Modeling Earthquake Damage in Nepal

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Problem Statement

- In 2015 USAID trained locals to rebuild buildings
- This model then can be used
  - predict potential building damage to identify if those buildings created post earthquake are in need of more technical retrofitting at this time

Gorkha Earthquake on April 25, 2015

About the earthquake:

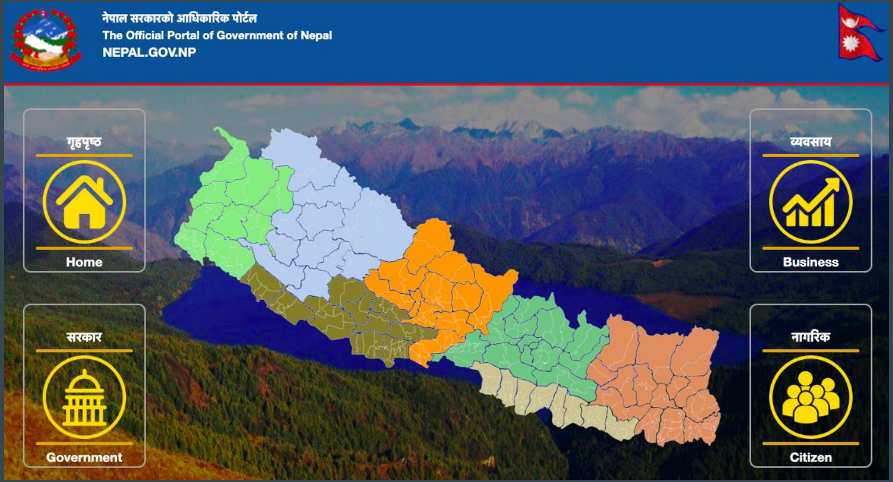
- 7.8Mw (moment magnitude)
- Near Kathmandu
  - central city in Nepal

Impact:

- 9,000 lives lost
- 100,00 injuries

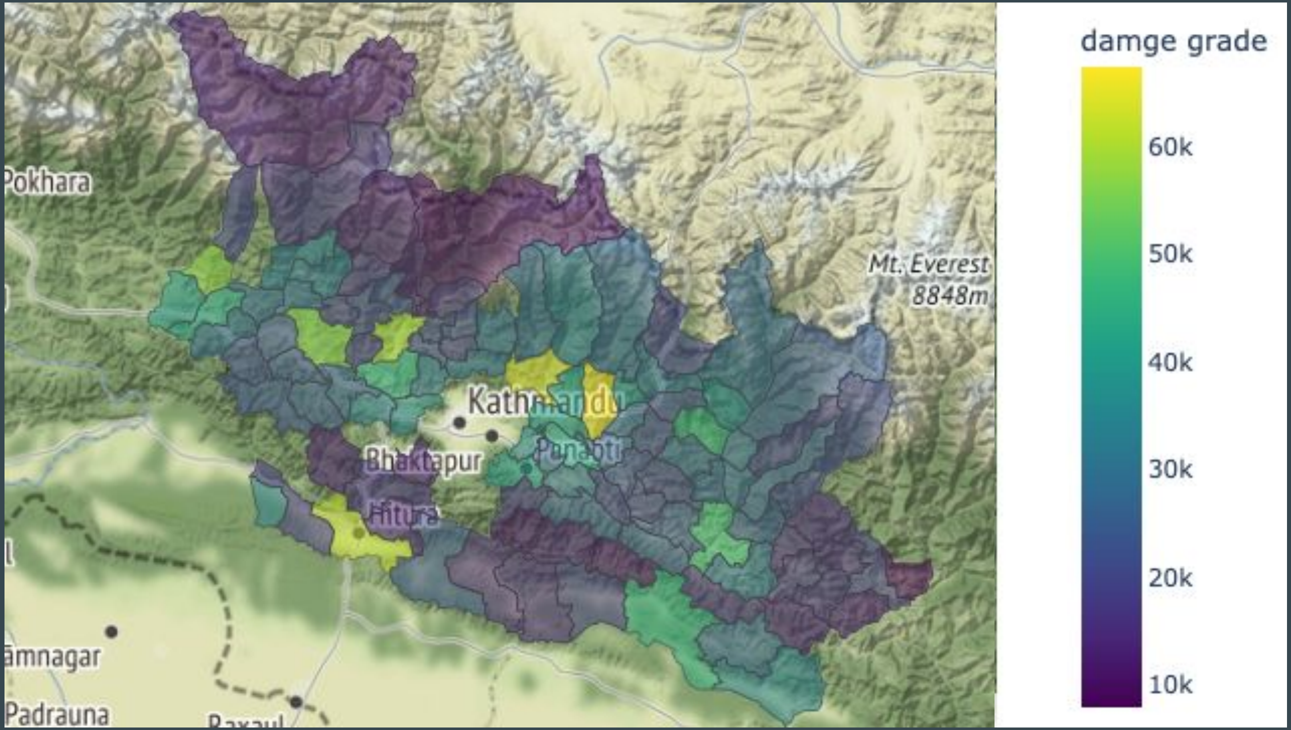
Massive Household Survey ~ 762,106 buildings, 11 districts, 77+ municipalities

- primary goal of to identify **beneficiaries** eligible for government assistance for housing reconstruction
- Assessed building damage in the earthquake-affected districts
- also collected census-level socio-economic information



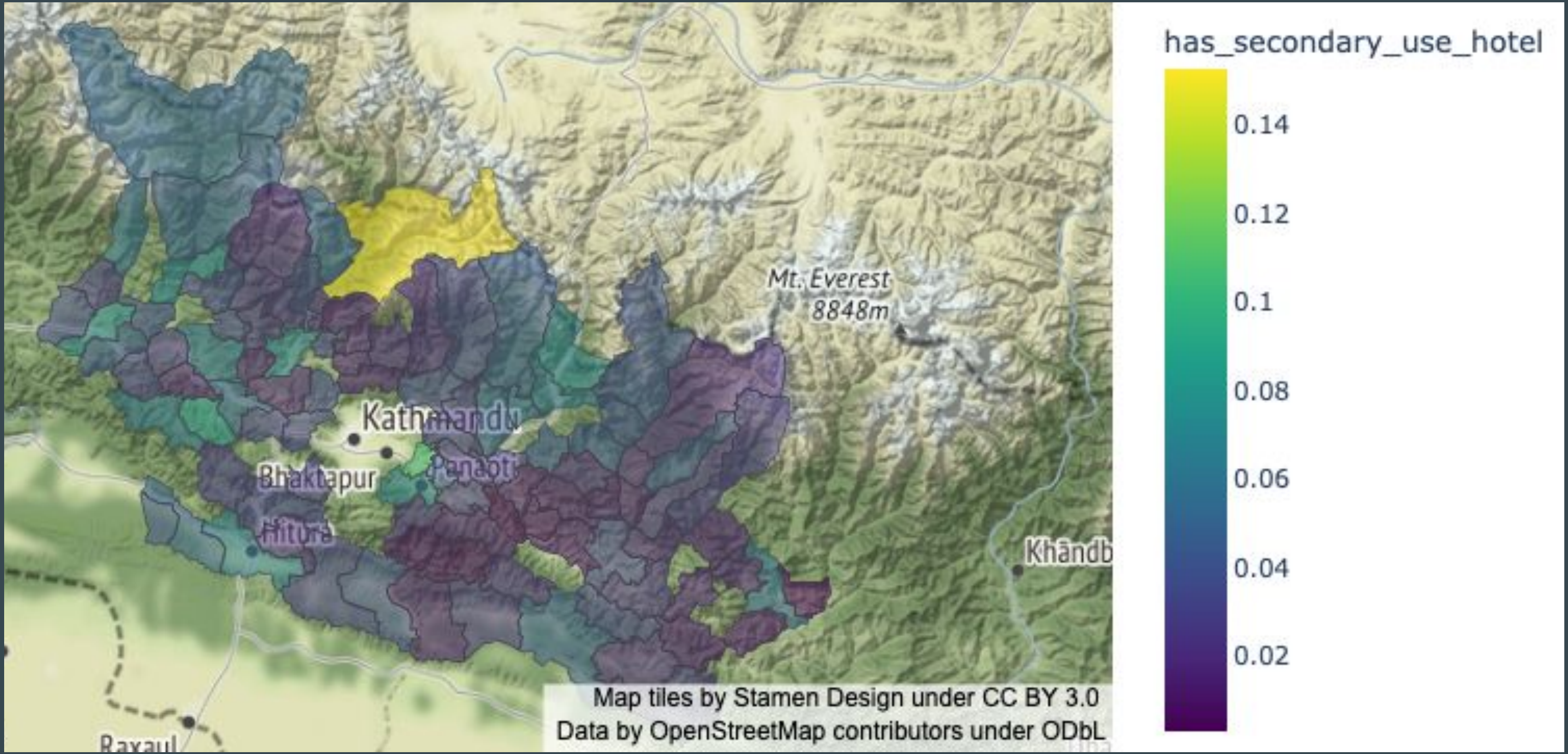
2015 NEPAL EARTHQUAKE OPEN DATA PORTAL

Target Variable

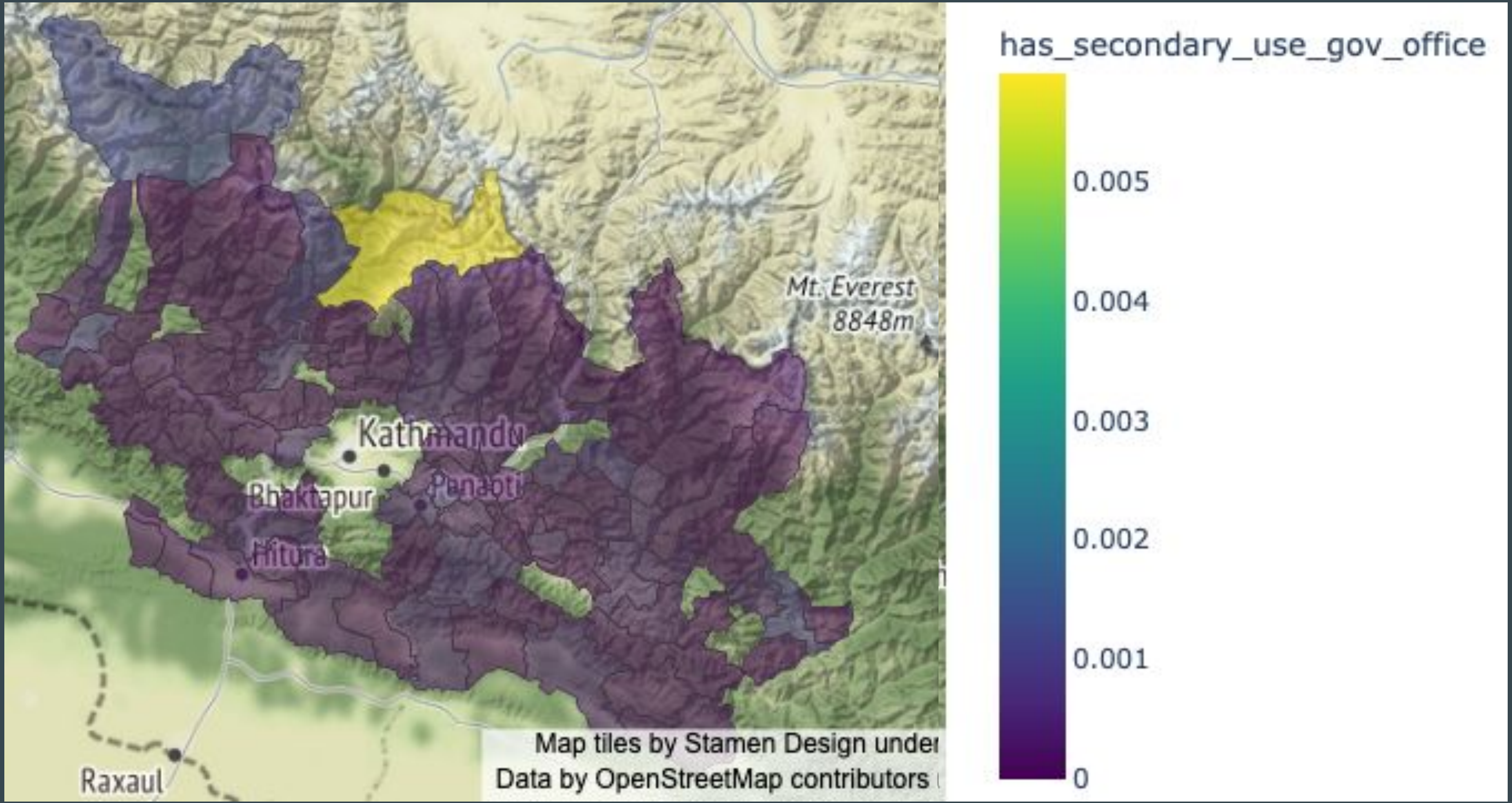


Damage Grade	Percent of Data
5 Total Collapse	36.1 %
4	24.1 %
3	17.9 %
3	17.9 %
2	11.4 %
1 Hairline cracks	10.3 %

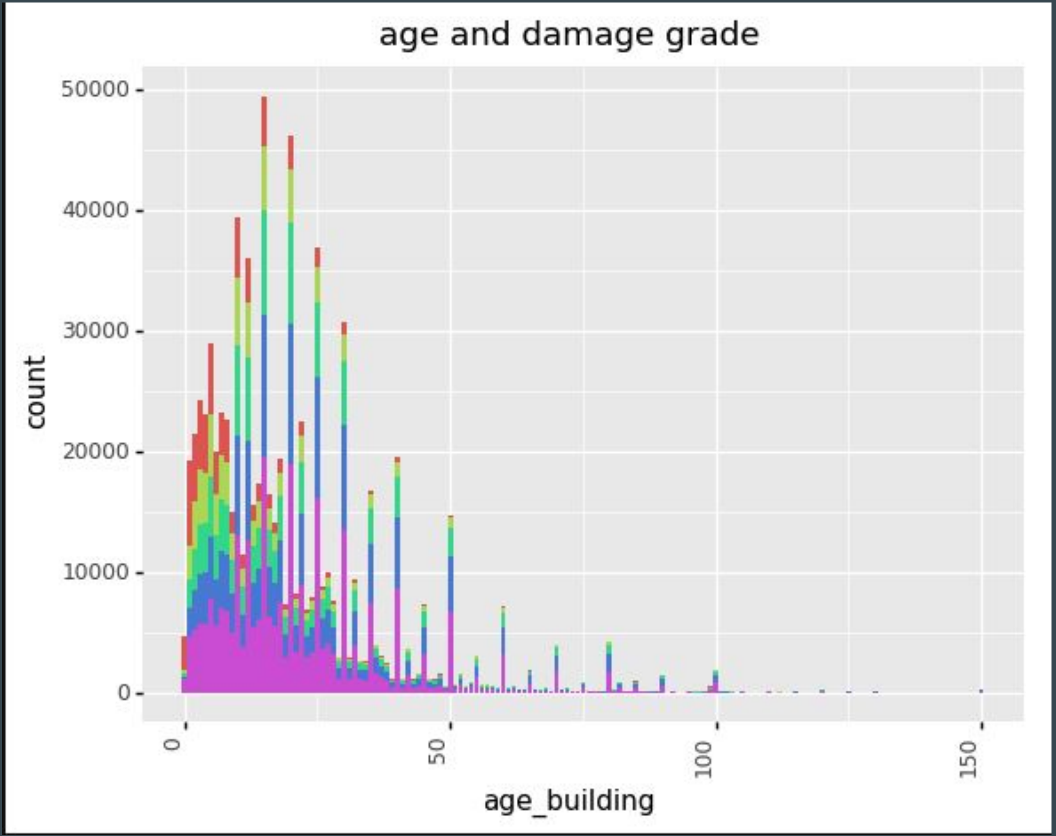
Looking at Densities of Secondary Building Usage



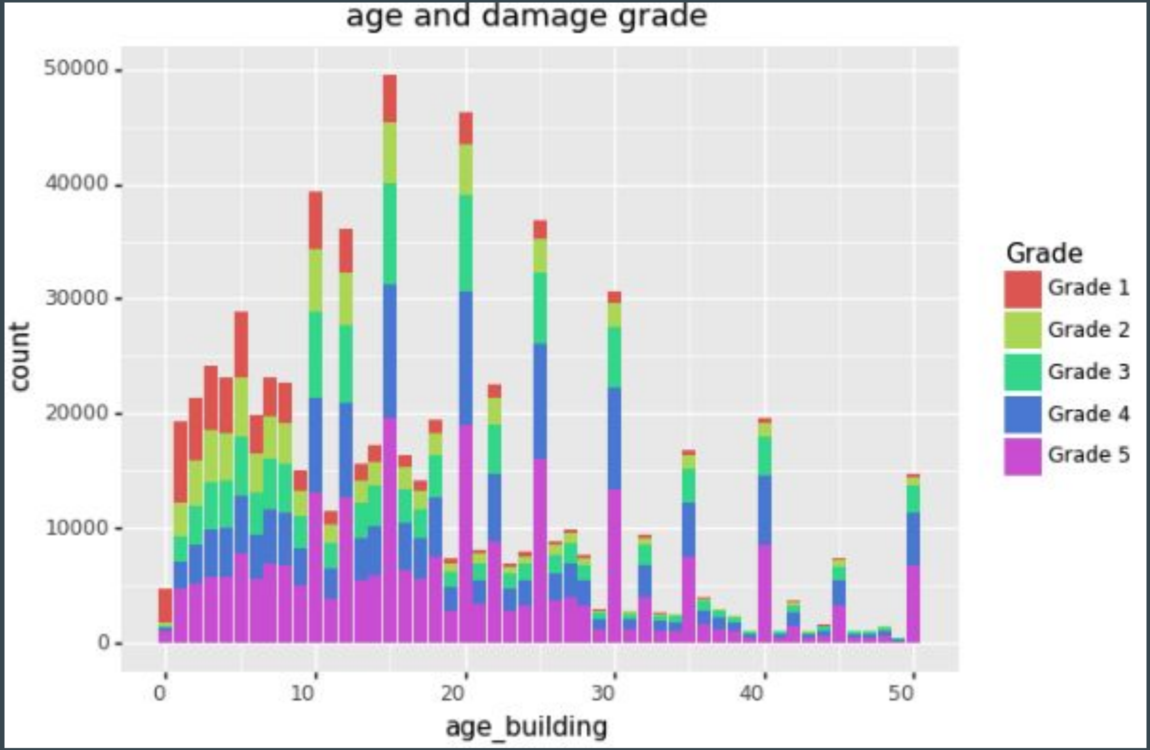
Looking at Densities of Secondary Building Usage Cont'd



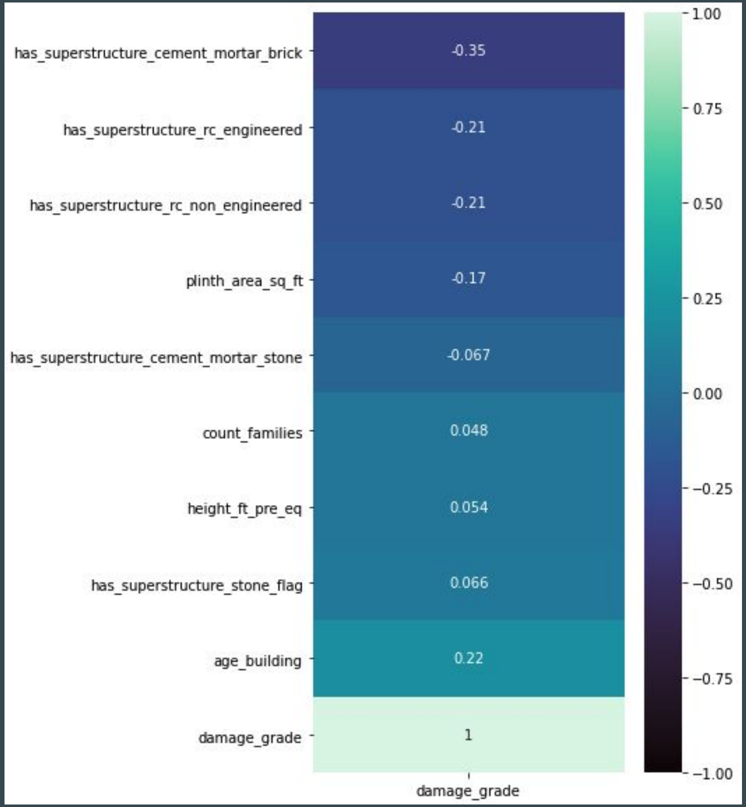
Exploration



Zooming in ...


age and damage grade
count
age_building
Grade
Grade 1
Grade 2
Grade 3
Grade 4
Grade 5
50000
40000
30000
20000
10000
0
0
10
20
30
40
50

Linear Relationships ...?

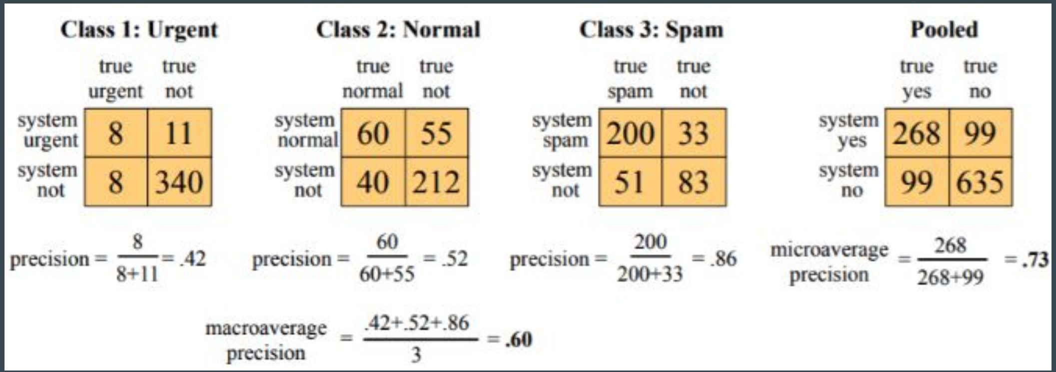


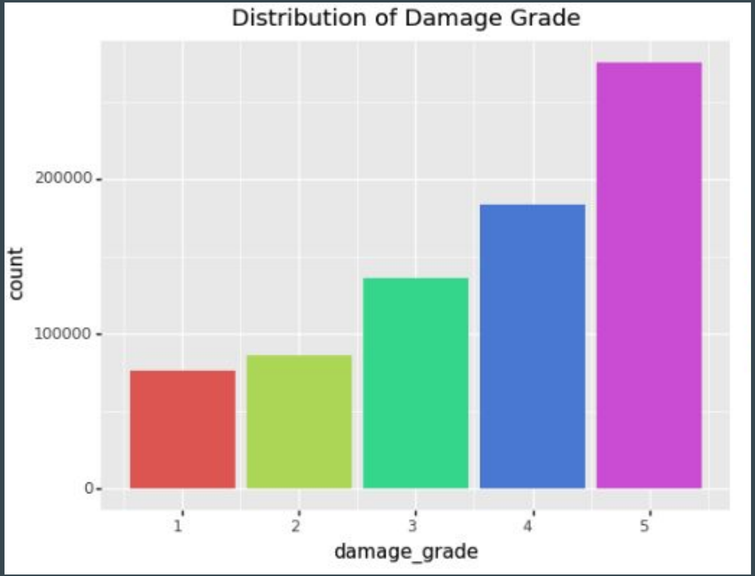
PSA: Correlation is not causation

Model Evaluation Metric

F1 Score:

- Macro
- **Micro**





Modeling Overview

- Logistic Regression
- Random Forest
- XGBoost

Best Model:

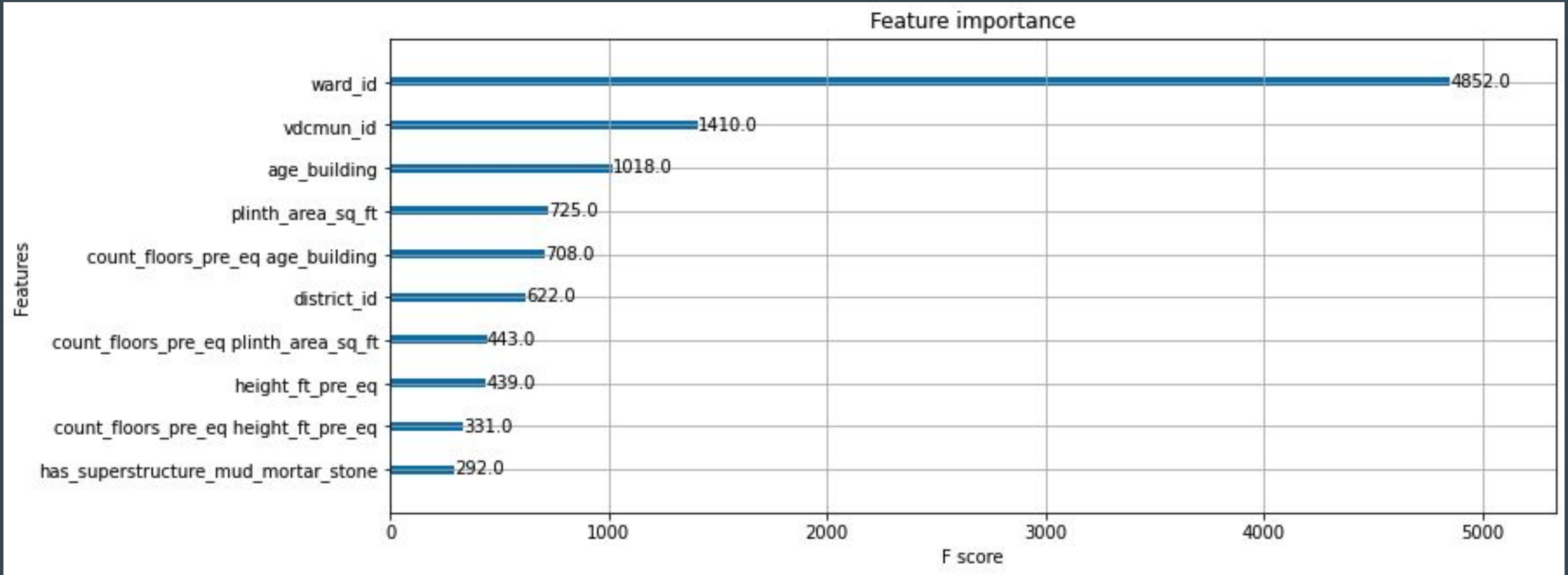
- Logistic Regression (multi_class='multinomial', C=0.1, solver='lbfgs')

Feature Engineering Attempt:

- Feature Interactions (100 to 200)

Feature Interactions

- Models with Polynomial Features performed similarly (the interactions were making top 10)



Important Features (Log Reg)

Coefficients	Word
-0.589	vdcmun_id
-0.553	ward_id
-0.358	has_superstructure_mud_mortar_stone
-0.16	has_secondary_use_agriculture
-0.12	count_floors_pre_eq

Coefficients	Word
1.0514	district_id
0.19	roof_type_bamboo_timber_light_roof
0.189	roof_type_rcc_rb_rbc
0.175	has_secondary_use
0.13	ground_floor_type_rc

Model Evaluation

- F1 Score Micro/Macro & Accuracy for reference
    - Hardest class to classify was buildings with damage grade 3

Metric	Logistic Regression	XGBoost	Random Forest
Accuracy	66%	58%	56%
Micro	66%	58%	56%
Macro	64%	54%	52%

Conclusion

- Functional model to utilize for the damage predictions to identify those in need of more technical retrofitting
    - Out performs baseline by about 30%

Future Work:

- Could utilize the geo coordinates to gather geospatial characteristics for each location
- Build a functional tool that is user friendly for locals to use in building eval

Questions ?

Thank you!

Streamlit multipage notes

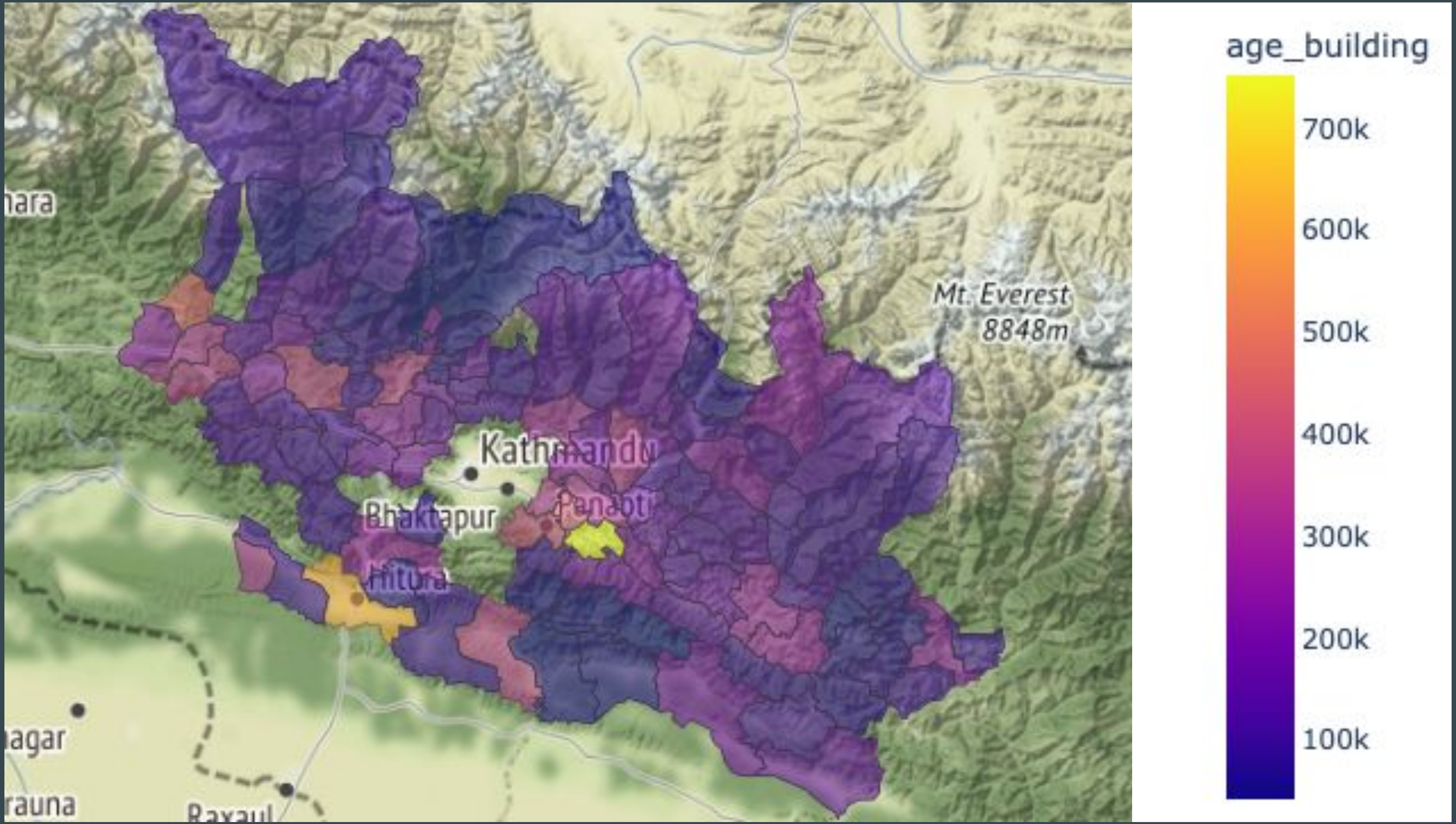
https://towardsdatascience.com/creating-multipage-applications-using-streamlit-efficiently-b58a58134030

https://towardsdatascience.com/a-multi-page-interactive-dashboard-with-streamlit-and-plotly-c3182443871a

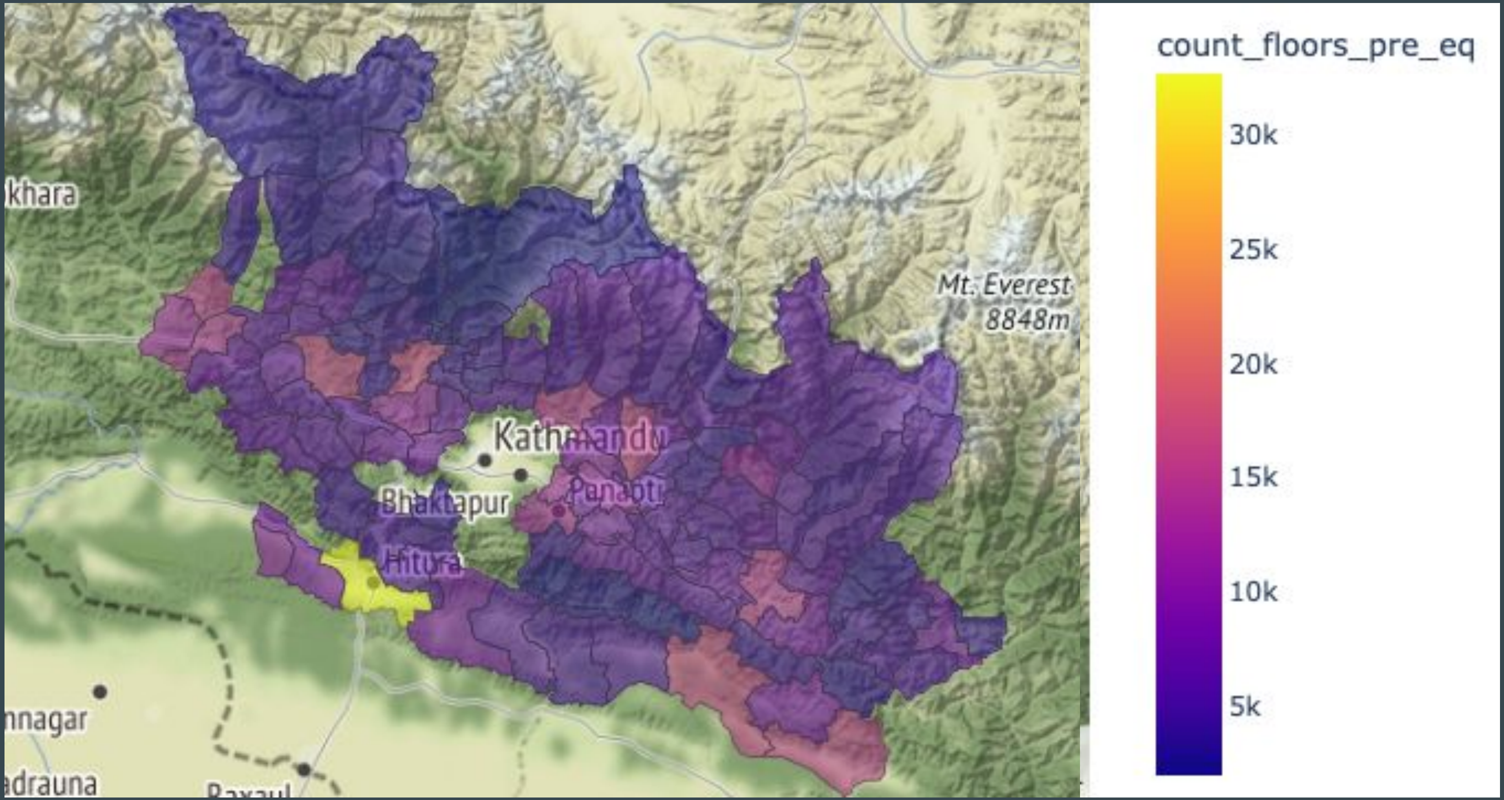
Data resource:

https://observablehq.com/collection/@arkoblog/opendataportal

Distribution of Building Age



Distribution of Count of Floors Pre - Earthquake



Distribution of Count of Floors Post - Earthquake