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Computer Science

Housing Price Estimation Using Satellite Imagery

CS 230: Deep Learning
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Introduction

- **Motivation:** Successful vision-based models have been trained to do complicated tasks such as poverty prediction in Africa [1]. Considering the ongoing focus on vision-based predictive models and Zillow's Zestimate competition [2], **we aimed** to combine high-resolution satellite images with property features in order to improve house price estimation models.
- **Method:** We use a pre-trained NN (Inception-v3 [3]) for image encoding and train our model on feature-only and feature-and-image datasets. We show that images can boost the prediction performance since they provide valuable information about the neighborhood.

Challenges

- Our data did not include images. They are collected from Google Maps API using latitude and longitude.
- Most accessible sources of relevant data are small. We use transfer learning to deal with this issue.
- Existing models perform reasonably well when provided with rich features, but we expect our model to perform well on datasets with fewer features too.
- Moreover, we tried to boost the performance of Zillow's price prediction model, but it proved to be a challenging task since we had to treat it as a black box model.

Data and Features

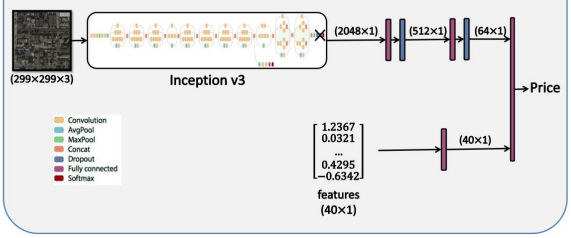
- LA Property Tax Information (available due to federal Open Data Policy) [4]:
  - Over 2 million real-estate properties in LA county, from 2006 to 2017.
  - 50 features (e.g. floor area, # of bedrooms)
  - Preprocessed to remove non-residential properties, price outliers and unrelated features.
- **640x640** satellite images collected using Google Maps Static API (~8GB):
  - Different zoom levels are available, we chose the one that shows both the building itself and enough of its surroundings.
  - Each image is encoded using **Inception-v3** [3], resulting in a 2048-D vector.
  - Preprocessed to fit the input assumptions of Inception-v3's neural network.

Size	Features	Mean ($)	Standard Deviation ($)
53,942	40	130274.4	4884069.7

Data statistics after preprocessing

Model

- Given the satellite images as input to the Inception-v3 model (pretrained on ImageNet), encoded vectors of size 2048 are extracted from hidden layers.
- After passing through fully-connected layers, vectors are then concatenated with property features and fed to a fully-connected layer:



Results and Discussion

- We use multiple tree-based estimators as the baseline, Extra-Tree regressors have the best performance. We also use a feed-forward neural network as the second baseline.
- An image-only model performs poorly because it does not have access to valuable features like the house floor area.
- The F+I model outperforms all other models. Intuitively, the cost of a house is ~(size)×(price per SqFt). While features provide the model with the first factor, images help it improve its estimation for the second.

Model	Train R^2	Test R^2	Train RMSE	Test RMSE
F (non NN)	0.999	0.869	915	1638332
F (NN)	0.968	0.868	901141	1645641
I (NN)	0.001	0.001	5032166	4524723
F+I (NN)	0.990	0.951	500241	998014

F: features only (no image), I: image only, F+I: both

Conclusion and Future Work

- By adding satellite images to our prediction model, we were able to improve R^2 by ~10% and reduce RMSE by ~40% compared to the baseline.
- **Next steps:**
  - Using different image zoom levels or a combination of them
  - Fine tuning last layers of the Inception-v3 network
  - Adding data from more cities/countries to the dataset and see how generalizable the model is from one location to another.

References

[1] N. Jean et. al., Combining satellite imagery and machine learning to predict poverty, Science, 353(6301): 790—794, 2016.

[2] https://www.kaggle.com/c/zillow-prize-1.

[3] C. Szegedy et. al., Rethinking the Inception Architecture for Computer Vision, CoRR, abs/1512.00567, 2015.

[4] https://data.lacounty.gov/Parcel-/Assessor-Parcels-Data-2017/vak5-2hqh

[5] A. J. Bency et. al., Beyond Spatial Auto-Regressive Models: Predicting Housing Prices with Satellite Imagery, WACV, 2017.