Elements Of Data Science - F2020

Week 8: Data Cleaning and Feature Engineering

11/9/2020

TODOs

- Readings:
    - PDSH 5.9 PCA
    - [Recommeded] PML Ch 8

- HW2, Due Thurs Nov. 12th, 11:59pm

- Answer and submit Quiz 8, **Sunday Nov 15th, 11:59pm ET**

Today

- **Data Cleaning**
  - Duplicates
  - Missing Data
  - Dummy Variables
  - Rescaling
  - Dealing With Skew
  - Removing Outliers
- **Feature Engineering**
  - Binning
  - One-Hot encoding
  - Derived
  - Unstructured Data: Natural Language Processing

Questions?

Data Cleaning

Why do we need clean data?

- Want one row per observation (remove duplicates)
- Most models cannot handle missing data (remove/fill missing)
- Most models require fixed length feature vectors (engineer features)

- Different models require different types of data (transformation)
  - Linear models: real valued features with similar scale
  - Distance based: real valued features with similar scale
  - Tree based: can handle real and categorical

Example Data and `.info()`

In [2]:
```
# read in example data
df_shop = pd.read_csv('../data/flowershop_data_with_dups.csv',
                      header=0,
                      parse_dates=['purchase_date'],
                      delimiter=',')

df_shop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   purchase_id      1001 non-null   int64
 1   lastname         1001 non-null   object
 2   purchase_date    1001 non-null   datetime64[ns]
 3   stars            1001 non-null   int64
 4   price            979 non-null    float64
 5   favorite_flower  823 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 47.0+ KB
```

Duplicated Data

- Only drop duplicates if you know data should be unique
  - Example: if there is a unique id per row

In [3]:
```
df_shop.duplicated().iloc[:3] # are first 3 rows duplicates?
```

Out[3]:
```
0    False
1    False
2    False
dtype: bool
```

In [4]:
```
df_shop[df_shop.duplicated(keep='first')] # default keep first duplicated row
```

Out[4]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
1000	1010	FERGUSON	2017-05-04	2	21.0183	daffodil

In [5]:
```
df_shop[df_shop.duplicated(keep=False)] # keep=False to show all duplicated rows
```

Out[5]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
10	1010	FERGUSON	2017-05-04	2	21.0183	daffodil
1000	1010	FERGUSON	2017-05-04	2	21.0183	daffodil

Duplicated Data for Subset of Columns

In [6]:
```
df_shop[df_shop.duplicated(subset='purchase_id',keep=False)].sort_values(by='purchase_id')
```

Out[6]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
10	1010	FERGUSON	2017-05-04	2	21.018300	daffodil
1000	1010	FERGUSON	2017-05-04	2	21.018300	daffodil
100	1101	WEBB	2017-07-13	2	8.004356	iris
101	1101	BURKE	2017-08-16	4	18.560260	daffodil

Dropping Duplicates

In [7]:
```
df_new = df_shop.drop_duplicates(subset=None     # consider subset of columns
                                 ,keep='first'   # or 'last' or False)
                                 ,inplace=False)
```

In [8]:
```
# or can use inplace to change the original dataframe
df_shop.drop_duplicates(subset=None,keep='first',inplace=True)
```

In [9]:
```
# drop rows with duplicates considering only a subset of columns
df_shop = df_shop.drop_duplicates(subset=['purchase_id'])
```

Missing Data

- Reasons for missing data
  - Sensor error (random?)
  - Data entry error (random?)
  - Survey-subject decisions (non-random?)
  - etc.

- Dealing with missing data
  - Drop rows
  - Impute from data in the same column
  - Infer from other features
  - Fill with adjacent data

Missing Data in Pandas: `np.nan`

- Missing values represented by `np.nan` : Not A Number

In [10]:
```python
# Earlier, we saw missing values in the dataframe summary
df_shop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 999 entries, 0 to 999
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   purchase_id      999 non-null    int64
 1   lastname         999 non-null    object
 2   purchase_date    999 non-null    datetime64[ns]
 3   stars            999 non-null    int64
 4   price            977 non-null    float64
 5   favorite_flower  821 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(2), object(2)
memory usage: 54.6+ KB
```

In [11]:
```python
np.nan == np.nan
```

Out[11]:
```
False
```

`.isna()` and `.notna()`

In [12]:
```
df_shop.loc[20:21,'price']
```

Out[12]:
```
20          NaN
21    10.525912
Name: price, dtype: float64
```

In [13]:
```
# isna returns True where data is missing, False otherwise
df_shop.loc[20:21,'price'].isna()
```

Out[13]:
```
20     True
21    False
Name: price, dtype: bool
```

In [14]:
```
# notna returns True where data is NOT missing, False otherwise
df_shop.loc[20:21,'price'].notna()
```

Out[14]:
```
20    False
21     True
Name: price, dtype: bool
```

In [15]:
```
# find rows where price is missing
df_shop[df_shop.price.isna()].head()
```

Out[15]:

	purchase_id	lastname	purchase_date	stars	price	favorite_flower
20	1020	CLARK	2017-01-05	3	NaN	NaN
41	1041	PETERS	2017-02-01	4	NaN	orchid
54	1054	GREEN	2017-02-13	5	NaN	daffodil
63	1063	BARNETT	2017-08-27	4	NaN	gardenia
145	1145	CARROLL	2017-07-29	3	NaN	tulip

Missing Data: Drop Rows

In [16]:
```
df_shop.shape
```

Out[16]: (999, 6)

In [17]:
```
# drop rows with nan in any column
df_shop.dropna().shape
```

Out[17]: (801, 6)

In [18]:
```
# drop only rows with nan in price using subset
df_shop.dropna(subset=['price']).shape
```

Out[18]: (977, 6)

In [19]:
```
# drop only rows with nans in all columns
df_shop.dropna(how='all').shape
```

Out[19]: (999, 6)

Missing Data: Drop Rows Cont.

In [20]:
```
# save a new dataframe with dropped rows
df_new = df_shop.dropna()
df_new.shape
```

Out[20]:
```
(801, 6)
```

In [21]:
```
# drop rows in current dataframe
df_new = df_shop.copy()
df_new.dropna(inplace=True)
df_new.shape
```

Out[21]:
```
(801, 6)
```

In [22]:
```
# How many total nan's?
df_shop.isna().sum().sum()
```

Out[22]:
```
200
```

Missing Data: Drop Rows

- Pros:
  - easy to do
  - simple to understand
- Cons:
  - potentially large data loss

Missing Data: Impute

- Impute: fill in with some data
- Use .fillna()
- Common filler values:
  - mean
  - median
  - "most frequent"
  - 0

Missing Data: Impute

In [23]:
```
df_shop.price.mean()
```

Out[23]:
```
23.408197893394266
```

In [24]:
```
# make a copy to keep our original df
df_new = df_shop.copy()
```

In [25]:
```
# fill missing price with mean of price
df_new.price = df_shop.price.fillna(df_shop.price.mean())
```

In [26]:
```
# check to make sure all nulls filled
sum(df_new.price.isna())
```

Out[26]:
```
0
```

In [27]:
```
# inplace works here as well
df_new.price.fillna(df_new.price.mean(),inplace=True)
```

In [28]:
```
# can also handle categorical data
df_new.favorite_flower.fillna(df_shop.favorite_flower.mode().iloc[0],inplace=True)
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 999 entries, 0 to 999
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   purchase_id      999 non-null    int64
 1   lastname         999 non-null    object
 2   purchase_date    999 non-null    datetime64[ns]
 3   stars            999 non-null    int64
```

Missing Data: Impute

- Pros:
  - easy to do
  - simple to understand
- Cons:
  - may missing feature interactions

Missing Data: Infer

- Predict values of missing features using a model
- Ex: Can we predict price based on any of the other features?
- Additional feature engineering may be needed prior to this

In [29]:
```
from sklearn.linear_model import LinearRegression

df_tmp = df_shop.copy()

not_missing = df_tmp.price.notna()
missing = df_tmp.price.isna()

lr = LinearRegression().fit(df_tmp.loc[not_missing,['stars']],
                            df_tmp[not_missing].price)

df_tmp.loc[missing,'price'] = lr.predict(df_tmp.loc[missing,['stars']])
```

Missing Data: Adjacent Data

- Use `.fillna()` with method:
    - ffill: propagate last valid observation forward to next valid
    - bfill: use next valid observation to fill gap backwards
- Use when there is reason to believe data not i.i.d. (eg: timeseries)

In [30]:
```
df_shop.price.loc[19:21]
```

Out[30]:
```
19    20.451789
20          NaN
21    10.525912
Name: price, dtype: float64
```

In [31]:
```
df_shop.price.fillna(method='ffill').loc[19:21]
```

Out[31]:
```
19    20.451789
20    20.451789
21    10.525912
Name: price, dtype: float64
```

Missing Data: Dummy Columns

- Data may be missing for a reason!
- Capture "missing" before filling

In [32]:
```
# storing a column of 1:missing, 0:not-missing
df_new['price_isnull'] = df_shop.price.isna().astype(int)

# can now fill missing values
df_new['price'] = df_shop.price.fillna(df_shop.price.mean())
```

Rescaling

- Often need features to be in the same scale
- Methods of rescaling
    - Standardization (z-score)
    - Min-Max rescaling
    - others...

In [33]:

```
# load taxi data
taxi = pd.read_csv('../data/yellow_tripdata_2017-01_subset10000rows.csv',
                   parse_dates=['tpep_pickup_datetime','tpep_dropoff_datetime'])

# create trip_duration
taxi['trip_duration'] = (taxi.tpep_dropoff_datetime - taxi.tpep_pickup_datetime).dt.seconds

# select subset
df_taxi = taxi[(taxi.trip_duration < 3600) & (taxi.tip_amount > 0) & (taxi.tip_amount < 10)]
```

In [34]:

```
df_taxi[['trip_duration','tip_amount']].agg(['mean','std','min','max'],axis=0)
```

Out[34]:

	trip_duration	tip_amount
mean	765.030683	2.405944
std	496.831608	1.552848
min	2.000000	0.010000
max	3556.000000	9.990000

Rescaling: Standardization

- rescale to 0 mean, standard deviation of 1
  - X_scaled = (X - X.mean()) / X.std()

In [35]:
```
from sklearn.preprocessing import StandardScaler

# instantiate
ss = StandardScaler()

# fit to the data
ss.fit(df_taxi[['trip_duration','tip_amount']])

# transform the data
X = ss.transform(df_taxi[['trip_duration','tip_amount']])
X[:2]
```

Out[35]:
```
array([[-0.50127786, -0.48040987],
       [-0.16512088, -0.90546941]])
```

In [36]:
```
df_new = pd.DataFrame(X,columns=['trip_duration_scaled','tip_amount_scaled'])
df_new.agg(['mean','std','min','max'],axis=0)
```

Out[36]:

	trip_duration_scaled	tip_amount_scaled
mean	4.622808e-17	-1.358307e-16
std	1.000080e+00	1.000080e+00
min	-1.535917e+00	-1.543059e+00
max	5.617987e+00	4.884357e+00

Rescaling: Min-Max

- rescale values between 0 and 1
- X_scaled = (X - X.min()) / (X.max() - X.min())
- removes negative values

In [37]:
```
from sklearn.preprocessing import MinMaxScaler

X = MinMaxScaler().fit_transform(df_taxi[['trip_duration','tip_amount']])

df_new = pd.DataFrame(X,columns=['trip_duration_scaled','tip_amount_scaled'])
df_new.agg(['mean','std','min','max'])
```

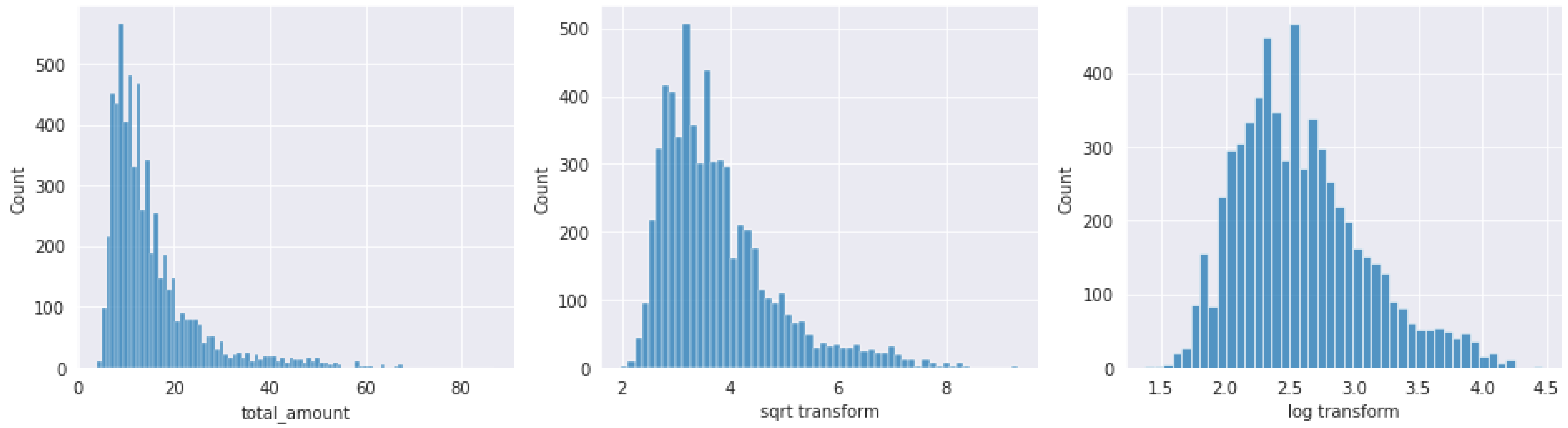
Out[37]:

	trip_duration_scaled	tip_amount_scaled
mean	0.214696	0.240075
std	0.139795	0.155596
min	0.000000	0.000000
max	1.000000	1.000000

Dealing with Skew

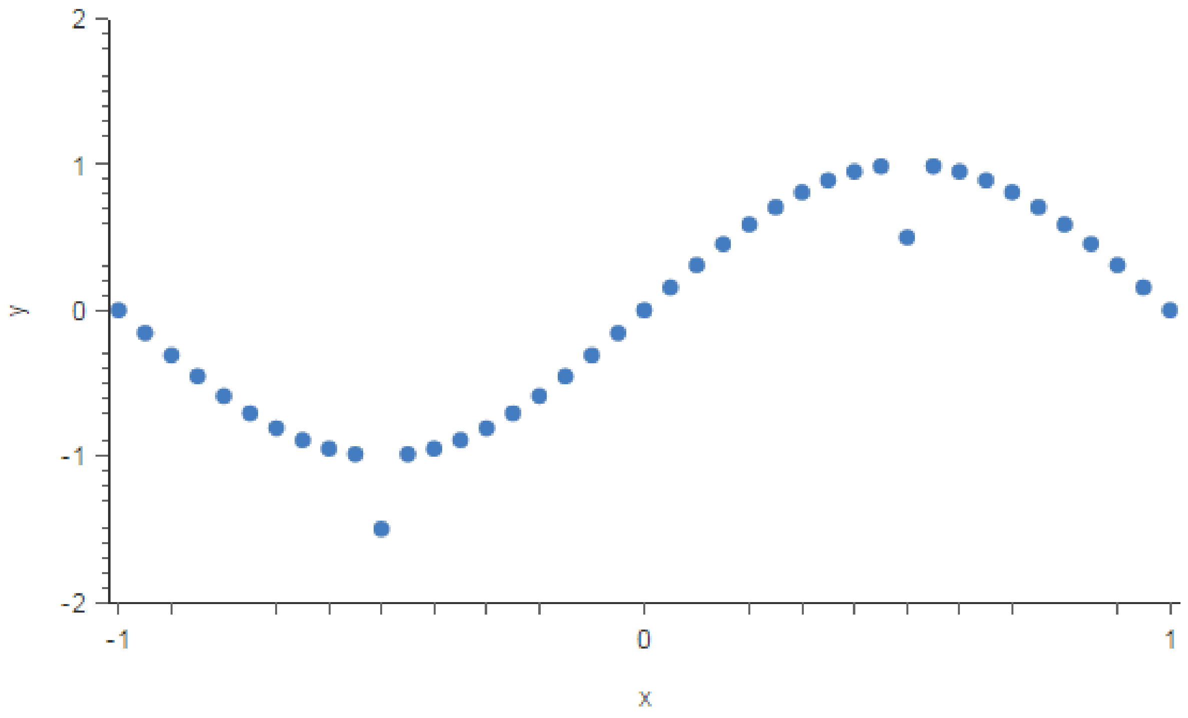
- Many models expect "normal", symmetric data (ex: linear models)
- Highly skewed: tail has larger effect on model (outliers?)
- Transform with `log` or `sqrt`

```
In [38]: fig,ax = plt.subplots(1,3,figsize=(16,4))
         sns.histplot(x=df_taxi.total_amount, ax=ax[0]);
         sns.histplot(x=df_taxi.total_amount.apply(np.sqrt), ax=ax[1]); ax[1].set_xlabel('sqrt transform');
         sns.histplot(x=df_taxi.total_amount.apply(np.log),  ax=ax[2]); ax[2].set_xlabel('log transform');
```



Outliers

- Similar to missing data:
    - human data entry error
    - instrument measurement errors
    - data processing errors
    - natural deviations



Outliers

- Why worry about them?
  - can give misleading results
  - can indicate issues in data/measurement

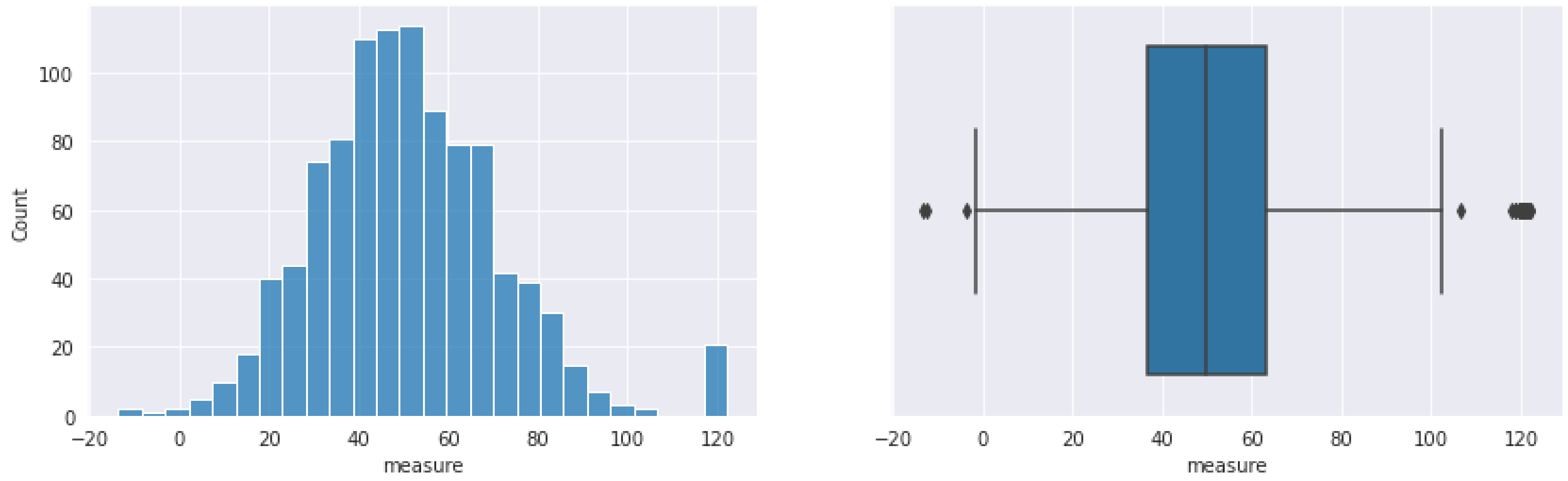
- Detecting Outliers
  - understand your data!
  - visualizations
  - 1.5*IQR
  - z-scores
  - etc..

Detecting Outliers

In [39]:

```
df = pd.DataFrame(np.random.normal(50,20,1000), columns=['measure'])
df = df.append(pd.DataFrame(np.random.normal(120,1,20), columns=['measure']))

fig,ax = plt.subplots(1,2, figsize=(14,4))
sns.histplot(x=df.measure,ax=ax[0]);
sns.boxplot(x=df.measure,ax=ax[1]);
```



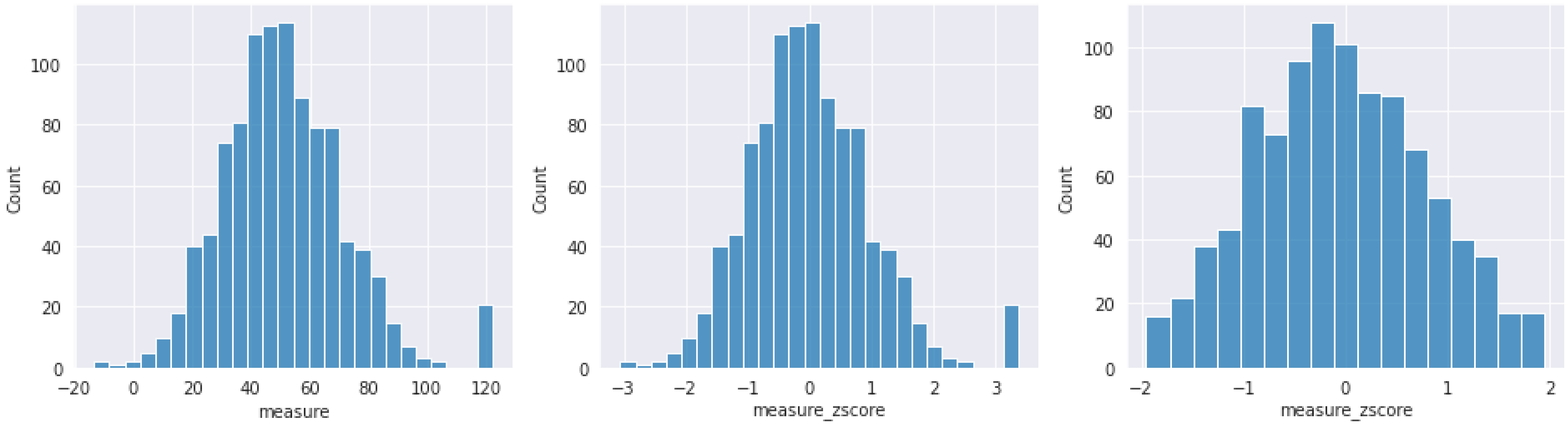
Detecting Outliers with z-score

In [40]:

```
# zscore
df['measure_zscore'] = (df.measure - df.measure.mean()) / df.measure.std()

fig, ax = plt.subplots(1,3,figsize=(16,4))
sns.histplot(x=df.measure,ax=ax[0]);
sns.histplot(x=df.measure_zscore, ax=ax[1]);

keep_idx = np.abs(df.measure_zscore) < 2
sns.histplot(x=df[keep_idx].measure_zscore, ax=ax[2]);
```



Other Outlier Detection Methods

- Many more parametric and non-parametric methods
  - Standardized Residuals
  - DBScan
  - ElipticEnvelope
  - IsolationForest
  - other Anomoly Detection techniques
  - See sklearn docs on Outlier Detection for more details

Dealing with Outliers

- How to deal with outliers?
  - drop data
  - treat as missing
  - encode with dummy variable first?

Data Cleaning Review

- duplicate data
- missing data
- rescaling
- dealing with skew
- outlier detection

Feature Engineering

- Binning
- One-Hot encoding
- Derived

Binning

- Transform continuous features to categorical
- Use:
    - pd.cut
    - sklearn.preprocessing.KBinsDiscretizer (combined binning and one-hot-encoding)

In [41]:
```
trip_duration_bins = [df_taxi.trip_duration.min(),
                      df_taxi.trip_duration.median(),
                      df_taxi.trip_duration.quantile(0.75),
                      df_taxi.trip_duration.max(),
                     ]
```

In [42]:
```
df_new = df_taxi.copy()
df_new['trip_duration_binned'] = pd.cut(df_taxi.trip_duration,
                                        bins=trip_duration_bins,          # can pass bin edges or number of bins
                                        labels=['short','medium','long'],
                                        right=True,                       # all bins right-inclusive
                                        include_lowest=True               # first interval left-inclusive
                                       )
df_new[['trip_duration','trip_duration_binned']].iloc[:4]
```

Out[42]:

	trip_duration	trip_duration_binned
1	516	short
2	683	medium
7	834	medium

One-Hot Encoding

- Encode categorical features for models that can't handle categorical (eg. Linear)
- One column per category, '1' in only one column per row
- Use `pd.get_dummies()` or `sklearn.preprocessing.OneHotEncoder`

In [43]:
```
pd.get_dummies(df_new.trip_duration_binned, prefix='trip_duration').iloc[:3]
```

Out[43]:

	trip_duration_short	trip_duration_medium	trip_duration_long
1	1	0	0
2	0	1	0
7	0	1	0

In [44]:
```
df_new.join(pd.get_dummies(df_new.trip_duration_binned, prefix='trip_duration')).iloc[:3,-5:]
```

Out[44]:

	trip_duration	trip_duration_binned	trip_duration_short	trip_duration_medium	trip_duration_long
1	516	short	1	0	0
2	683	medium	0	1	0
7	834	medium	0	1	0

In [45]:
```
pd.get_dummies(df_new).iloc[:3,-7:]
```

Out[45]:

	total_amount	trip_duration	store_and_fwd_flag_N	store_and_fwd_flag_Y	trip_duration_binned_short	trip_duration_binned_medium	trip_duration_binned_long
1	9.96	516	1	0	1	0	0
2	10.30	683	1	0	0	1	0
7	16.64	834	1	0	0	1	0

One-Hot Encoding with sklearn

In [46]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(categories=[['short','medium','long']],  # or leave as 'auto'
                    sparse=False,
                    handle_unknown='ignore')                  # will raise error otherwise

ohe.fit(df_new[['trip_duration_binned']])
ohe.categories_
```

Out[46]:
```
[array(['short', 'medium', 'long'], dtype=object)]
```

In [47]:
```
ohe.transform(df_new[['trip_duration_binned']])[:3]
```

Out[47]:
```
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 1., 0.]])
```

Bin and One-Hot Encode with sklearn

In [48]:
```
from sklearn.preprocessing import KBinsDiscretizer

# NOTE: We're not setting the bin edges explicitly
#       For control over bin edges, use Binarizer
kbd = KBinsDiscretizer(n_bins=3,
                       encode="onehot",     # or onehot (sparse), ordinal
                       strategy="quantile", # or uniform or kmeans (clustering)
                      ).fit(df_new[['trip_duration']])

kbd.bin_edges_
```

Out[48]:
```
array([array([2.000e+00, 4.780e+02, 8.700e+02, 3.556e+03])], dtype=object)
```

In [49]:
```
df_new[['trip_duration']].head(3)
```

Out[49]:

	trip_duration
1	516
2	683
7	834

In [50]:
```
kbd.transform(df_new[['trip_duration']])[:3]
```

Out[50]:
```
<3x3 sparse matrix of type '<class 'numpy.float64'>'
	with 3 stored elements in Compressed Sparse Row format>
```

In [51]:
```
kbd.transform(df_new[['trip_duration']])[:3].todense()
```

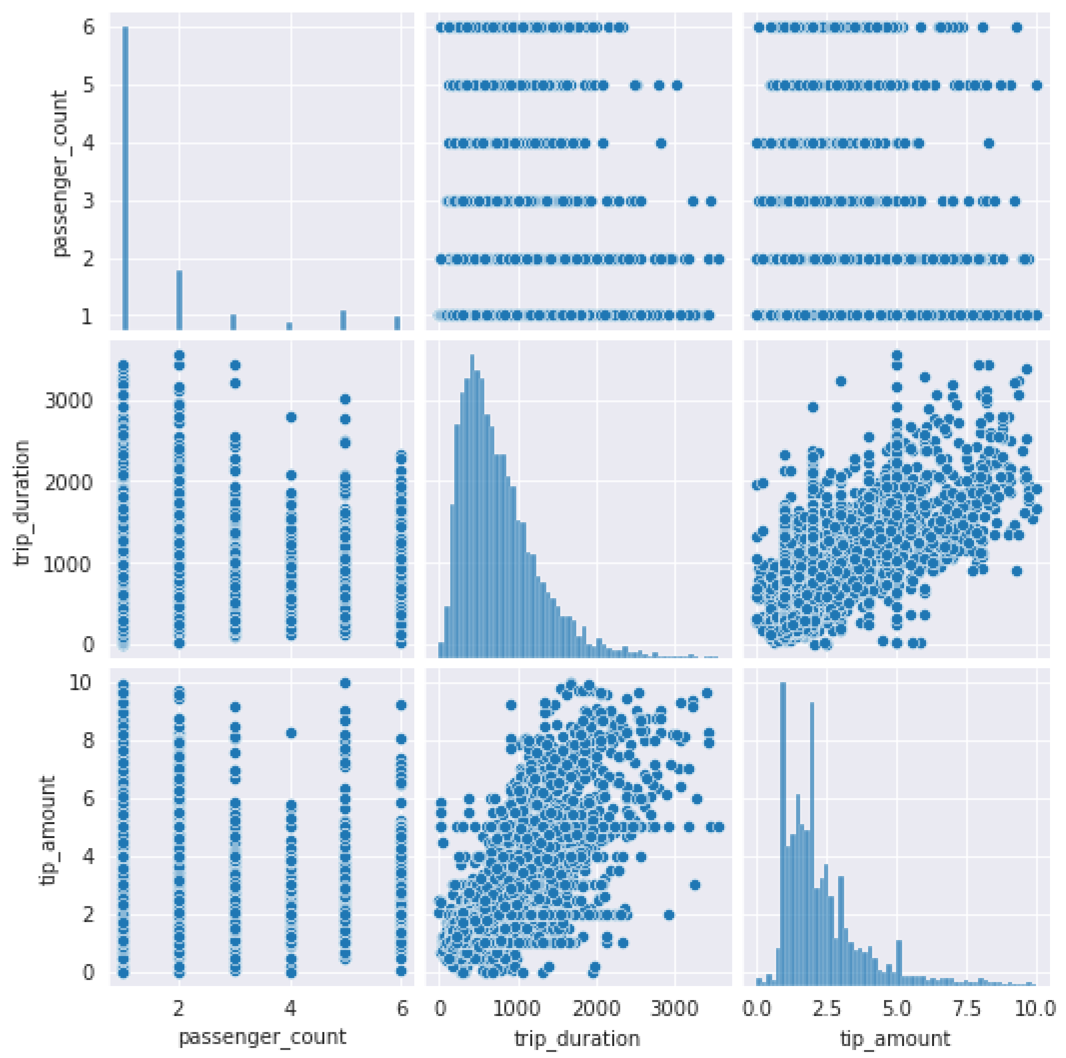
Out[51]:
```
matrix([[0., 1., 0.],
        [0., 1., 0.],
        [0., 1., 0.]])
```

Derived Features

- Anything that is a transformation of our data
- This is where the money is!

Polynomial Features

In [52]:
```
sns.pairplot(df_taxi[['passenger_count','trip_duration','tip_amount']]);
```



Polynomial Features Continued

In [53]:
```
from sklearn.preprocessing import PolynomialFeatures

pf = PolynomialFeatures(degree=2,
                        include_bias=False)
X_new = pf.fit_transform(df_taxi[['passenger_count','trip_duration']])

new_columns = ['passenger_count','trip_duration','passenger_count^2','passenger_count*trip_duration','trip_duration^2']
pd.DataFrame(X_new[3:5],columns=new_columns)
```

Out[53]:

	passenger_count	trip_duration	passenger_count^2	passenger_count*trip_duration	trip_duration^2
0	3.0	298.0	9.0	894.0	88804.0
1	1.0	396.0	1.0	396.0	156816.0

Natural Language Processing (NLP)

- Many NLP Tasks
  - topic modeling
  - sentiment analysis
  - entity recognition
  - machine translation
  - natural language generation
  - question answering
  - relationship extraction
  - automatic summarization
  - ...
- All depend on extracting features from unstructured text data

NLP: The Corpus

- **corpus:** collection of documents
- Each item a document
  - tweet
  - review
  - resume
  - book
  - article
  - sentence
  - ...

NLP: Doc Representation

In [54]:
```
doc_1 = "The cat in the hat."
doc_2 = "The quick brown cat jumped over the lazy cat."
corpus = [doc_1,doc_2]
```

- **tokens:** strings that make up a document ('the','cat',...)
- **terms:** unique set of strings in a documents
- **vocabulary:** set of unique terms that can be in any document
- **tokenization:** process of transforming document into tokens

NLP: Tokenization

- common tokenization method: split on whitespace

In [55]:
```
doc_1.split()
```
Out[55]:
```
['The', 'cat', 'in', 'the', 'hat.']
```

In [56]:
```
doc_2.split()
```
Out[56]:
```
['The', 'quick', 'brown', 'cat', 'jumped', 'over', 'the', 'lazy', 'cat.']
```

- Additional transformations depend on problem:
  - lowercase
  - remove stopwords
  - **stemming:** reduce token to stem (eg: "tokenization"->"tokeniz")
  - **lemmatization:** common form (eg: "tokenization"->"tokenize")
  - and tags?
  - remove special characters

NLP: Doc Representation

- Most common representaion: Bag of Words (BOW)
  - split document into tokens
  - ignore order (lose context!)

In [57]:
```python
sorted(doc_1.lower().replace('.','').split())
```

Out[57]:
```
['cat', 'hat', 'in', 'the', 'the']
```

In [58]:
```python
sorted(doc_2.lower().replace('.','').split())
```

Out[58]:
```
['brown', 'cat', 'cat', 'jumped', 'lazy', 'over', 'quick', 'the', 'the']
```

NLP: n-grams

- create new terms as combinations of n tokens
- captures local context
- vocabulary increases quickly

Unigrams: n = 1

```
In [59]: sorted(doc_1.lower().replace('.','').split())
```

```
Out[59]: ['cat', 'hat', 'in', 'the', 'the']
```

Bigrams: n = 2

```
In [60]: tmp = ("<start> "+doc_1+" <end>").lower().replace('.','').split()
         sorted([(tmp[i]+'_'+tmp[i+1]) for i in range(len(tmp)-1)])
```

```
Out[60]: ['<start>_the', 'cat_in', 'hat_<end>', 'in_the', 'the_cat', 'the_hat']
```

NLP: Term Frequency

- **Term Frequency (TF):** Number of times a particular term occurs in a document

In [61]:
```
tokens = []
for doc in corpus:
    tokens.extend(doc.lower().replace('.','').split())
vocab = sorted(list(set(tokens)))
vocab
```

Out[61]: ['brown', 'cat', 'hat', 'in', 'jumped', 'lazy', 'over', 'quick', 'the']

In [62]:
```
termfreq = np.zeros((len(corpus),len(vocab)))
for doc_idx,doc in enumerate(corpus):
    for term_idx,term in enumerate(vocab):
        for token in doc.lower().replace('.','').split():
            if term == token:
                termfreq[doc_idx,term_idx]+=1
df_termfreq = pd.DataFrame(termfreq,index=['doc1','doc2'],columns=vocab)
df_termfreq
```

Out[62]:

	brown	cat	hat	in	jumped	lazy	over	quick	the
doc1	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	2.0
doc2	1.0	2.0	0.0	0.0	1.0	1.0	1.0	1.0	2.0

NLP: Term Frequency

- **Document Frequency (DF):** Number of documents a term occurs in

```
In [63]: docfreq = df_termfreq.sum()
         docfreq.sort_values(ascending=False)

Out[63]: the       4.0
         cat       3.0
         quick     1.0
         over      1.0
         lazy      1.0
         jumped    1.0
         in        1.0
         hat       1.0
         brown     1.0
         dtype: float64
```

Stopwords

- **stopwords:** terms that (generally) have high DF and aren't informative
- ex: 'a', 'about','above',...
- often removed prior to analysis

In [64]:
```
stopwords = ['the','a', 'an']

tokens = []
for doc in corpus:
    tokens.extend(doc.lower().replace('.','').split())
vocab = sorted(list(set(tokens)))
vocab = [x for x in vocab if x not in stopwords]
vocab
```

Out[64]:
```
['brown', 'cat', 'hat', 'in', 'jumped', 'lazy', 'over', 'quick']
```

NLP: CountVectorizer

In [65]:
```
from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(stop_words=None,                     # can use 'english', but arguments against: https://scikit-learn.org/stabl
                     ngram_range=(1,1),                   # only unigrams
                     token_pattern= r'(?u)\b\w\w+\b',     # at least one word-character surrounded by boundaries
                     min_df=1,                            # has to occur in at least one document
                     max_df=1.0,                          # can occur in at most 100% of the documents
                    )
X = cv.fit_transform(corpus)
cv.vocabulary_
```

Out[65]:
```
{'the': 8,
 'cat': 1,
 'in': 3,
 'hat': 2,
 'quick': 7,
 'brown': 0,
 'jumped': 4,
 'over': 6,
 'lazy': 5}
```

In [66]:
```
X
```

Out[66]:
```
<2x9 sparse matrix of type '<class 'numpy.int64'>'
	with 11 stored elements in Compressed Sparse Row format>
```

In [67]:
```
X.todense() # term frequencies
```

Out[67]:
```
matrix([[0, 1, 1, 1, 0, 0, 0, 0, 2],
        [1, 2, 0, 0, 1, 1, 1, 1, 2]])
```

NLP: Tf-Idf

- What if some terms are still uninformative?
- Can we downweight terms that are in many documents?
- **Term Frequency - Inverse Document Frequency (TfIdf)**
    - `tfidf(t,d) = tf(t, d) * idf(t)`
    - `idf(t) = log [ n / docfreq(t) ] + 1`

In [68]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer()
X = tfidf.fit_transform(corpus)
X.todense()
```

Out[68]:
```
matrix([[0.        , 0.33425073, 0.46977774, 0.46977774, 0.        ,
         0.        , 0.        , 0.        , 0.66850146],
        [0.33241213, 0.47302794, 0.        , 0.        , 0.33241213,
         0.33241213, 0.33241213, 0.33241213, 0.47302794]])
```

NLP: Example 20Newsgroups

In [69]:
```
from sklearn.datasets import fetch_20newsgroups

ngs = fetch_20newsgroups()

# grab 100 docs
docs = ngs['data'][:100]
docs[0]
```

Out[69]:
```
"From: lerxst@wam.umd.edu (where's my thing)\nSubject: WHAT car is this!?\nNntp-Posting-Host: rac3.wam.umd.edu\nOrganization: University of Maryland, College Park\nLines: 15\n\n I was wondering if anyone out there could enlighten me on this car I saw\nthe other day. It was a 2-door sports car, looked to be from the late 60s/\nearly 70s. It was called a Bricklin. The doors were really small. In addition,\nthe front bumper was separate from the rest of the body. This is \nall I know. If anyone can tellme a model name, engine specs, years\nof production, where this car is made, history, or whatever info you\nhave on this funky looking car, please e-mail.\n\nThanks,\n- IL\n   ---- brought to you by your neighborhood Lerxst ----\n\n\n\n\n"
```

In [70]:
```
cv = TfidfVectorizer(ngram_range=(1,2), #unigrams + bigrams
                     stop_words=None,
                     min_df=2,
                     max_df=.8
                    ).fit(docs)
X = cv.transform(docs)
X.shape
```

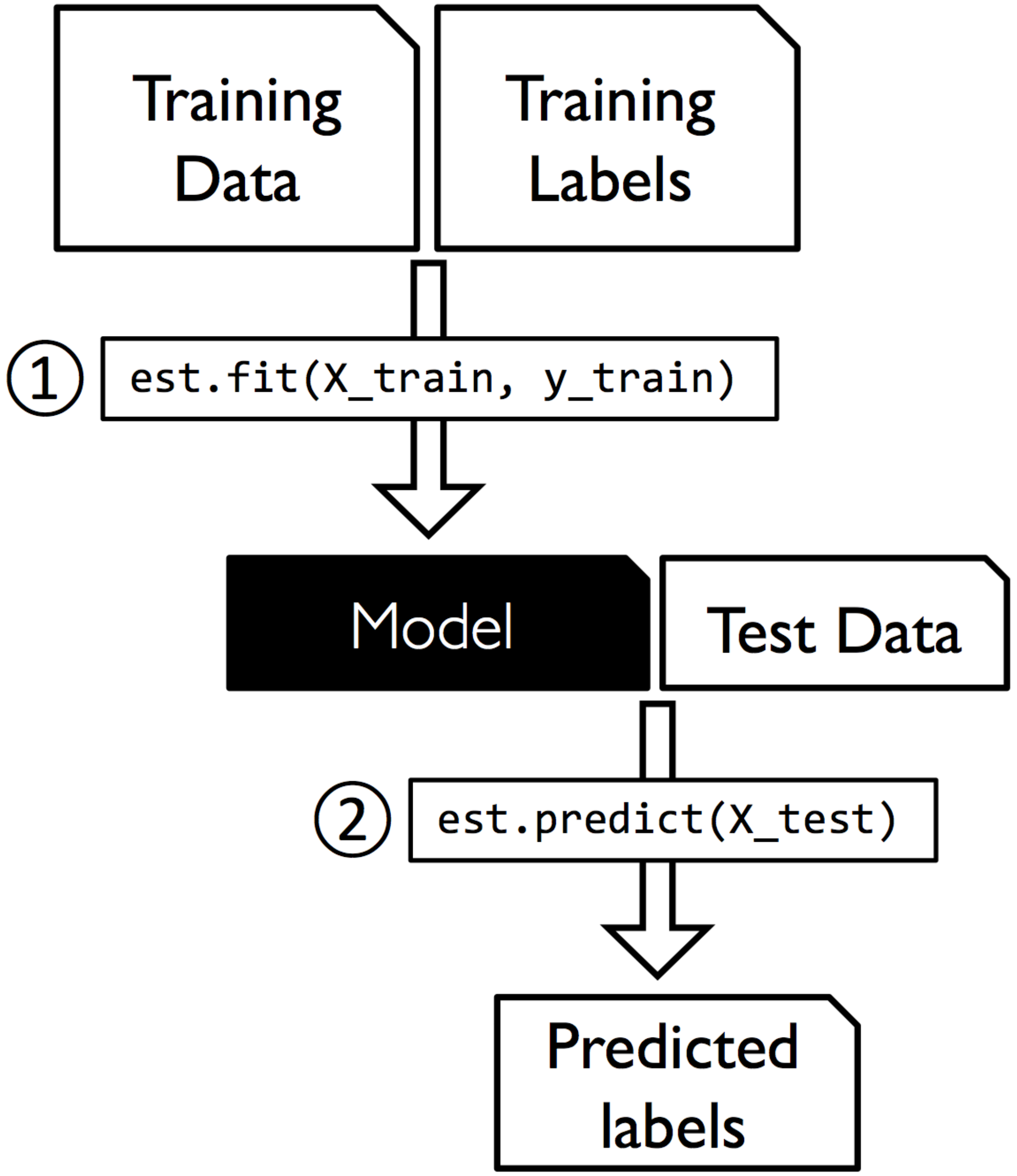
Out[70]:
```
(100, 3894)
```

In [71]:
```
list(cv.stop_words_)[:5]
```

Out[71]:
```
['hayward to', 'accidents in', 'or thought', 'list long', 'in they']
```

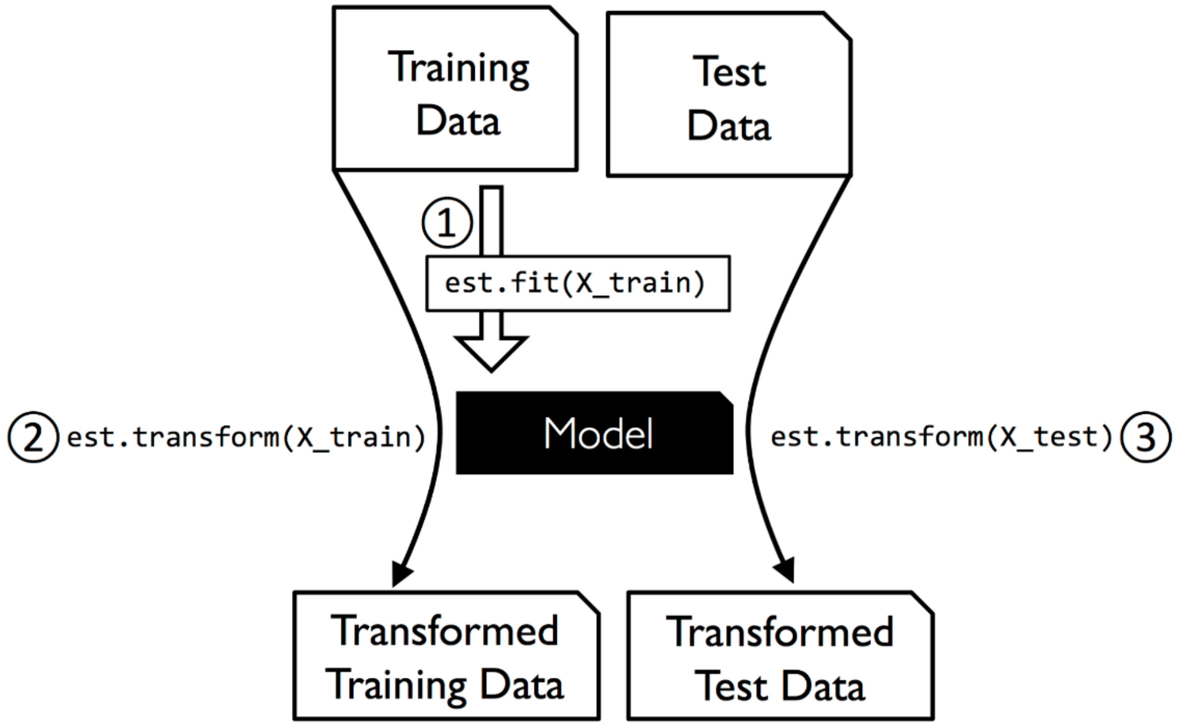
Predicting with Train/Test Split

- When training a model for prediction



Transforming with Train/Test Split

- When performing data transformation



Next

- Feature Selection
- Dimensionality Reduction
- Topic Modeling

Questions?