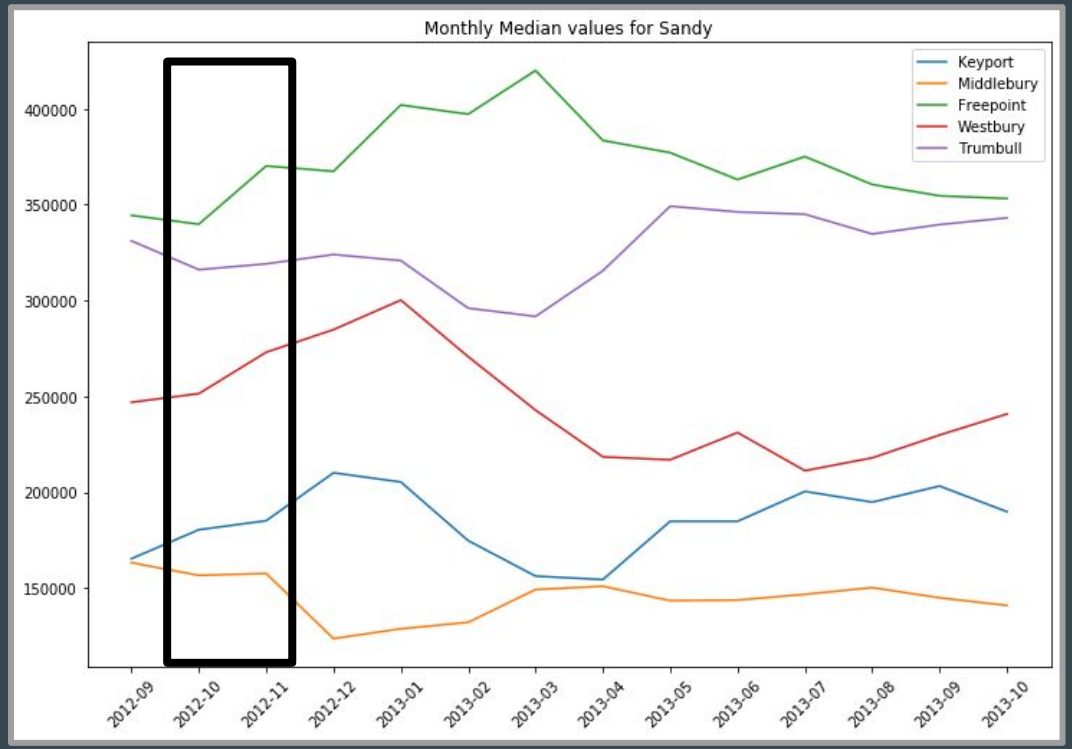
Comparing to National Trends:

- Generally follows the year trends of the nation

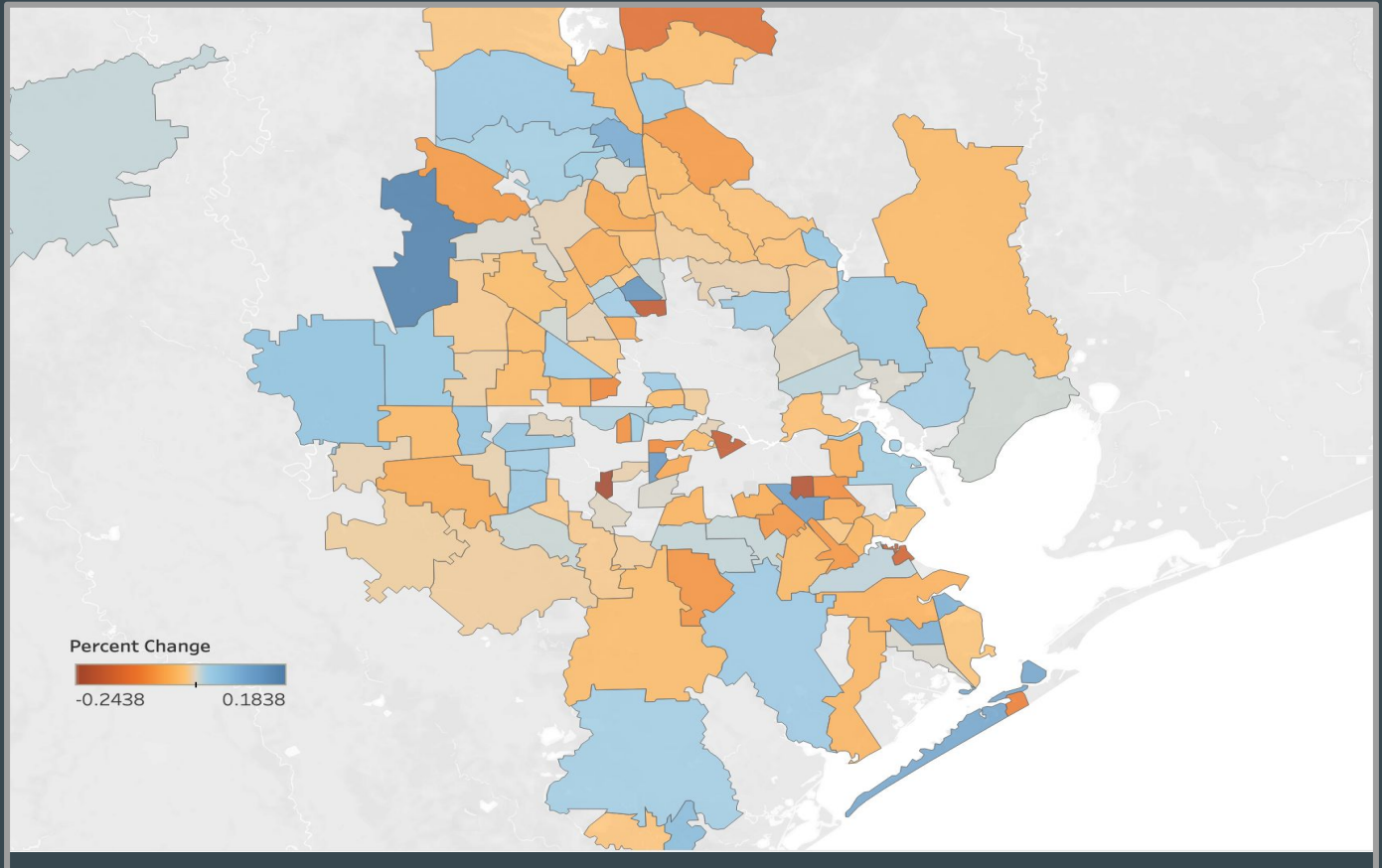




Hurricane Sandy--narrowing down to affected months



Hurricane Harvey- August 17, 2017 - September 3, 2017

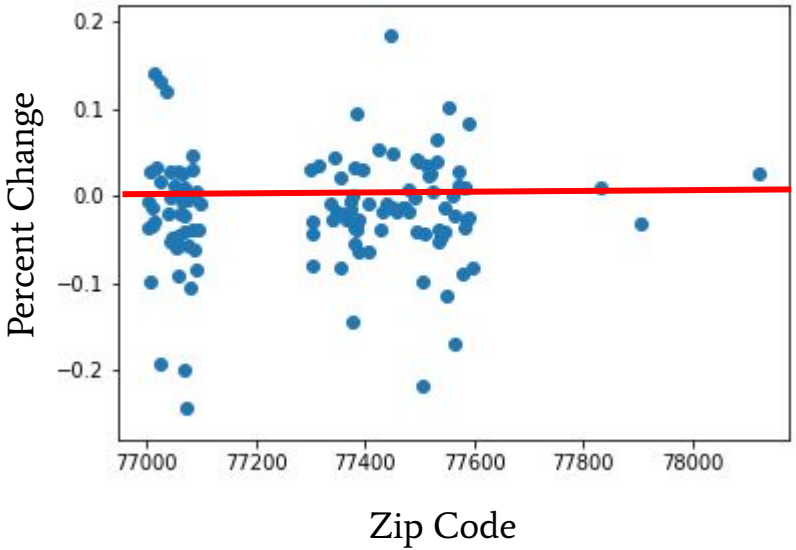


Hurricane Harvey

Takeaways:

- Mean percent change ~ -0.0174 or about minus 2%
- Most positive percent change ~ 18% in city of Hockley
- Most negative percent change ~ 24% in Houston

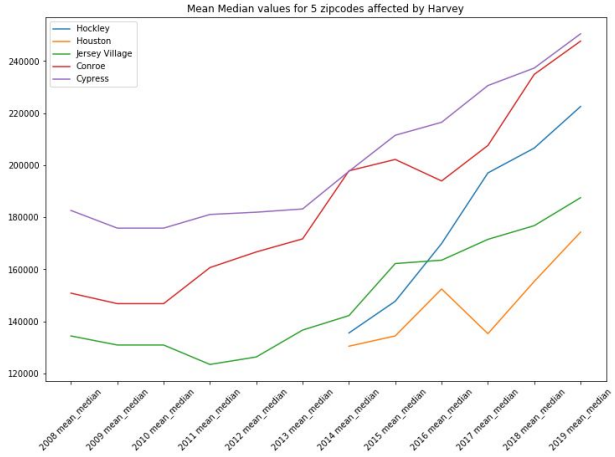
Percent Change for each zipcode from Harvey

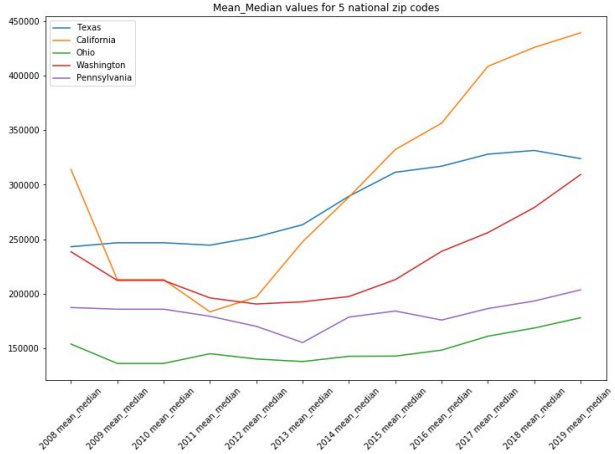


Hurricane Harvey

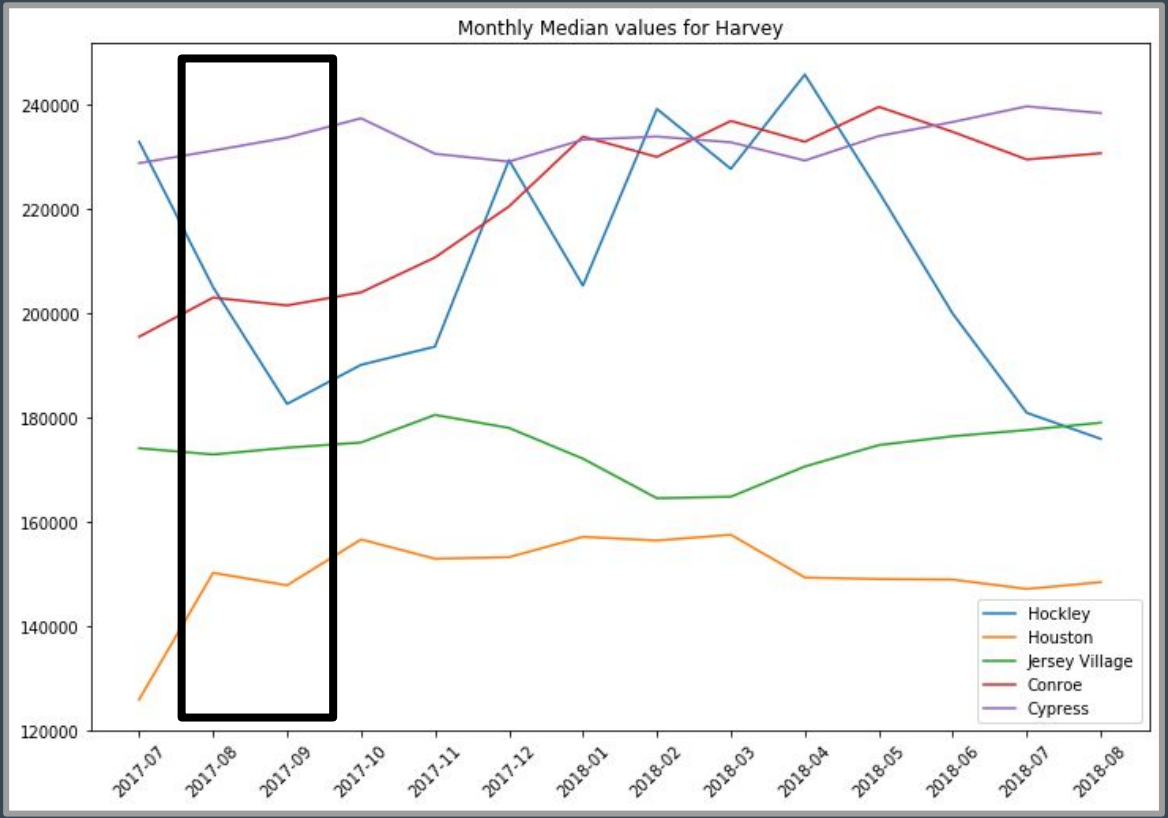
Comparing to National Trends:

- Generally follows the year trends of the nation





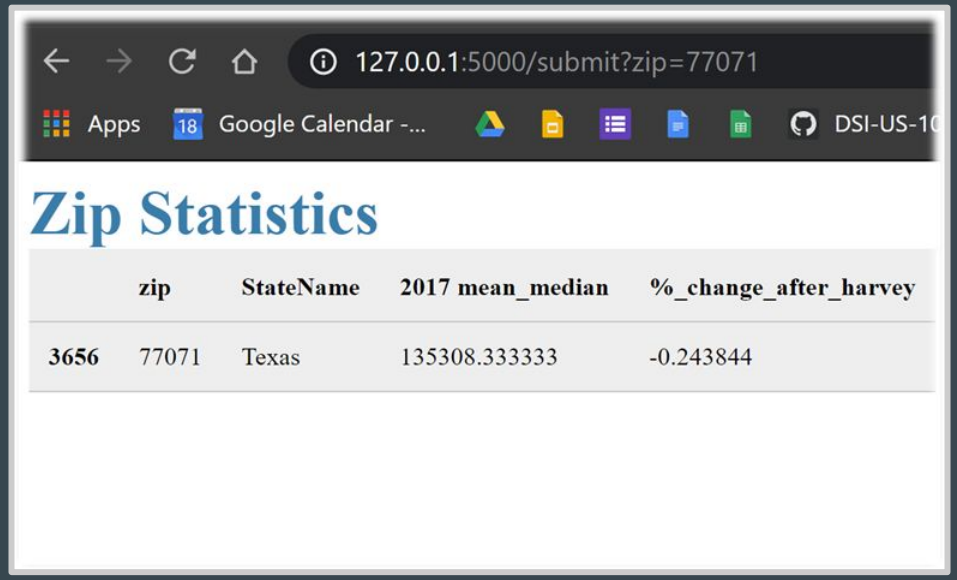
Hurricane Harvey--narrowing down to affected months



Flask-our interactive application

Home page

Results Page



	zip	StateName	2017 mean_median	%_change_after_harvey
3656	77071	Texas	135308.333333	-0.243844

Live Flask Demo URL

Closing Metrics

	Context Official U.S. hurricane damage	Compare National median sale price after storm	Actual Median sale price after storm in affected zip	Normalize Percentage Delta
Dorian 2019	$1.2B	+5.7%	+1%	-470 BPS
Sandy 2012	$70B	+8.7%	+0.8%	-790 BPS
Harvey 2017	$125B	-1.7%	-1.7%	No Change

Possible Next Steps

- Why are the most negatively impacted zip codes adjacent to the most positively impacted zip codes? (Elevation, levies, state/fed resources)
- How can we best feature engineer zoning laws and real estate regulations into a machine learning model? (Binary dummies, ordinal)
- What kind of model might we want to use? (regressor/classifier/hybrid)
- Scale this concept to other natural disasters (Earthquake, fire, tornado)