HDB RE-SALE PRICING PREDICTION

WHAT DRIVES HDB PRICES?

STRATEGY

- By applying Machine learning to predict HDB prices,
- we can utilize ML visualizations to see which features are used to do the prediction
- and hence … proxy these features as a driver/drivers for HDB re-sale pricing.

SLIDESHOW OVERVIEW

- 1) PROBLEM STATEMENT
- 2) DATA OVERVIEW
- 3) DATA CLEANING, FEATURE ENGINEERING. EDA
- 4) AUTO-ML, HYPER-PARAMETER TUNING, ML Visualizations
- 5) Challenges & Thoughts

PROBLEM STATEMENT

- Understand the drivers of prices of the houses
  - We will attempt to understand this via:
    - Exploratory/general data analysis (EDA)
    - as well as machine learning and the analysis of how the machine read the information.

DATA OVERVIEW

- Given 5 different sets of data, I've combined them into:

looks about right lets join them

```
new_df = pd.concat([a,b[a.columns],c[a.columns],d[a.columns],e[a.columns]]).reset_index().drop(columns=["index"])
new_df
```

[15]:

	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date	resale_price	Month	Year
0	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977	9000.0	1	1990
1	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	04 TO 06	31.0	IMPROVED	1977	6000.0	1	1990
2	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	10 TO 12	31.0	IMPROVED	1977	8000.0	1	1990
3	1990-01	ANG MO KIO	1 ROOM	309	ANG MO KIO AVE 1	07 TO 09	31.0	IMPROVED	1977	6000.0	1	1990
4	1990-01	ANG MO KIO	3 ROOM	216	ANG MO KIO AVE 1	04 TO 06	73.0	NEW GENERATION	1976	47200.0	1	1990

851294 rows × 13 columns

DATA CLEANING

- Blocks have a letter appended at the back EG. BLK 333A, 333B, etc.
    - Removed them without amending the block#
- flat_type -> has 'MULTI GENERATION' & 'MULTI-GENERATION' -> convert them to just one kind
- Flat_model -> changing everything to caps to remove extra categoriues of data
- No null/empty values which is great
- No duplicated values either (Similar values are normal since more than 1 kind of a room will be available eg. 3 rooms in CCK will have a similar data format)

DATA CLEANING - DROPPING COLUMNS

- "Street" since the values too unique even after dropping the town name from the street name I had 434 values
- "Month" since I have successfully splitted it already

FEATURE ENGINEERING - NEW FEATURES

- Column "Month" consist of month and year

month
1990-01
1990-01
1990-01
1990-01
1990-01

Month	Year
1	1990
1	1990
1	1990
1	1990
1	1990

- Column town narrowed further into regions

town
ANG MO KIO
ANG MO KIO
ANG MO KIO
ANG MO KIO
ANG MO KIO

Region
NORTH-EAST
NORTH-EAST
NORTH-EAST
NORTH-EAST
NORTH-EAST

FEATURE ENGINEERING: ENCODING STRATEGIES

- Label encoding for columns like:
  - Flat_type, storey range, region

```
['1 ROOM',
 '2 ROOM',
 '3 ROOM',
 '4 ROOM',
 '5 ROOM',
 'MULTI GENERATION',
 'EXECUTIVE']
```

```
0
1
2
3
4
5
6
```

```
'01 TO 03', '01 TO 05', '04 TO 06', '06 TO 10', '07 TO 09',
'10 TO 12', '11 TO 15', '13 TO 15', '16 TO 18', '16 TO 20',
'19 TO 21', '21 TO 25', '22 TO 24', '25 TO 27', '26 TO 30',
'28 TO 30', '31 TO 33', '31 TO 35', '34 TO 36', '36 TO 40',
'37 TO 39', '40 TO 42', '43 TO 45', '46 TO 48', '49 TO 51']
```

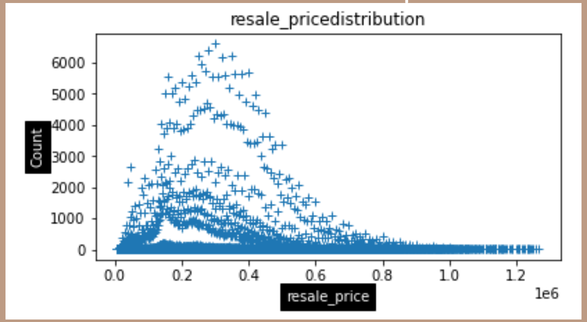
- Binary encoding (Hash + one hot mix):
  - Town (27 values) & flat_model (20 values)

town
ANG MO KIO
ANG MO KIO
ANG MO KIO
ANG MO KIO
ANG MO KIO

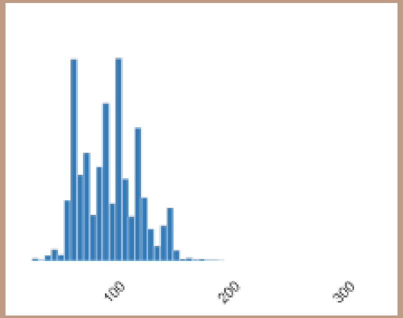
	town_0	town_1	town_2	town_3	town_4	town_5
0	0	0	0	0	0	1
1	0	0	0	0	0	1
2	0	0	0	0	0	1
3	0	0	0	0	0	1
4	0	0	0	0	0	1

EDA - BRIEF, NOTHING TOO EYE CATCHING...

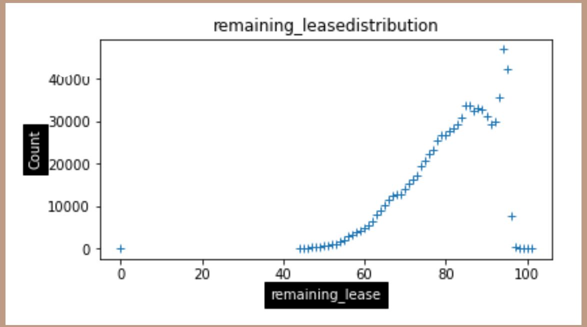
- Left skew on resale price



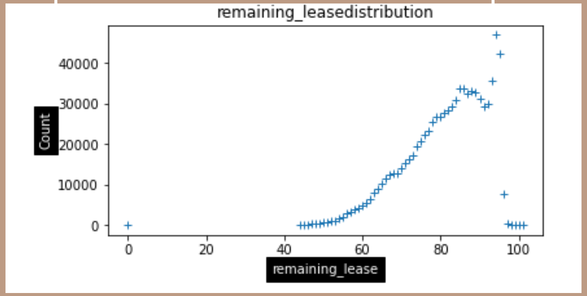
- Left skew on floor area



- Right skew on floor



- Right skew on remaining lease

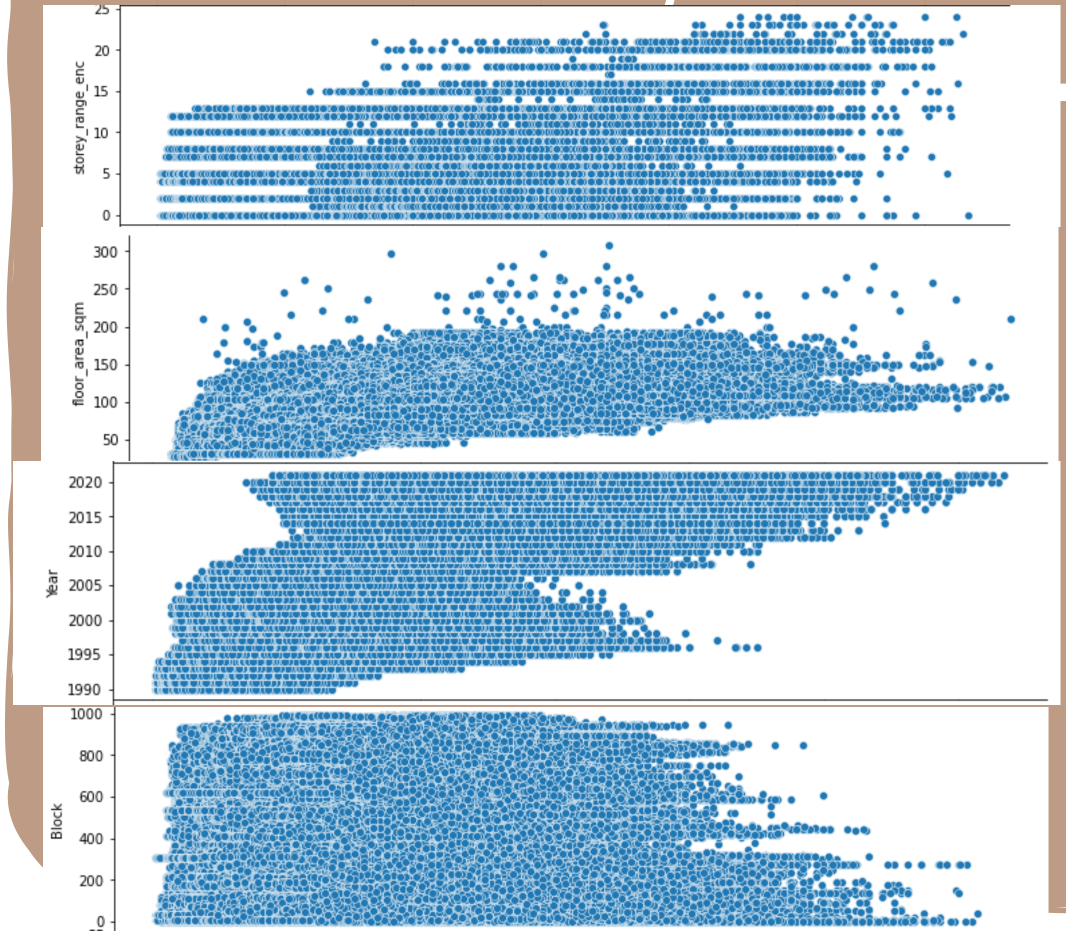


Strategies:

1) Normalize data to give a mean of 1 and SD of 0 to "center" the data

2) pick bootstrapping models which bypass severe outliers and overtly skewed data (I picked the random forest)

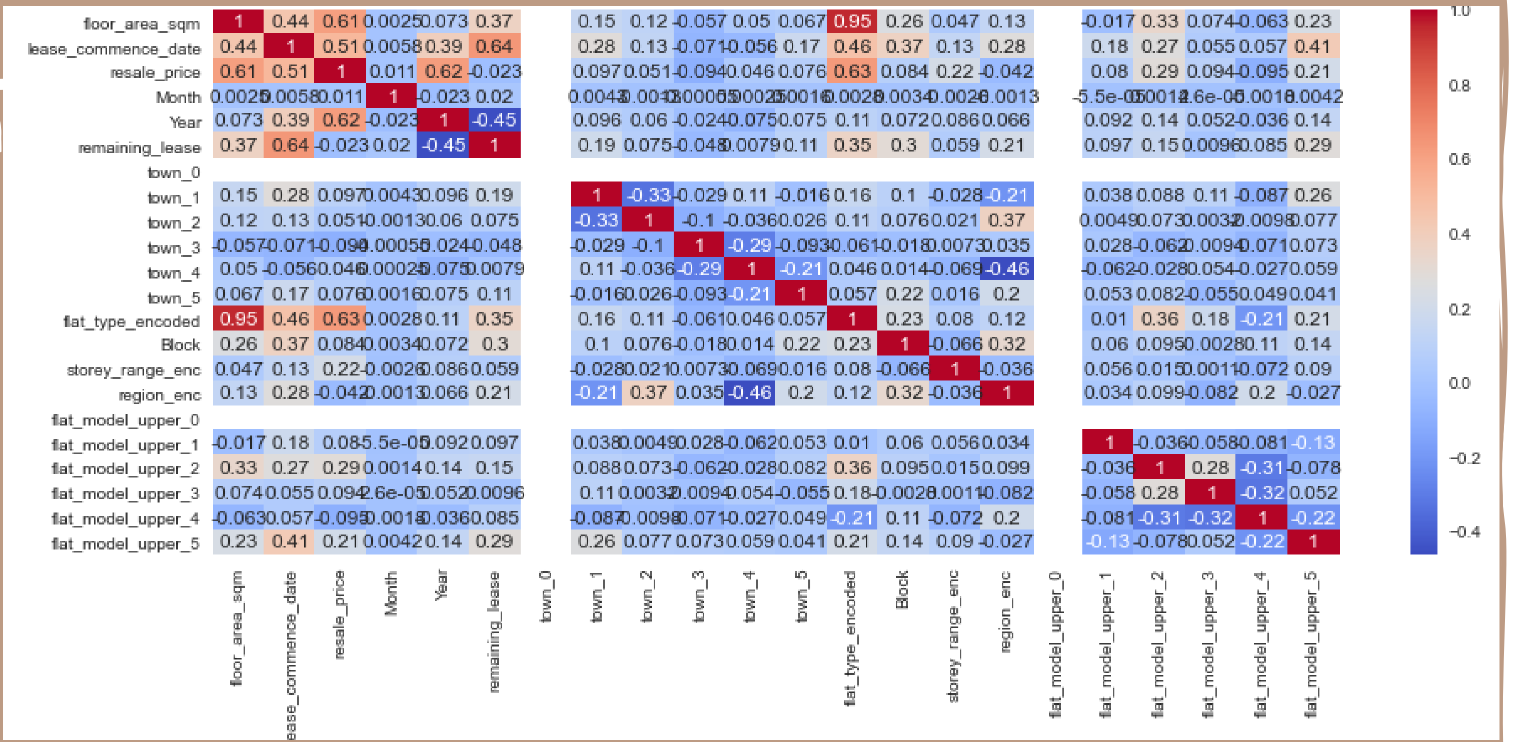
EDA - BRIEF, NICE TO KNOWS



- Typically higher floors have a higher price floor
- The lesser floor area you have the lower the price ceiling
- The later your building was created the more likely your re-sale price is going to be good.
- And unsurprisingly the price ceiling for low block no.s (Terraces etc.) is rather high

EDA - BRIEF, NOTHING TOO EYE CATCHING…

Nothing really correlates too much with resale price either, only moderately at 0.6/1.0 for floor area & 0.5 for year of construction.



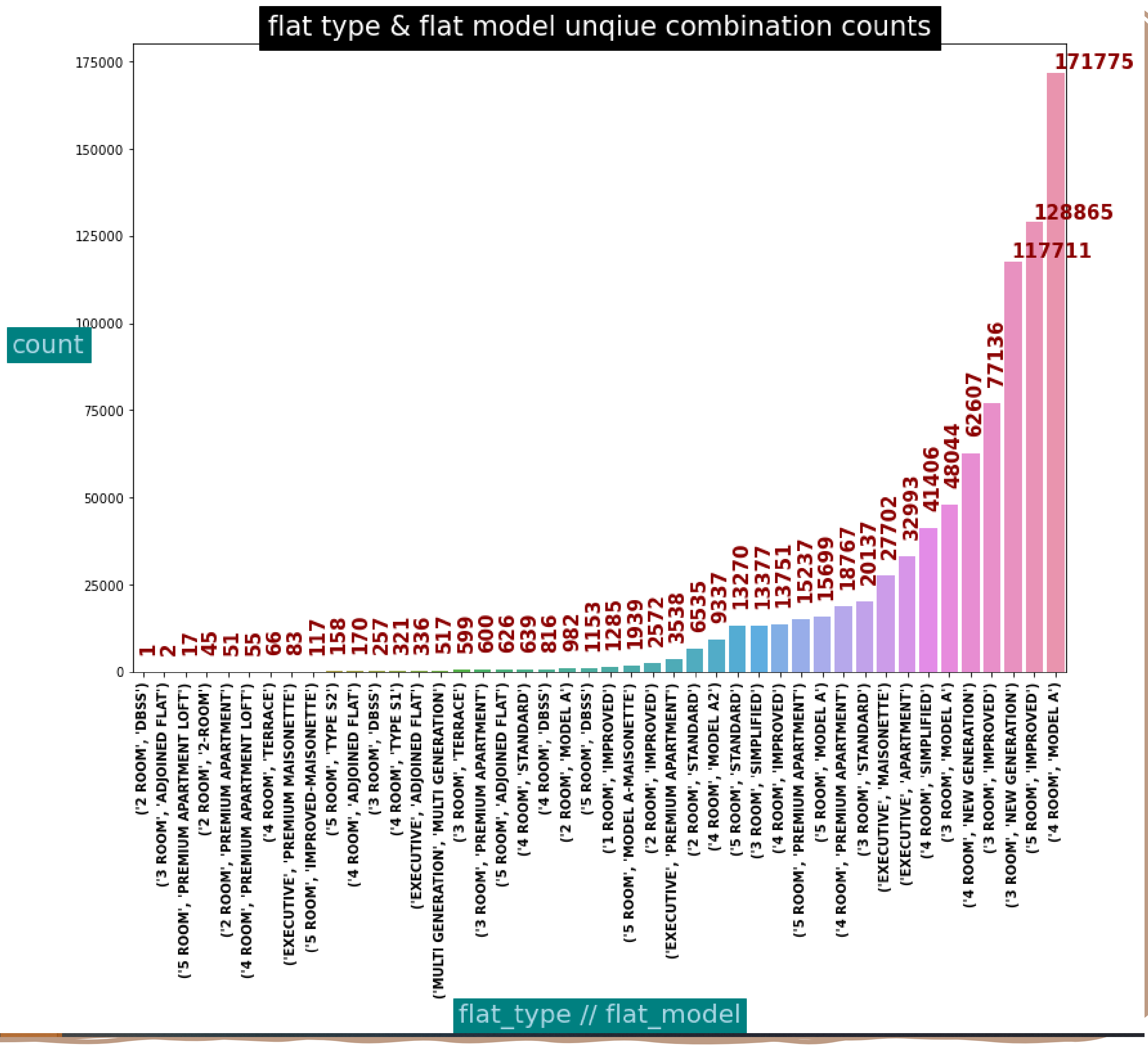
I removed the flat type since floor area per square metre is almost completely identical to it as a measure

EDA -

POSSIBLE DATA EXCLUSIONS

Very sparse data for certain combinations of flat_type & flat_model

Possibly dropping combinations with less than 1000 instances each might improve the model



AUTO-ML - (HYPEROPT)

	KNN	rf	RF_worse
r_2	0.95	0.98	0.96
mae	24523.91	14263.15	20824.81
rmse	35721.67	20910.33	32405.70

```
model = HyperoptEstimator(regressor=random_forest_regression('rf'), preprocessing=a
                         , algo=tpe.suggest, max_evals=30, trial_timeout=30)
model.fit(x_train_scale1.to_numpy(), y_train.to_numpy())
```

```
100%| | 1/1 [00:05<00:00,  5.38s/trial, best loss: 0.539114586848605]
100%| | 2/2 [00:27<00:00, 27.95s/trial, best loss: 0.45965640809331465]
100%| | 3/3 [00:32<00:00, 32.40s/trial, best loss: 0.45965640809331465]
100%| | 4/4 [00:32<00:00, 32.63s/trial, best loss: 0.45965640809331465]
100%| | 5/5 [00:32<00:00, 32.56s/trial, best loss: 0.45965640809331465]
100%| | 6/6 [00:32<00:00, 32.57s/trial, best loss: 0.45965640809331465]
100%| | 7/7 [00:32<00:00, 32.57s/trial, best loss: 0.45965640809331465]
100%| | 8/8 [00:32<00:00, 32.58s/trial, best loss: 0.45965640809331465]
100%| | 9/9 [00:32<00:00, 32.59s/trial, best loss: 0.45965640809331465]
100%| | 10/10 [00:27<00:00, 27.87s/trial, best loss: 0.06246893764854211]
100%| | 11/11 [00:32<00:00, 32.57s/trial, best loss: 0.06246893764854211]
100%| | 12/12 [00:09<00:00,  9.46s/trial, best loss: 0.06246893764854211]
100%| | 13/13 [00:32<00:00, 32.49s/trial, best loss: 0.06246893764854211]
100%| | 14/14 [00:27<00:00, 27.93s/trial, best loss: 0.04859198593343972]
100%| | 15/15 [00:32<00:00, 32.74s/trial, best loss: 0.04859198593343972]
100%| | 16/16 [00:32<00:00, 32.71s/trial, best loss: 0.04859198593343972]
100%| | 17/17 [00:32<00:00, 32.67s/trial, best loss: 0.04859198593343972]
100%| | 18/18 [00:32<00:00, 32.71s/trial, best loss: 0.04859198593343972]
100%| | 19/19 [00:32<00:00, 32.63s/trial, best loss: 0.04859198593343972]
100%| | 20/20 [00:10<00:00, 10.05s/trial, best loss: 0.04859198593343972]
100%| | 21/21 [00:32<00:00, 32.95s/trial, best loss: 0.04859198593343972]
100%| | 22/22 [00:10<00:00, 10.45s/trial, best loss: 0.04859198593343972]
```

- RMSE = Square root of sum of squared distances between our target variable and predicted values.
- MAE = the average magnitude of errors in a set of predictions, without considering their directions (better for sets with alot of outliers which is this dataset)
- R2 provides a measure of how well future samples are likely to be predicted by the model

MAE here is the chosen metric of choice

AUTO-ML - (OPTUNA) - HYPERPARAMETER TUNING

```
[I 2021-08-23 03:01:41,319] Trial 49 finished with value: 14263.14926630103 and parameters: {'n_estimators': 97, 'max_dept
h': 29.856901218249337}. Best is trial 0 with value: 14263.14926630103.
```

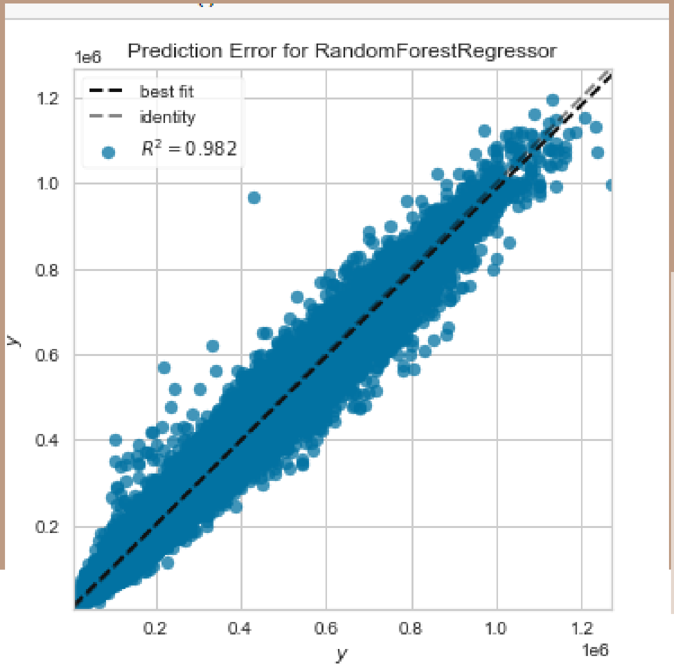
Unfortunately, Gridsearch is crashing consistently and Optuna doesn't improve my parameters despite 50 rounds of tuning IE the first round was still better than all subsequent trials

MODEL RESULTS – A RANDOM PREDICTION

```
print("prediction:", pd.DataFrame(rf.predict(x_test_scale1),columns=["pred"]).pred.iloc[-1],
      "\nActual:     ", y_test.iloc[-1])
```

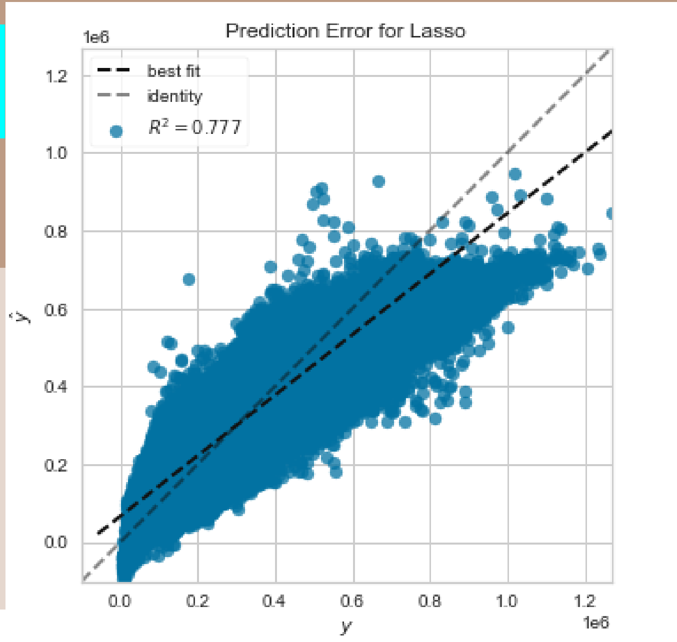
```
prediction: 336486.3636363637
Actual:     325000
```

Roughly every prediction will be on average 14k away from the actual re-sale price

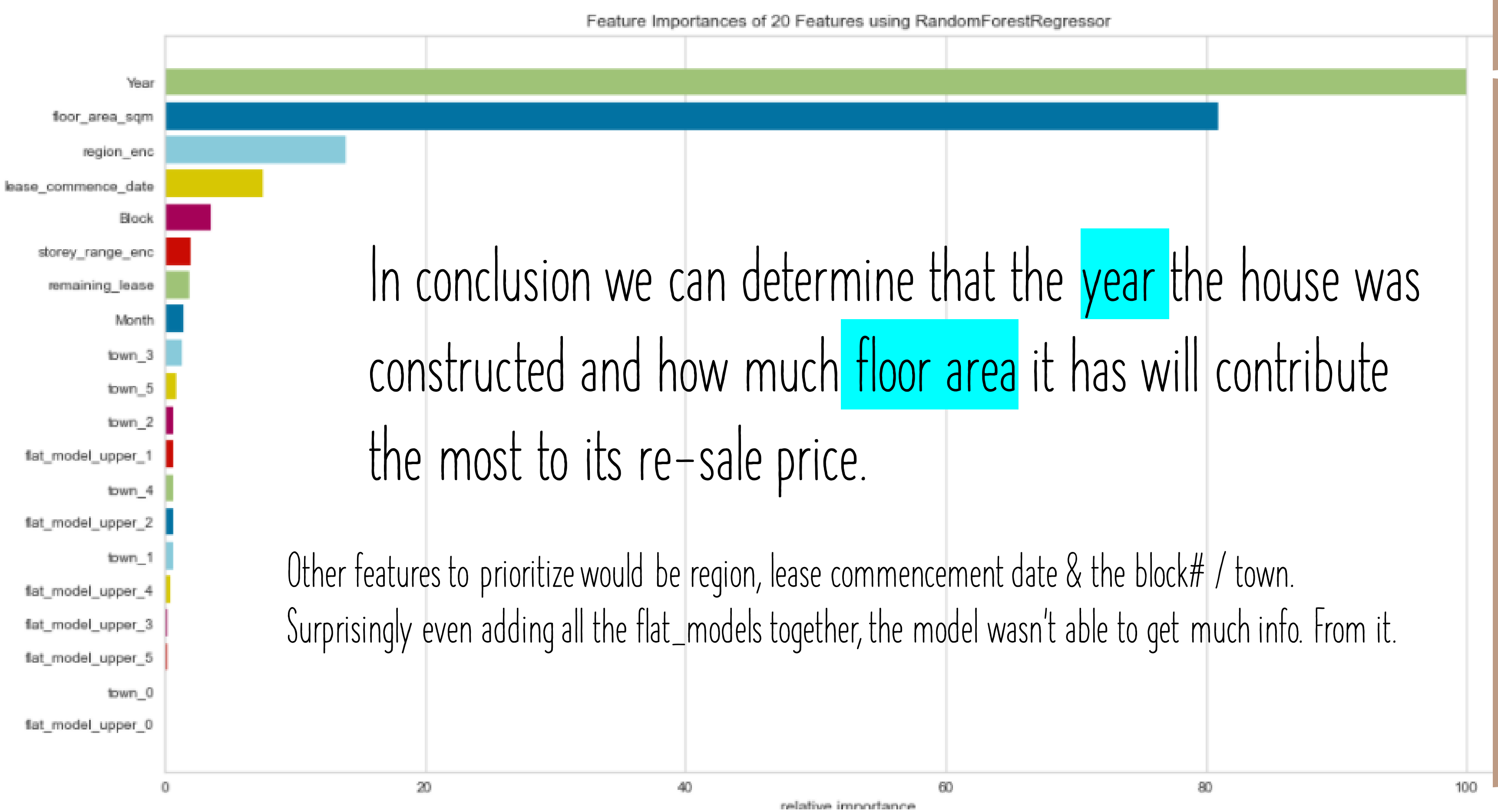


This graph plots predictions against actual results to show how accurate the model is

on the right u can tell that a linear lasso model isnt doing too well in the regression prediction



ML VISUALIZATIONS



In conclusion we can determine that the year the house was constructed and how much floor area it has will contribute the most to its re-sale price.

Other features to prioritize would be region, lease commencement date & the block# / town.
Surprisingly even adding all the flat_models together, the model wasn't able to get much info. From it.

Ft. Importance:

- relative importance of each feature when making a prediction

the sum of splits over the number of splits (across all tress) that include the feature, proportionally to the number of samples it splits.

CHALLENGES & THOUGHTS

- Challenges
  - Not enough memory, spent hours re-running code only to have it ending in a memory issue. -> lost variables to invert my encoded data.
  - Unable to augment data with features such as nearby MRT / Business park since this varies between the blocks itself and requires on the ground knowledge and/or manual updating / scraping of data
  - Getting better quality data (more features) would also result in the model requiring to be re-trained
- Thoughts
  - Could possibly try minmaxscaler to center the data instead of merely normalizing the data with the standard scaler.
  - Could create a pipeline for ease of ML ops in the future

THE END

https://github.com/lolasery/for_holmusk