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Feature Engineering Cookbook for Machine Learning

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12-15 minutes

When it comes to classic ML feature engineering is one if not the most important factors to improving your scores and speeding up your model without even bothering to tune or get fancy with your model.

There is not a lot of resources and books out there that cover feature engineering in depth, so I wanted to compile a list of code snippets covering most of the techniques I found online and used over time that were critical to most of the projects I worked on. These techniques mostly apply to decision tree and regression-type models (not deep learning).

My goal here was to give the coding examples and not cover the ins and outs on how each technique works and how they impact various models metrics, I am assuming you already heard of most of these techniques and that you will experiment to discover what works best for each project you're working on.

If I missed anything, please mention it in the comments, and I will update the post with a mention.

I use the following datasets in this post:

- Titanic

- News articles

I uploaded everything to this GitHub repo: https://github.com/michaelabehsera/feature-engineering-cookbook

```
%matplotlib inline
import pandas as pd
import numpy as np
import missingno as msno
from numpy import random
import matplotlib.pyplot as plt
```

Let's take a look at how many null values there are in each column. It seems `Age` and `Cabin` are the most commonly-null features. We will focus on replacing null values for `Age`.

```
df.isnull().sum()PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Mean/Median Imputation

```
df['Age'].fillna((df['Age'].mean()),
inplace=True)
df['Age'].fillna((df['Age'].median()),
inplace=True)
```

```
print('Now Age has {} null
values.'.format(df.isnull().sum()['Age']))
```

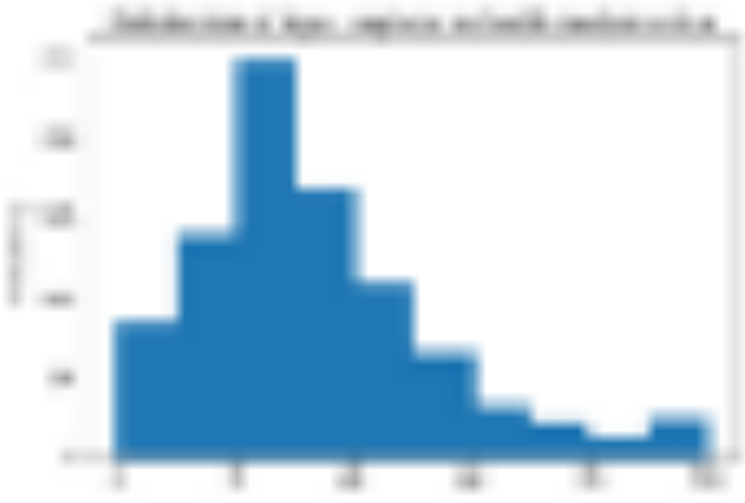
Replacing with 0 or -1

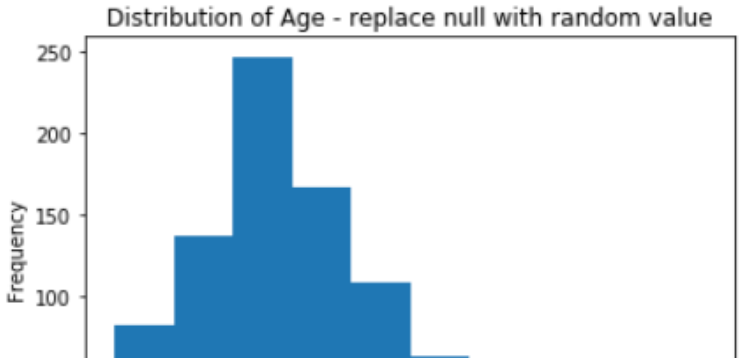
```
df['Age'].fillna(value=0, inplace=True)
```

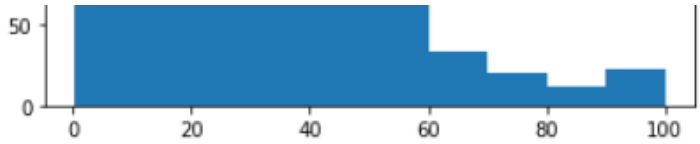
Replacing with a Random Number. Random Sampling Imputation

We can replace age with random numbers between 1 and 100 as follows.

```
null_rows = df['Age'].isnull()
num_null_rows = sum(null_rows)rand =
random.randint(1, 101,
size=num_null_rows)df.loc[null_rows, 'Age'] =
randdf['Age'].plot.hist(title='Distribution of
Age - replace null with random value')plt.show()
```







A smarter approach would be to replace Age with random samples from the non-null distribution of Age (as, with the previous approach, we would have generated just as many 99-year-olds as 25-year-olds).

```
rand = np.random.choice(df.loc[~null_rows,
'Age'], replace=True, size=num_null_rows)
df.loc[null_rows, 'Age'] = rand
df['Age'].plot.hist(title='Distribution of Age -
replace null with samples from distribution of
Age')
plt.show()
print('Note the lack of 100 year olds in the
above plot compared to the previous plot.')
```

Indicating Missingness

We could also use an additional 0/1 variable to indicate to our model when Age is missing.

```
df['Age_Missing'] = np.where(df['Age'].isnull(),
1, 0)
```

Imputation of NA by Values at the End of the Distribution

```
df['Age'].fillna(df.Age.mean() + df.Age.std() *
3, inplace=True)
```

Replacing With Values of Your Choosing Based on an Assumption.

```
df['Age'].fillna(value='My Unique Value',
```

```
inplace=True)
```

Using Regression to Impute Attribute Missing Values

We will use these variables to predict missing values for Age (we could use others, but would need to convert from text).

```
from sklearn.linear_model import LinearRegression
numeric_vars = ['Pclass', 'SibSp', 'Parch',
'Fare']
null_rows = df[numeric_vars +
['Age']].isnull().any(1)  # rows where Age or any
feature var. is null
```

Fit regression model to the non-null rows of data, predict the null rows.

```
lr = LinearRegression()
lr.fit(df.loc[~null_rows, numeric_vars],
df.loc[~null_rows, 'Age'])
df.loc[null_rows, 'Age'] =
lr.predict(df.loc[null_rows, numeric_vars])
```

Standard Scaler

```
from sklearn.preprocessing import StandardScalerx
= StandardScaler().fit_transform(x)
```

MinMax Scaler

```
from sklearn.preprocessing import MinMaxScalerx =
MinMaxScaler().fit_transform(x)
```

Robust Scaler

```
from sklearn.preprocessing import RobustScalerx =
RobustScaler().fit_transform(x)
```

Mean/median imputation or random sampling

If we have reasons to believe that the outliers are due to mechanical error or problems during measurement. This means, if the outliers are in nature similar to missing data, then any of the methods discussed for missing data can be applied to replace outliers. Because the number of outliers is in nature small (otherwise they would not be outliers), it is reasonable to use the mean/median imputation to replace them.

Identify Outliers with Quantiles

```
q25 = df['Age'].quantile(0.25)
q75 = df['Age'].quantile(0.75)
IQR = q75 - q25
    # Any value higher than ulimit or below
llimit is an outlier

ulimit = q75 + 1.5*IQR
llimit = q25 - 1.5*IQR
print(ulimit, llimit, 'are the ulimit and
llimit')
print('Imply Age outliers:')
df['Age'][np.bitwise_or(df['Age'] > ulimit,
df['Age'] < llimit)]
```

```
64.8125 -6.6875 are the ulimit and llimit
Imply Age outliers:
```

```
Out[35]: 33     66.0
         54     65.0
         96     71.0
         116    70.5
         280    65.0
         456    65.0
         493    71.0
         630    80.0
         672    70.0
         745    70.0
         851    74.0
         Name: Age, dtype: float64
```

Identify Outliers with Mean

Using the mean and standard deviation to detect outliers should only be done with data that is not very skewed. Age is somewhat skewed so this could be an issue.

```
ulimit = np.mean(df['Age']) + 3 *
np.std(df['Age'])
llimit = np.mean(df['Age']) - 3 *
np.std(df['Age'])
ulimit, llimit#out: (73.248081099510756,
-13.849845805393123)
```

Discretization

```
# Re-read data and fill nulls with mean (could
use other null-filling method)df =
pd.read_csv('train.csv')not_null =
~df['Age'].isnull()# Get the bin edges using
np.histogramnum_bins = 10
_, bin_edges = np.histogram(df['Age'][not_null],
bins=num_bins)# Optionally create labels# labels
= ['Bin_{}'.format(i) for i in range(1,
len(intervals))]
labels = [i for i in range(num_bins)]# Create new
feature with pd.cutdf['discrete_Age'] =
pd.cut(df['Age'], bins=bin_edges, labels=labels,
```

```
include_lowest=True)
```

Trimming

```
# Let's first remove any missing values
df['Age'].fillna((df['Age'].mean()),
inplace=True)# Get the outlier values
index_of_high_age = df[df.Age > 70].index# Drop
them
df = df.drop(index_of_high_age, axis=0)
```

Winsorization (Top Coding Bottom Coding)

```
# Get the value of the 99th percentile
ulimit = np.percentile(df.Age.values, 99)# Get
the value of the 1st percentile (bottom 1%)
llimit = np.percentile(df.Age.values, 1)# Create
a copy of the age variable
df['Age_truncated'] = df.Age.copy()# Replace all
values above ulimit with value of ulimit
df.loc[df.Age > ulimit, 'Age_truncated'] =
ulimit# Replace all values below llimit with
value of llimit
df.loc[df.Age < llimit, 'Age_truncated'] = llimit
```

Rank Transformation (When the Distances Don’t Matter so Much)

```
from scipy.stats import rankdata# This is like
sorting the variable and then assigning an index
starting from 1 to each valuerankdata(df['Age'],
method='dense')
```

One-Hot-Encoding and Pandas Get Dummies

One-Hot-Encoding

```
from sklearn.preprocessing import OneHotEncoder
one =
OneHotEncoder(sparse=False).fit_transform(df[['Parch']])

#Convert transformed column from numpy to a
DataFrame and merge new column with older
one.onecol = pd.DataFrame(one)
results = pd.merge(onecol, df, left_index=True,
right_index=True)
```

Get Dummies

```
# Generally, pd.get_dummies is an easier approach
to one-hot
encodingpd.get_dummies(df['Sex']).head()
```

Dropping First

In models which use all features at once (most models apart from tree ensemble models, etc), it is wise to drop the first dummy variable, as it can be derived from the others (e.g. here we know if someone is Female based on whether they are Male, so we can drop Female).

```
df['Male'] = pd.get_dummies(df['Sex'],
drop_first=True)
```

Mean Encoding

We calculate the mean of the target variable for each class of the variable we wish to encode and replace that variable by these means.

```
# Calculate the mean encodingmeans_pclass =
df[['Survived']].groupby(df['Pclass']).apply(np.mean)
means_pclass.columns = ['Mean Encoding']
means_pclass# Merge the encoding into our
```

```
dataframe (by matching Pclass to the index of our
prob. ratio dataframe)df = pd.merge(df,
means_pclass, left_on=df.Pclass,
right_index=True)
```

Probability Ratio Encoding

```
def probability_ratio(x):
    probability_eq_1 = np.mean(x)
    probability_eq_0 = 1.0 - probability_eq_1
    return probability_eq_1 / probability_eq_0#
Calculate the probability ratio encoding
prob_ratios_pclass =
df[['Survived']].groupby(df['Pclass']).apply(lambda
x: probability_ratio(x))
prob_ratios_pclass.columns = ['Prob Ratio
Encoding']
prob_ratios_pclass# Merge the encoding into our
dataframe (by matching Pclass to the index of our
prob. ratio dataframe)
df = pd.merge(df, prob_ratios_pclass,
left_on=df.Pclass, right_index=True)
df.head()
```

Weight of Evidence Encoding

```
def weight_of_evidence(x):
    probability_eq_1 = np.mean(x)
    probability_eq_0 = 1.0 - probability_eq_1
    return np.log(probability_eq_1 /
probability_eq_0)# Calculate the probability
ratio encodingwoe_pclass =
df[['Survived']].groupby(df['Pclass']).apply(lambda
x: weight_of_evidence(x))
```

```
woe_pclass.columns = ['WOE Encoding']
woe_pclassdf = pd.merge(df, woe_pclass,
left_on=df.Pclass, right_index=True)
```

Label Encoding

Cat.codes

```
# You can use cat.codes to convert the variable
into a binary onedf['Sex'] =
df['Sex'].astype('category')# Cat.codes only
works if the dtype is
'category'df['Sex'].cat.codes.head()
```

Factorize

Also achieves a similar end to `cat.codes`, but gives us the labels of each category.

```
label, val = pd.factorize(df['Sex'])
df['IsFemale'] = label
```

Binary Encoding

#Can also use np.where to specify which values should be 1 or 0, as follows

```
df['Sex_Binary'] =
np.where(df['Sex'].isin(['Male','Female']), 1, 0)
```

Creating Columns Based on Hour/Min…

```
df = pd.read_csv('news_sample.csv')time =
pd.to_datetime(df['time'])
```

Pandas come with packed with DateTime properties which you could check out here: https://pandas.pydata.org/pandas-docs/stable/api.html#datetimelike-properties. You can even get a column with microseconds. Here are some of the ones I use most.

- Month
- Min
- Seconds
- Quarter
- Semester
- Day (number)
- Day of the week
- Hr

```
df[‘Month’] = time.dt.month
df[‘Day’] = time.dt.day
df[‘Hour’] = time.dt.hour
df[‘Minute’] = time.dt.minute
df[‘Seconds’] = time.dt.second
```

Creating an isweekend Column

```
df['is_weekend'] =
np.where(df['Day'].isin([5,6]), 1, 0)
```

We’ve seen that mixed variables are those which values contain both numbers and labels.

How can we engineer this type of variable to use it in machine learning?

What we need to do in these cases is extract the categorical part in one variable and the numerical part in a different variable. Therefore, we obtain 2 variables from the original one.

There is not much to cover here besides giving one fake example.

```
data = ['Apple', 'Banana', '2', '6']lst_strings =
[]
lst_int = []for i in data:
    if i == 'Apple':
```

```
        lst_strings.append(i)
    elif i == 'Banana':
        lst_strings.append(i)
    if i == '2':
        lst_int.append(int(i))
    elif i == '6':
        lst_int.append(int(i))
```

Let's say there is a small % of values within a large group of categories in a feature, you can grab them and call them “other” in order to reduce the values in the dataset and potentially reduce overfitting.

These observations can be re-categorized by:

- Replacing the rare label by most frequent label
- Grouping the observations that show rare labels into a unique category (with a new label like ‘Rare’, or ‘Other’)

Replacing the Rare Label by Most Frequent Label

```
val_counts = df['Age'].value_counts()
uncommon_ages =
val_counts[val_counts<3].index.values
most_freq_age = val_counts.index[0]
df.loc[df['Age'].isin(uncommon_ages), 'Age'] =
most_freq_age
```

Grouping the Observations that Show Rare Labels Into a Unique Category (With a New Label like ‘Rare’, or ‘Other’)

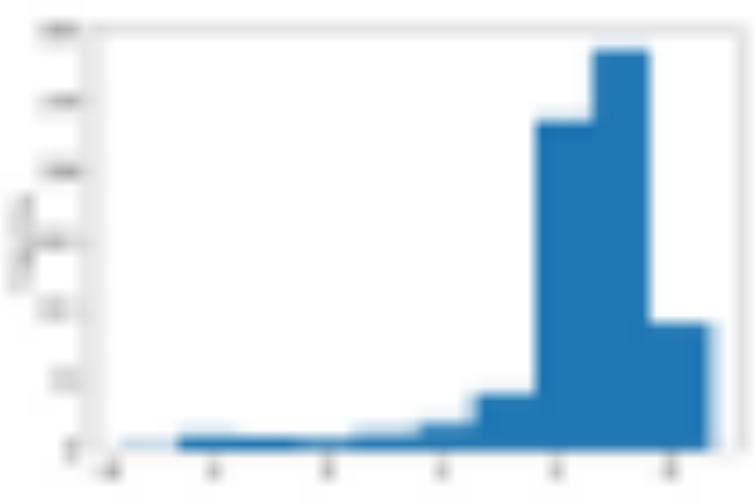
```
val_counts = df['Age'].value_counts()
uncommon_ages =
val_counts[val_counts<3].index.values
df.loc[:, 'Age_is_Rare'] = 0
```

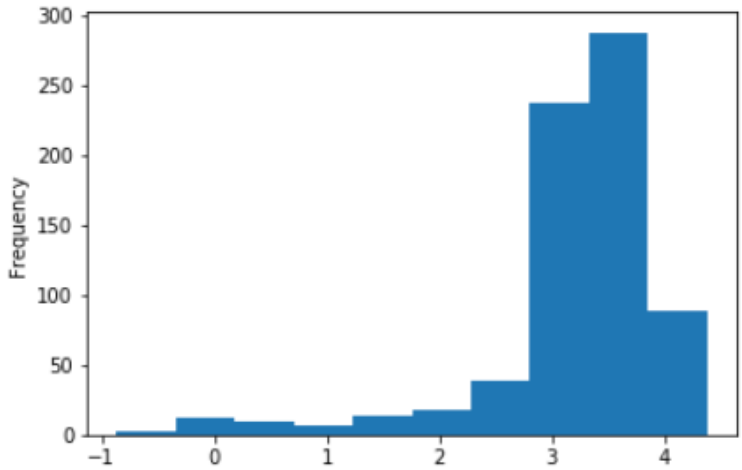
```
df.loc[df['Age'].isin(uncommon_ages),
'Age_is_Rare'] = 1
df.loc[:, 'Age_is_Rare'].head()
```

Particularly for linear models, it can be useful to transform input features (or the target) prior to fitting the model, such that their distribution appears normal, or approximately normal (i.e. symmetric and bell-shaped).

Gaussian Transformation

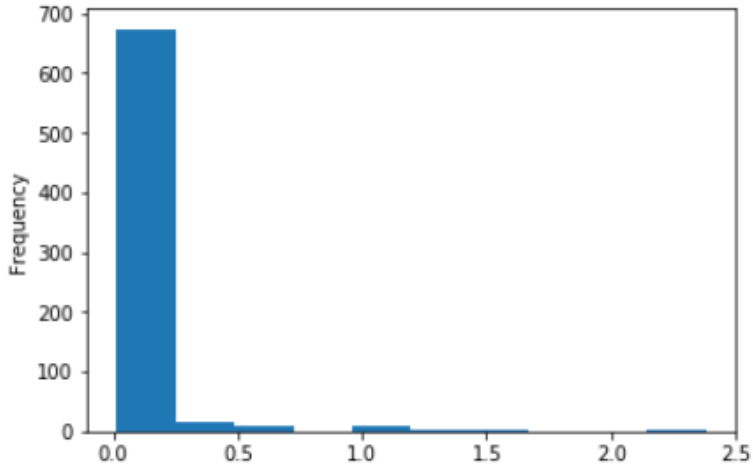
```
df['Age'].plot.hist()df['Age Log'] =
df['Age'].apply(np.log)df['Age Log'].plot.hist()
```





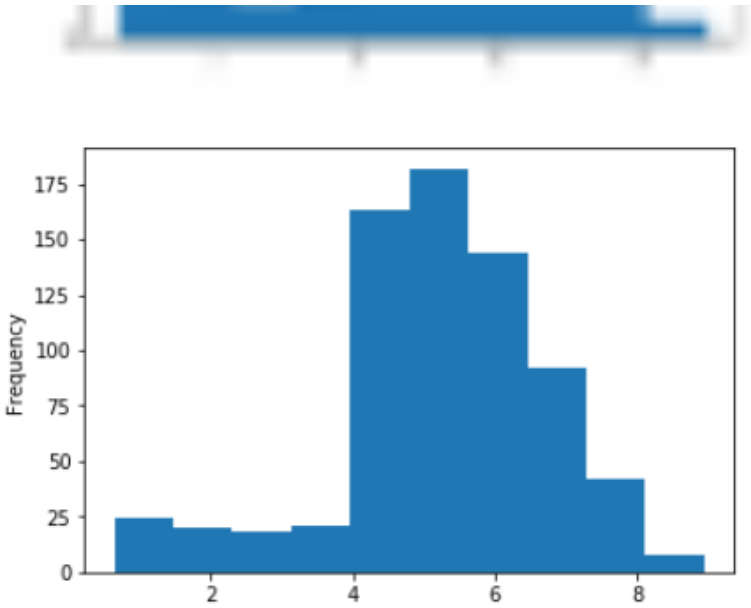
Reciprocal Transformation

```
df['Age Reciprocal'] = 1.0 / df['Age']df['Age
Reciprocal'].plot.hist()
```



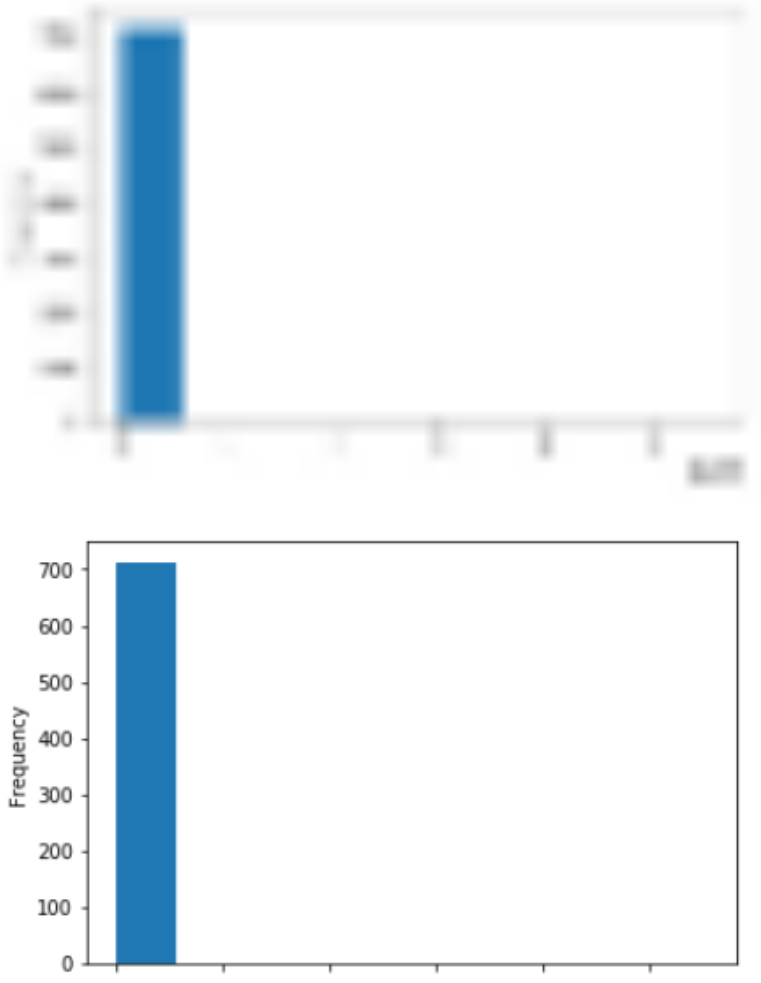
Square Root Transformation

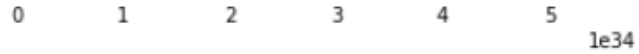
```
df['Age Sqrt'] = np.sqrt(df['Age'])df['Age
Sqrt'].plot.hist()
```



Exponential Transformation

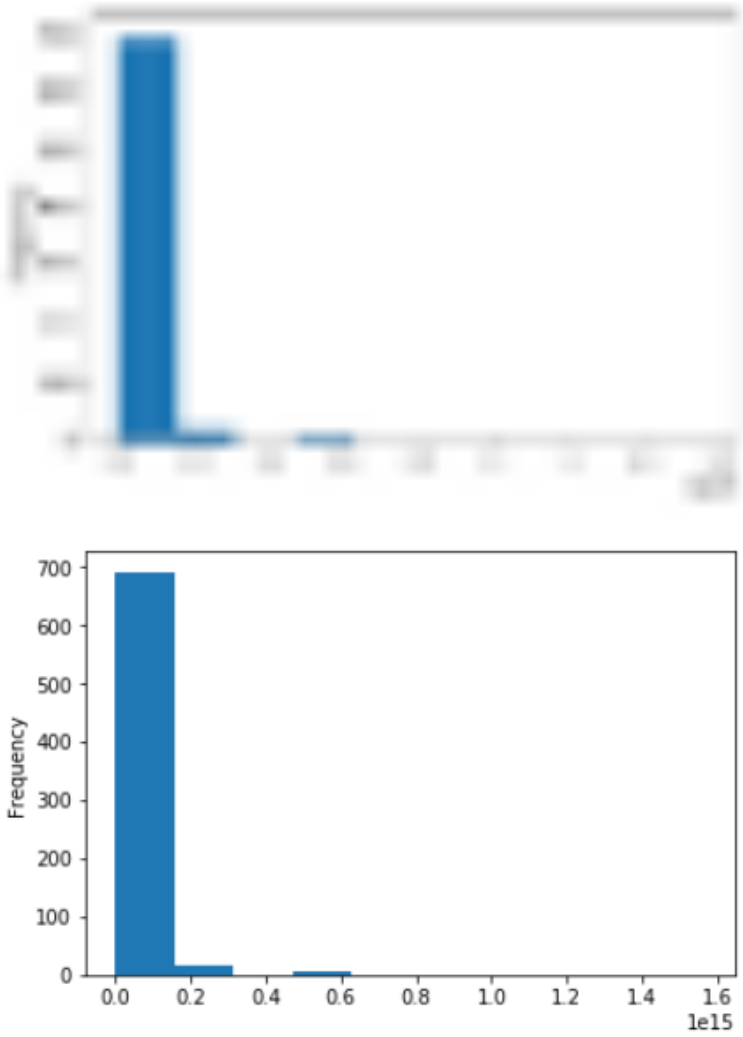
```
df['Age Exp'] = np.exp(df['Age'])df['Age
Exp'].plot.hist()
```





Boxcox Transformation

```
from scipy.stats import boxcoxdf['Age BoxCox'] =
boxcox(df['Age'])[0]
df['Age BoxCox'].plot.hist()
```



Perhaps, for example, older passengers who also paid a higher fare had a *particularly* high chance of not surviving on the Titanic. In such a case we would call that an *interaction* effect between `Age` and `Fare`. To help our model take account of this interaction effect, we can add a new variable `Age * Fare`.

```
df = pd.read_csv('train.csv')df['Age_x_Fare'] =
df['Age'] * df['Fare']
```

This is of course just one example of an interaction feature, this is a powerful technique and could use some creativity on your part based on the dataset you're dealing with.