Basic feature engineering

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Overview

- Huge topic and, after basic cleaning, this is where you'll spend the most time
- Good features are much more important than the model, assuming you pick good one like RF or gradient boosting

Synthesizing new vars from strings

- Before label encoding, try to derive features from string features
- E.g., Apt data: count words in description or number of features or derive column indicating apt has a doorman, garage, …

description	features
Top Top West Village location, beautiful Pre-w...	[Laundry In Building, Dishwasher, Hardwood Flo...
Building Amenities - Garage - Garden - fitness...	[Hardwood Floors, No Fee]

Simple string computations

- First normalize

```
df['description'] = df['description'].fillna('')
df['description'] = df['description'].str.lower()
df['features'] = df['features'].fillna('')
df['features'] = df['features'].str.lower()
```

- Then, identify key words or subphrases

```
df[‘doorman’] = df['features'].str.contains(‘doorman’)
…
```

doorman	parking	garage	laundry
False	False	False	False
True	False	False	False
False	False	False	True

Deriving numeric columns

- Longer feature list, description, num photos could be predictive

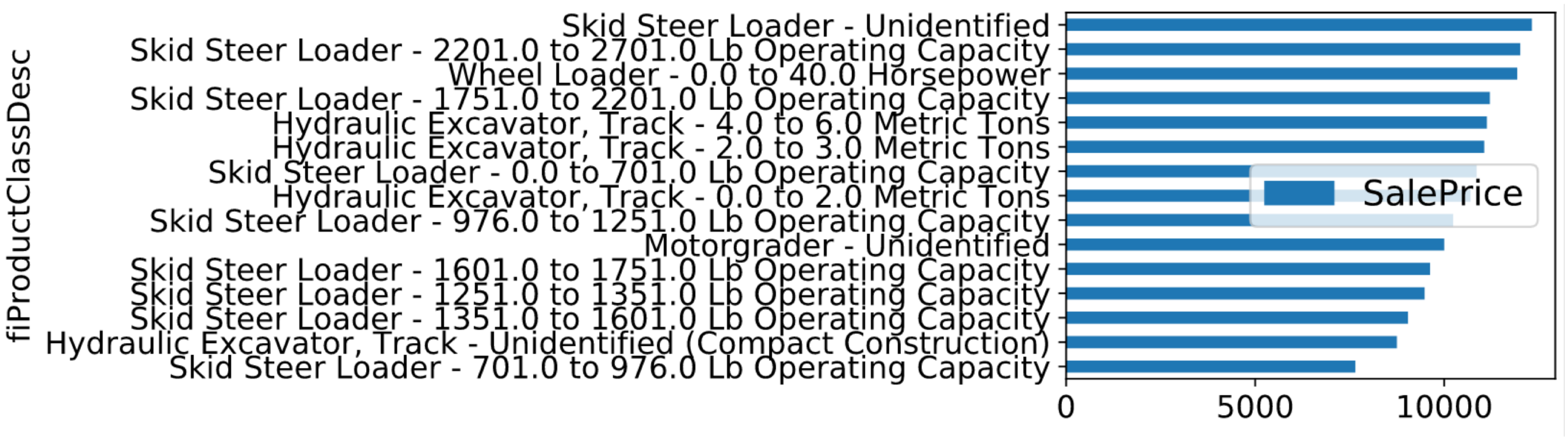
```
df["num_desc_words"] = df["description"].apply(lambda x: len(x.split()))
df["num_features"]   = df["features"].apply(lambda x: len(x.split(",")))
df["num_photos"]     = df["photos"].apply(lambda x: len(x.split(",")))
```

- Ever have to wait for siblings to take a shower? Maybe there is some predictive power in the ratio of bedrooms to bathrooms

```
df["beds_to_baths"] = df["bedrooms"]/(df["bathrooms"]+1) # avoid div by 0
```

Splitting more complicated strings

- Bulldozers with higher operating capacity get higher prices, according to marginal plot



Splitting product class description string

- We can make the information more explicit by splitting the description into four pieces (and put into 4 new columns):

Track Type Tractor, Dozer - 20.0 to 75.0 Horsepower

description *lower* *upper* *units*

- Description is a categorical variable, chosen from a finite set of categories such as “Skip Steer Loader”
- Lower and upper are numerical features
- Units is a category, such as “Horsepower”

Mechanics for splitting strings

- First split into description and spec on ‘-’ char
- Then use regex to extract lower, upper, units

Track Type Tractor, Dozer - 20.0 to 75.0 Horsepower

description *lower* *upper* *units*

```
df_split = df_raw.fiProductClassDesc.str.split(' - ',expand=True)
df['fiProductClassDesc'] = df_split.values[:,0]
df['fiProductClassSpec'] = df_split[:,1] # temporary column
…
pattern = r'([0-9.\+]*)(?: to ([0-9.\+]*)|\+) ([a-zA-Z ]*)’
df_split = df['fiProductClassSpec'].str.extract(pattern, expand=True)
```

For details see https://mlbook.explained.ai/bulldozer-feateng.html

Injecting external data

- Sometimes we can inject data from outside our provided data set to increase model performance
- E.g., if sales for a store are 0, maybe that day was a national holiday or there was a hurricane
- E.g., GPS location is important for rent price, but maybe proximity to cool neighborhood is stronger / more precise?
- E.g., home sales could be affected by many factors external to data set; what is consumer confidence? How many IPOs recently? What is unemployment rate? Emigration rate for area?

Injecting external neighborhood info

- Rent data set has longitude and latitude coordinates, but a more obvious price predictor would be a categorical variable identifying the neighborhood, though, a numeric feature might be more useful
- Use proximity to desirable neighborhoods as a numeric feature
- Forbes magazine has an article with neighborhood names; using a mapping website, we can estimate GPS for them
- Compute so-called *Manhattan distance* (also called *L1 distance*) from each apartment to each neighborhood center

Injecting L1 proximity mechanics

- Iterate over neighborhoods and use vector math to compute new column per neighborhood

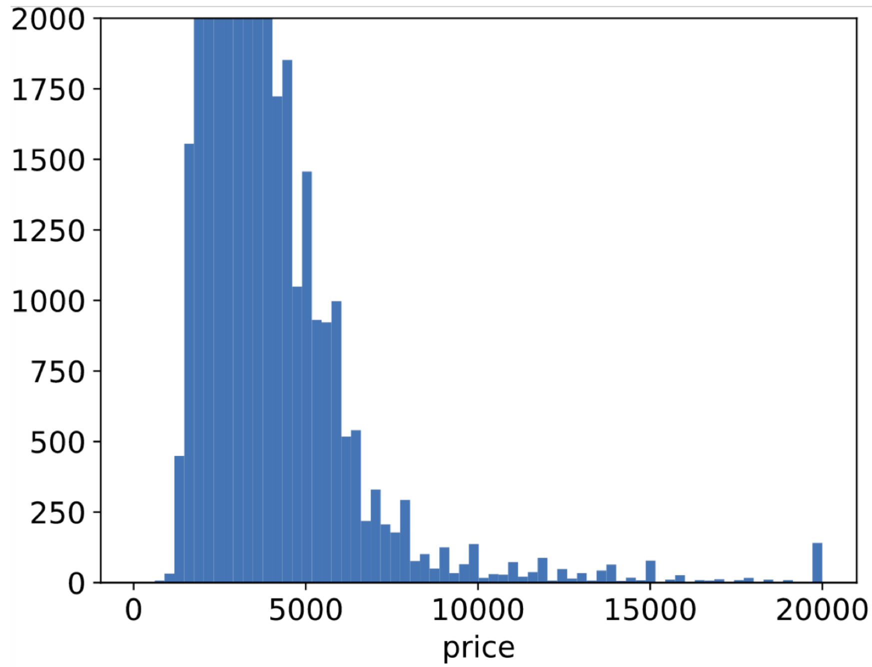
```
hoods = {
    "hells"   : [40.7622, -73.9924],
    "astoria" : [40.7796684, -73.9215888], … }
for hood,loc in hoods.items():
    # compute manhattan distance
    df[hood] = np.abs(df.latitude - loc[0]) + \
               np.abs(df.longitude - loc[1])
```

- BTW, dropping longitude and latitude and retraining a model shows a similar OOB score and shallower trees in my tests

Log in, exp out for regression

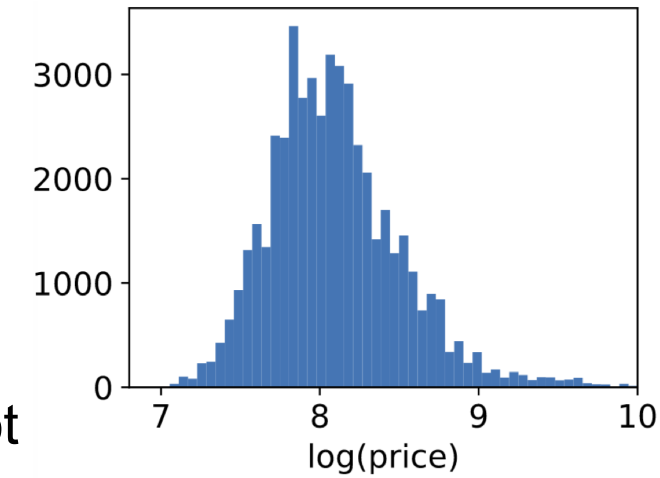
(Could be considered a part of data cleaning)

- Apt rent: consider distribution of prices clipped to less than $20,000 and zoomed in
- There's a very long right tail, which skews RF predictions based upon mean of leaf y's and also training based upon MAE/MSE
- Many target y, such as prices, are best compared as ratios and long tail makes MAE/MSE subtraction even more wonky



Transforming the target variable

- Goal: a tighter, more uniform target space
- Optimally, the distribution of prices would be a narrow "bell curve" distribution without tail
- Even restricted to $1k..$10k it's still skewed
- Check out what **log** does to distribution of ALL prices, not just < $20k! (shrinks large values a lot and smaller values a little)
- Max price drops from millions to 10 without having to think or clip prices
- RF on unclipped prices gets R^2~=0, but RF trained on log(unclipped price) gets R^2~=0.87



- Recall subtraction in log dollars domain is a ratio in dollar domain
- Training with MSE therefore compares squared ratio of y to $\hat{y}$

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Effect on target space

```
y_pred_log = rf.predict(X_test)
y_pred = np.exp(y_pred_log)
```

- Revisit small region of New York City with outliers
- RF on raw prices predicts $358,575
- RF on log(price) predicts 9.92 (in log $)
- Transform predicted price back to $ space with exp => $20,395
- Average in the log price space is less sensitive to outliers

	bedrooms	bathrooms	street_address	price	log(price)
39939	1	1	west 54 st & 8 ave	2300	7.7407
21711	1	1	300 West 55th Street	2400	7.7832
15352	1	1	300 West 55th Street	3350	8.1167
48274	1	1	300 West 55th Street	3400	8.1315
29665	1	1	333 West 57th Street	1070000	13.8832
30689	1	1	333 West 57th Street	1070000	13.8832