DSI Project 2

Ames Housing Data and Kaggle Challenge

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Problem Statement

In this project, we aim to **create and iteratively refine a regression model to predict the price** of a property in Ames, Iowa. This can help to prevent over or under selling, and assist **both prospective buyers and sellers** to reach their goals more effectively.

We will like to better understand which features of a property will potentially increase the sale price of a house, as well as what features may hurt the prospects of a house sale. This information is extremely valuable to **prospective sellers, as they will then be able to carry out targeted improvements** to their home before trying to sell it.

This model can also be **useful to developers** who are looking to develop an area in a certain neighborhood. They will be able to negotiate at a better price with each other during a transaction and achieve a win-win situation.

Available Data

1) We are given 2 datasets, 1 each for training and for testing
   a) The train dataset has 2051 rows, each representing a housing sale, and 81 columns representing different features of the property
   b) The test dataset has 879 rows and 80 columns (minus SalePrice which the model will help us predict)
2) Features include both numeric (lot frontage, lot area) and and categorical variables (sale type, overall quality, overall condition)

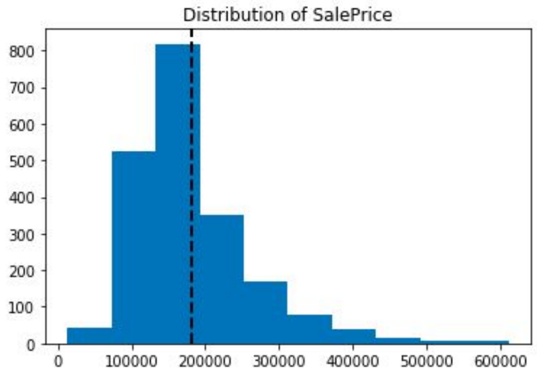
Exploratory Data Analysis

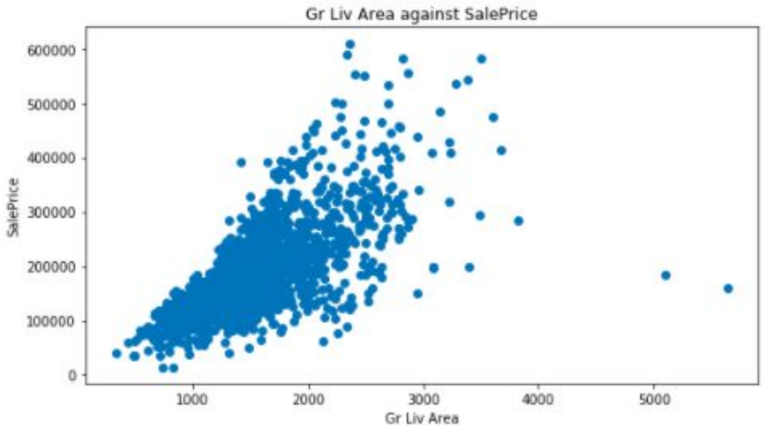
1. Inspecting Data
2. Handling Missing Data
3. Refining Data Types
4. Reviewing of Features
5. Exploratory Visualisations
    a. Distribution of features
    b. Correlation of features

1. Inspecting Data

Potential Outliers

- We compared the ground living area and the sale price. Potential outliers were identified. Apparently, two properties have a very low price for a very large ground living area. So we decided to remove these outliers.





	saleprice	gr liv area
616	284700	3820
960	160000	5642
1885	183850	5095

2. Data Cleaning - Null Values

- The training data came with an abundance of null values.
- For some of the missing nulls we made educated guesses, for examples, entries under Garage-'suffix' were null across the board, which suggested the lack of a garage.
- Larger values of missing nulls indicate more intentionality and would also suggest the lack of- rather than a simple error.
- Using other pieces of data contextually, we could make best guesses for some of the remaining missing values.

Pool QC	2042
Misc Feature	1986
Alley	1911
Fence	1651
Fireplace Qu	1000
Lot Frontage	330
Garage Qual	114
Garage Finish	114
Garage Cond	114
Garage Yr Blt	114
Garage Type	113

Bsmt Exposure	58
BsmtFin Type 2	56
Bsmt Cond	55
Bsmt Qual	55
BsmtFin Type 1	55
Mas Vnr Type	22
Mas Vnr Area	22
Bsmt Half Bath	2
Bsmt Full Bath	2
Garage Cars	1
Garage Area	1
Total Bsmt SF	1
Bsmt Unf SF	1
BsmtFin SF 2	1

2. Imputing Missing Data - Garage Year Built?

- Data on Garages seems to show that missing data is due to absence of feature
- There are multiple ways to handle the data for ‘Year Built’

```python
def Garage_Age(date):

    if date == 'NA':
        age = 0

    elif date < 1950:
        age = 1

    elif date < 1960:
        age = 2

    elif date < 1970:
        age = 3

    elif date < 1980:
        age = 4

    elif date < 1990:
        age = 5

    elif date < 2000:
        age = 6

    else:
        age = 7

    return age
```

3. Refining Data Types

There are three type of data in the data sets:

1) Nominal
2) Ordinal
3) Continuous

Methods used to refine:

1) One Hot Encoding for Nominal Data
2) Binarizing Ordinal Data

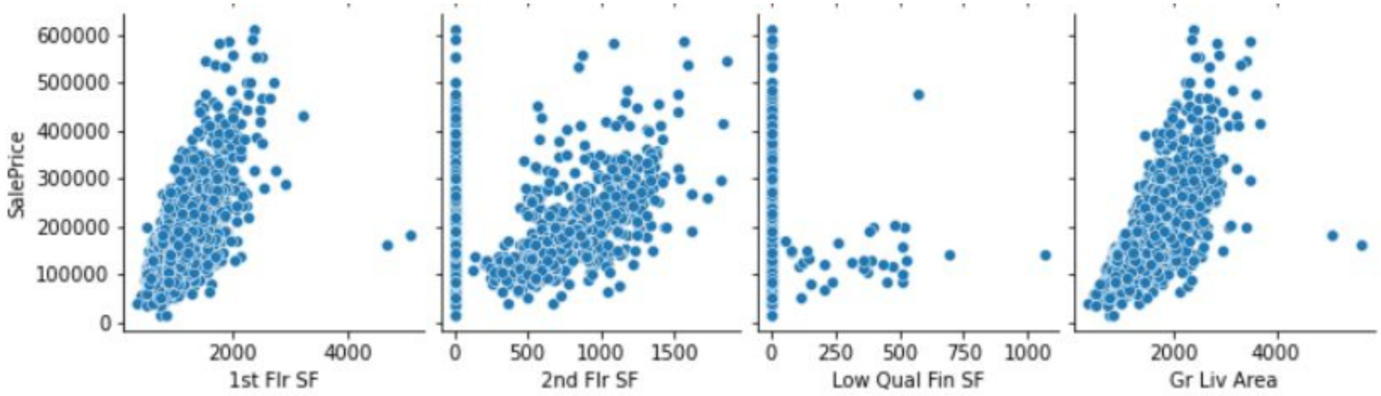
```
#Apply dummies to the below features
train = pd.get_dummies(train, columns=['ms subclass','ms zoning',
                                       'lot config','neighborhood','condition 1',
                                       'bldg type','house style',
                                       'roof style','exterior 1st',
                                       'exterior 2nd','foundation',
                                       'sale type','lot shape',
                                       'land contour','mas vnr type',
                                       'garage type'],drop_first=True)
```

```
housing.replace(to_replace = {
    'Bsmt Cond': {'Ex': 5, 'Gd': 4, 'TA':3, 'Fa':2, 'Po': 1, 'NA': 0},
    'Bsmt Exposure': {'Gd': 4, 'Av':3, 'Mn':2, 'No': 1, 'NA': 0},
    'Bsmt Qual': {'Ex': 5, 'Gd': 4, 'TA':3, 'Fa':2, 'Po': 1, 'NA': 0},
    'BsmtFin Type 1': {'GLQ': 6, 'ALQ': 5, 'BLQ': 4, 'Rec': 3, 'LwQ': 2, 'Unf': 1, 'NA': 0},
    'BsmtFin Type 2': {'GLQ': 6, 'ALQ': 5, 'BLQ': 4, 'Rec': 3, 'LwQ': 2, 'Unf': 1, 'NA': 0},
    'Electrical': {'SBrkr': 4, 'FuseA': 3, 'FuseF':2, 'FuseP':1, 'Mix': 0},
    'Exter Cond': {'Ex': 4, 'Gd': 3, 'TA':2, 'Fa':1, 'Po': 0},
    'Exter Qual': {'Ex': 4, 'Gd': 3, 'TA':2, 'Fa':1, 'Po': 0},
```

4. Reviewing of Features

- Distribution
- Correlation

	1st Flr SF	2nd Flr SF	Low Qual Fin SF	Gr Liv Area	SalePrice
1st Flr SF	1.000000	-0.284643	-0.025900	0.524200	0.655012
2nd Flr SF	-0.284643	1.000000	-0.011392	0.661448	0.251401
Low Qual Fin SF	-0.025900	-0.011392	1.000000	0.070367	-0.047147
Gr Liv Area	0.524200	0.661448	0.070367	1.000000	0.727456
SalePrice	0.655012	0.251401	-0.047147	0.727456	1.000000

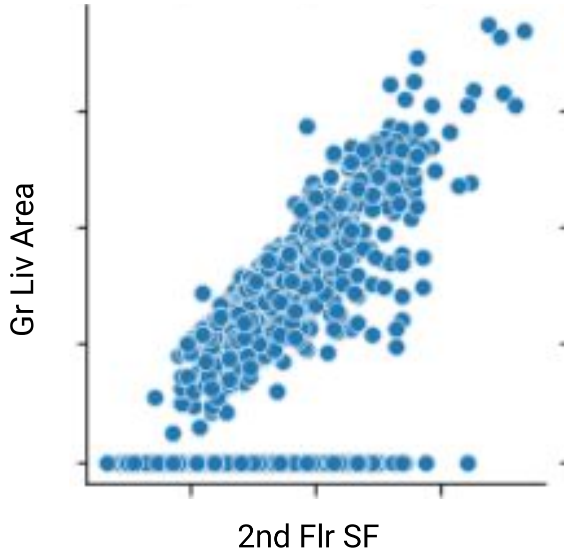


Feature Engineering - Total living Area and 2nd Flr Area

- There is a strong correlation between total living area and 2nd floor area

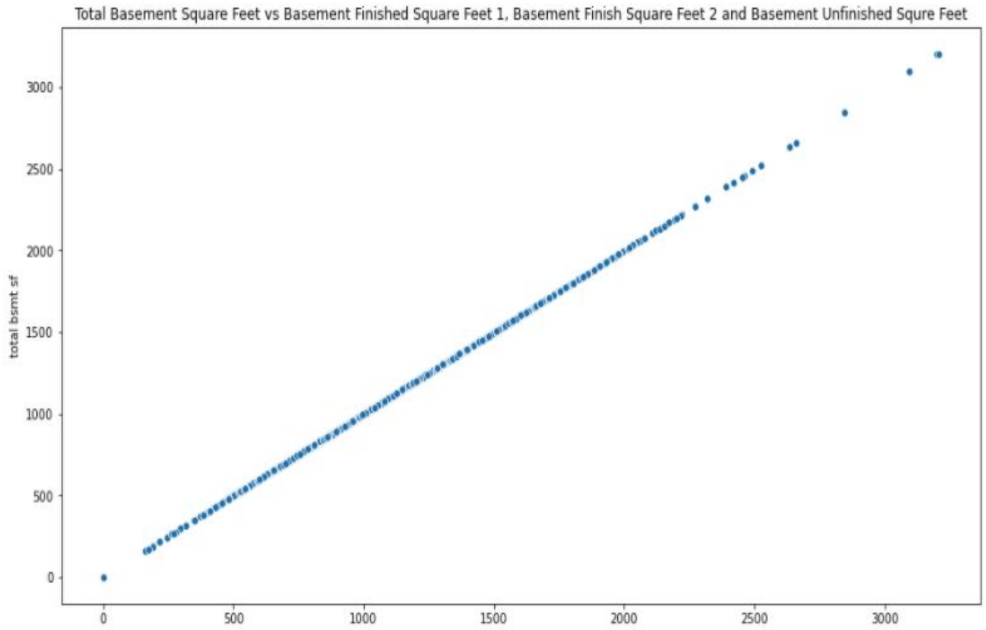
- We created an interaction term between the two of them by multiplying the columns together

	1st Flr SF	2nd Flr SF
1st Flr SF	1.000000	-0.284643
2nd Flr SF	-0.284643	1.000000
Low Qual Fin SF	-0.025900	-0.011392
Gr Liv Area	0.524200	0.661448
SalePrice	0.655012	0.251401



Feature Engineering - Total Basement SF

- We have grouped some related features together to find the multicollinearity between them.
- An example will be total basement square feet vs basement finished SF 1, basement finish SF 2 & basement unfinished SF.

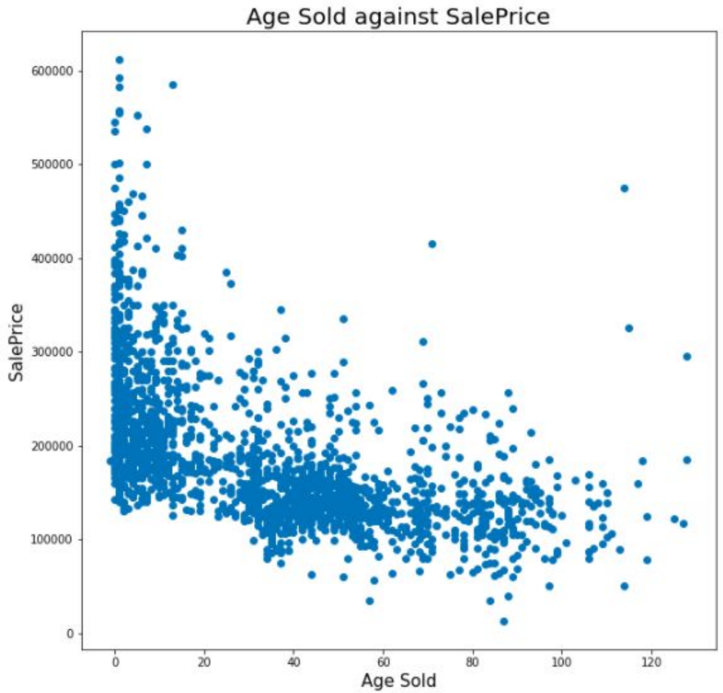


Feature Engineering

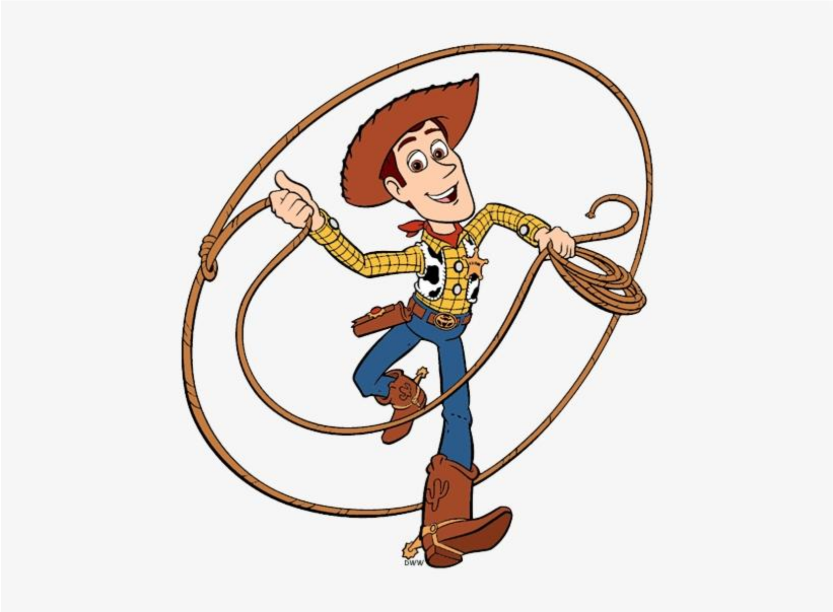
We also used Year Built and Year Sold to compute age of the house at the time of sale

As expected, the new feature seems to be negatively correlated with Sale Price

With Age Sold, we can drop Year Built and Year Sold



Feature Selection - Lasso



Feature Selection - Lasso

- After carrying out some manual feature engineering through EDA, we run a LassoCV model to extract the most significant features.

- We then select ~30 features to run our final model on.

```
In [26]: lasso_coef[lasso_coef['Coef'] != 0]
Out[26]:
```

	Coef
Gr Liv Area	15977.143740
Overall Qual	11375.216542
Total Bsmt SF	8756.170340
BsmtFin SF 1	8643.835651
Gr * 2nd Flr SF	6649.451064
...	...
Bsmt Cond	-2114.511188
Roof Style_Mansard	-2386.959796
Mas Vnr Type_BrkFace	-2622.287293
House Age/Remod	-3304.440763
House Age	-4482.171566

122 rows × 1 columns

Polynomial Featuring

- A group member tried out Polynomial Transform after selecting the top 20 significant features.
- As it turns out, overall quality and living area are great predictors to the sale price of the property.
- Second to that, space in living areas drives property prices.

	cross_lasso_coef
overallqual grlivarea	22332.831999
overallqual totalbsmtsf	11230.168666
exterqual 1stflrsf	9491.450044
grlivarea kitchenqual	9409.077022
bsmtfinsf1 bsmtqual	8398.212179
bsmtqual lotarea	7893.851745
exterqual bsmtfinsf1	7474.638404
garagecars masvnrarea	7149.667280
yearbuilt	6955.356019
neighborhood_nridght masvnrarea	5850.418403
neighborhood_stonebr saletype_new	5526.362356
bsmtexposure masvnrarea	5349.586740
overallqual lotarea	5229.672350
neighborhood_stonebr lotarea	5213.551578
neighborhood_nridght saletype_new	5180.371860
bsmtfinsf1 yearbuilt	4331.471078
bsmtqual totalbsmtsf	4157.320869
kitchenqual lotarea	3878.979819
kitchenqual 1stflrsf	3874.718972
grlivarea exterqual	3367.114289

Polynomial Features

1stflrsf totalbsmtsf	-3050.555350
masvnrarea lotarea	-4584.422594
bsmtfinsf1 1stflrsf	-4588.793175
grlivarea bsmtfinsf1	-4968.495143

Overfitting??

- While this step did seem to improve the predicted values, it resulted in some perplexing coefficient values
- Prediction vs Explainability tradeoff

Model Building

1) Linear Regression Model
2) Lasso Regression Model
3) Ridge Regression Model

All of us attempted the model building using the above methods. Out of the three, all of us went ahead with Lasso Regression Model as it came out with the best R2 and RMSE.

Model Evaluation - Baseline Model

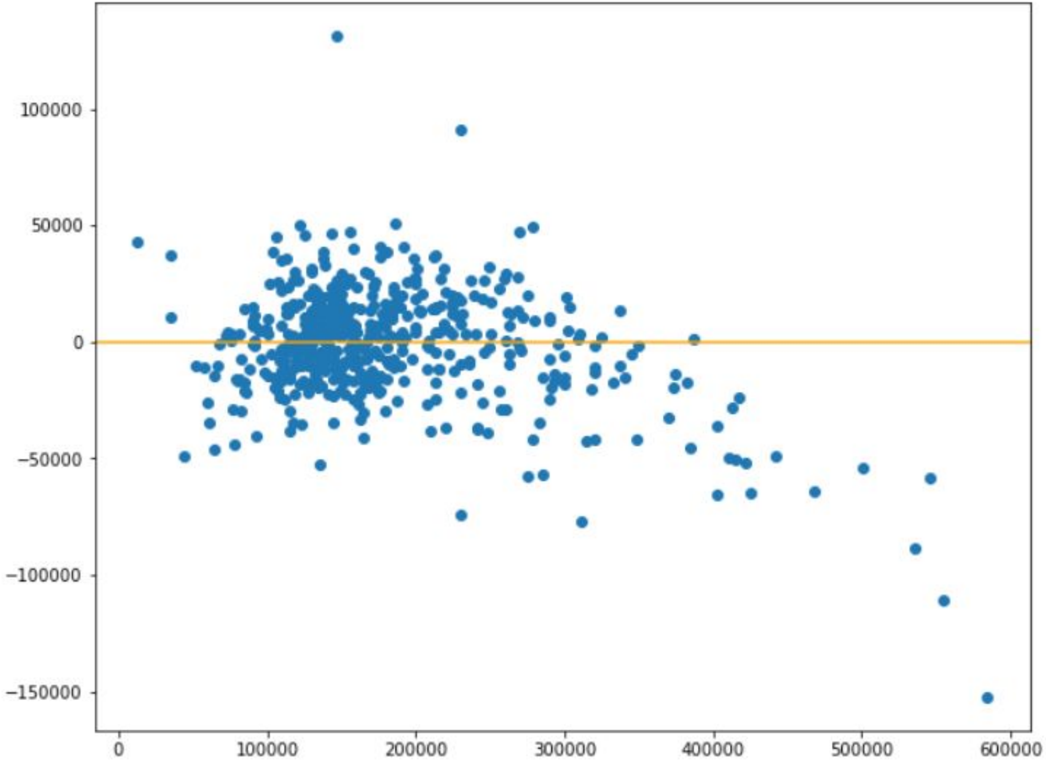
- We create a baseline model that will carry out predictions **before** any feature engineering is done

- This allows us to check if any feature engineering done will improve our predictions or make it worse

Submission and Description	Private Score	Public Score
Projected Prices.csv 41 minutes ago by Ahmad Zaini Chia add submission details	30664.76719	27971.22437
Projected Prices (Baseline).csv 41 minutes ago by Ahmad Zaini Chia	31355.10280	34341.94705

Model Evaluation - Residual Plots

- We carry out predictions on the training data and compare to the actual sale prices
- The house prices between $100 000 and $300 000 are reasonably well predicted
- Beyond that range the predictions are not as accurate



Conclusions

Key Takeaways from the Project:

a) The large amount of null values were very daunting to clean at the start. By breaking down the null values into portions, and observing peripheral data from the dataframe, it made it easier to make an educated guess on how to fill the null values.
b) The EDA gave a better understanding for correlated features, however, feature engineering was responsible for removing most of the features leaving only the strongest correlations.

Recommendations - Features

1. Living area above ground (including 1st and 2nd floor area)
2. Overall material and finish of the house, as well as overall condition and functionality
3. Basement area, how much of it is finished properly, and exposure
4. Contour of land and lot area
5. Age of Garage and how many cars it can fit
6. Exterior quality, Masonry veneer area
7. Kitchen quality
8. Number of fireplaces

Recommendations - Neighbourhoods

Our data shows that the neighborhoods that are preferred by buyers are:

1. Northridge Heights
2. Stone Brook
3. Northridge
4. Crawford

There are a few neighborhoods which buyers seem to less keen on:

1. North Ames
2. Old Town
3. Edwards
4. College Creek

	Coef
Gr Liv Area	20939.281837
Overall Qual	12696.495431
Neighborhood_NridgHt	9774.751251
Kitchen Qual	6061.871298
Neighborhood_StoneBr	6007.745054
Exter Qual	5849.265761
1st Flr SF	5209.239407
Bldg Type_1Fam	5048.036571
Bsmt Exposure	4949.408384
Neighborhood_NoRidge	4328.878574
Sale Type_New	3894.979859
BsmtFin SF 1	3621.771796
Misc Feature_Gar2	3607.479906
Mas Vnr Area	3182.515499
Overall Cond	3138.471337
Garage Cars	3088.840744
Bsmt Full Bath	3030.032085

Exterior 1st_BrkFace	2788.488703
Screen Porch	2767.753589
Roof Matl_WdShngl	2639.956252
Neighborhood_Crawfor	2520.936241
Misc Feature_Othr	2464.757324
Fireplaces	2352.464453
Bsmt Qual	2081.423146
Functional	2071.796310
Roof Style_Hip	2017.793792
Land Contour_HLS	1951.775606
BsmtFin Type 1	1839.864386
Neighborhood_Somerst	1802.577985
Garage Area	1790.953199
Condition 1_Norm	1526.961079
Pool QC	-3322.206877
House Age	-4586.816286
Misc Val	-8406.758079

Improvements

1) More features can included such as nearest public transportation, how many times the property had been switched hands and etc…

2) Additionally, the focus of the project could be switched, since the best predictors tend to be obvious even to a layperson, perhaps studying the 5th-10th best predictors could give developers the means to edge out the competition.
   - E.g Adding a fireplace or a specific roof tile would drive property prices

Is the model generalizable?

- In order for the model to be used widely, the model would need to focus on the more general features such as area, number of rooms that will be readily available across cities.

- Conversely, we will need to go through the exploratory data analysis again to understand the nuances of housing in the particular area and adapt the model accordingly. However, this will require greater resource investment.