```markdown
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# Group Project 1
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<a name="Lab-Description"></a>
## Lab Description
Your groups have been assigned by Nationwide, and now it is time to begin working together to build towards your Capstone
presentations! Your first group project will be to gather the additional county auditor data, clean it, merge it, and begin to
understand it for those counties that are considered part of the Columbus Ohio MSA: Franklin, Fairfield, Licking, Delaware, Hocking,
Madison, Morrow, Perry, Pickaway, and Union. We have already worked with Franklin, Fairfield, and Licking County auditor datasets
during Unit 2, and will continue working with these datasets, but your job as a group is to combine all pf the county datasets
together.

A copy of auditor data for all of these counties is attached to this entry on Blackboard. Note that Franiklin, Fairfield, and
Licking county data is not included since that data was already made available in Unit 2 Exercises. Additionally, Union County data
is unavailable at this time - Bonus points to any team who can figure out how to get it!

Group Project 1 presentations will be at the beginning of class on June 20, and are to be 10 minutes or less in length.
Presentations for this first group project can be done by one ore more members of the group. You will be graded on the following for
this first group presentation:

- Presentation of basic statistics and charts showing how your team chose to sample (or not sample) data files, what format you
stored it in, and any interesting facts you found while reviewing basic statistics about the data.
- What your team would like to study next about the data.
- Presentation succinctness: less than 10min in duration, highlight main points, highlight any key questions or concerns about the
data that your team had as you performed the work.
Remember that this data can and should be used by your group during your Capstone work, so take your time building it well. This is
your team's chance to perform its first practice run at presenting to an audience - enjoy it! The pressure to have robust data and
impressive data visualization and modeling techniques can wait until your Capstone.


This notebook relies on the [GeoPandas](library) to process data from a [geographic information system]
(https://en.wikipedia.org/wiki/Geographic_information_system).
```

In [ ]:

In [33]:
```python
import sys
!{sys.executable} -m pip install geopandas
```

```
Requirement already satisfied: geopandas in /anaconda3/lib/python3.7/site-packages (0.5.0)
Requirement already satisfied: pyproj in /anaconda3/lib/python3.7/site-packages (from geopandas) (2.2.0)
Requirement already satisfied: shapely in /anaconda3/lib/python3.7/site-packages (from geopandas) (1.6.4.post2)
Requirement already satisfied: fiona in /anaconda3/lib/python3.7/site-packages (from geopandas) (1.8.6)
Requirement already satisfied: pandas in /anaconda3/lib/python3.7/site-packages (from geopandas) (0.24.2)
Requirement already satisfied: click<8,>=4.0 in /anaconda3/lib/python3.7/site-packages (from fiona->geopandas) (7.0)
Requirement already satisfied: attrs>=17 in /anaconda3/lib/python3.7/site-packages (from fiona->geopandas) (19.1.0)
Requirement already satisfied: click-plugins>=1.0 in /anaconda3/lib/python3.7/site-packages (from fiona->geopandas) (1.1.1)
Requirement already satisfied: six>=1.7 in /anaconda3/lib/python3.7/site-packages (from fiona->geopandas) (1.12.0)
Requirement already satisfied: munch in /anaconda3/lib/python3.7/site-packages (from fiona->geopandas) (2.3.2)
Requirement already satisfied: cligj>=0.5 in /anaconda3/lib/python3.7/site-packages (from fiona->geopandas) (0.5.0)
Requirement already satisfied: pytz>=2011k in /anaconda3/lib/python3.7/site-packages (from pandas->geopandas) (2018.9)
Requirement already satisfied: python-dateutil>=2.5.0 in /anaconda3/lib/python3.7/site-packages (from pandas->geopandas) (2.8.0)
Requirement already satisfied: numpy>=1.12.0 in /anaconda3/lib/python3.7/site-packages (from pandas->geopandas) (1.16.2)
```

Get Auditor Data

Gather the county auditor data for those Ohio counties that are considered part of the Columbus Ohio MSA: Franklin, Fairfield, Licking, Delaware, Hocking, Madison, Morrow, Perry, Pickaway, and Union.

Get Franklin County Auditor Data

In [34]:
```
import pandas as pd

# load full dataset for initial analysis
franklin = pd.read_csv('../data/county_auditor/OH-Franklin/Parcel.csv')
```

Sample Franklin County Auditor Data

Franklin county auditor data containing real estate information is quite large - 400,000+ rows. Therefore, we will sample (reduce) the data for initial data cleansing and construction for later combination with other datasets from other central Ohio counties. We will only be looking at 10% of the entire dataset. This is a somewhat arbitrary, but a good place to start, since we are unsure of what will interest us at this time.

We are calling the `sample_file()` function (in samplingu2.py) to do this. Two arguments are required when the function is called, `input_file` and `output_file` , to specify the source and target files, respectively. A keyword argument, `fraction` , can be specified to set the desired size of the output file relative to the input file; the default value is 0.1.

The Franklin County Auditor's website offers the ability to generate datasets (https://apps.franklincountyauditor.com/reporter)or to download the data files via FTP.

**LETS DECIDE which is the approach we'll use here (currently using FTP, but data is old <=2015)

We will first load the data file, then sample it using the `sample_file()` function provided by samplingu2.py, and finally we will store the sampled output as a data file which we can use again in further steps.

The `pandas` package can be used to read the franklin county data file:

In [35]:
```
import samplingu2

# sample the data (default is 10% of all rows)
samplingu2.sample_file('../data/county_auditor/OH-Franklin/Parcel.csv',
            '../data/county_auditor/OH-Franklin/franklin_auditor_subset.csv')
franklin = pd.read_csv('../data/county_auditor/OH-Franklin/franklin_auditor_subset.csv')
```

Madison and Morrow County Auditor Data

This data is stored as Geographic Information System (GIS) data so loading it won't be as straightforward as reading a text file. To access the data, we'll use the GeoPandas library, which will load the GIS data into a DataFrame so we can work with it in the same way as the other datasets.

In [36]:
```
import geopandas
madison = geopandas.read_file("zip://../data/county_auditor/OH-Madison/Parcels.zip")
morrow = geopandas.read_file("zip://../data/county_auditor/OH-Morrow/Morrow_Parcels.zip")
```

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In [37]:
```
#Upon initial examination of the madison/morrow geopandas data,
#we realized we have the sales data in a csv files that seems more in line with the Franklin data

madison = pd.read_csv('../data/county_auditor/OH-Madison/salesresults_2019-03-20.csv')
morrow = pd.read_csv('../data/county_auditor/OH-Morrow/salesresults_2019-03-20.csv')
```

NOTE: We are not sampling Madison or Morrow county because these are very small files to begin with (<200 rows)

Examine Data

We would like a glimpse of the data for each of these, so we will use the head() function

We will view the first few rows using the DataFrame's *head()* method. We'll increase the number of columns displayed to 200 to accommodate the datasets we'll be working with.

In [38]:
```
pd.set_option('display.max_column', 200)
franklin.head()
```

Out[38]:

	ParcelNumber	PID	AEXMLND	AEXMBLD	AEXMTOT	APPRLND	APPRBLD	APPRTOT	AudMap	AudRtg	LandUse	Cauv	SCHOOL	HOMESTD	MAILAD1	MAII
0	010-000045	10000045.0	0	17700	17700	22600	40300	62900	D021	43.0	510.0	0.0	COLUMBUS CSD	NaN	SUSANNA K WARREN	
1	010-000061	10000061.0	0	19600	19600	6800	26400	33200	J010	48.0	510.0	0.0	COLUMBUS CSD	NaN	QUIGLEY ENTERPRISES LLC	
2	010-000103	10000103.0	0	3300	3300	3200	6500	9700	F039	36.0	599.0	0.0	COLUMBUS CSD	NaN	INNOCENT HARSHAW	
3	010-000129	10000129.0	0	569600	569600	196200	765800	962000	A030	1.0	401.0	0.0	COLUMBUS CSD	NaN	JASON BOWERS	
4	010-000004	10000004.0	0	62500	62500	14500	77000	91500	I017	80.0	520.0	0.0	COLUMBUS CSD	NaN	CENTRAL OHIO COMMUNITY IMPROVEMENT CORP	

In [39]:
```
# revisit - Is there a way to see datatypes for all columns?
```

In [40]:
```
pd.set_option('display.max_column', 200)
madison.head()
```

Out[40]:

	Parcel	Owner	PropertyAddress	MailingAddress	LandUse	Acres	LegalDescription	NeighborhoodCode	SaleDate	SalePrice	Seller	YearBuilt	Style
0	01-00219.001	HOSTETLER FERMAN L & MARY ELLEN HOSTETLER JT L...	5155 PRICE HILLIARDS RD	5155 PRICE HILLIARDS ROAD PLAIN CITY OH 43064	111	80.000	80.00A 7791	1111102 - DARBY-PLAINCITY-CANAAN-N JEFF AG	3/11/2019 12:00:00 AM	0	HOSTETLER FERMAN L & MARY ELLEN HOSTETLER JT L...	2000	F1 FRAME ONE STY
1	01-00310.000	J & M MILLS LLC	AMITY PK	154 BEECH DR DELAWARE OH 43015	100	2.453	2.4532A 1479	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	2/25/2019 12:00:00 AM	0	J & M MILLS LLC	UNAVAILABLE	UNAVAILABLE
2	01-00310.000	J & M MILLS LLC	AMITY PK	154 BEECH DR DELAWARE OH 43015	100	2.453	2.4532A 1479	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	2/25/2019 12:00:00 AM	0	MILLER AARON P TRUSTEE	UNAVAILABLE	UNAVAILABLE
3	01-00310.001	J & M MILLS LLC	AMITY PK	154 BEECH DR DELAWARE OH 43015	500	1.638	1.638A 1479	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	2/25/2019 12:00:00 AM	0	J & M MILLS LLC	UNAVAILABLE	UNAVAILABLE
4	01-00310.001	J & M MILLS LLC	AMITY PK	154 BEECH DR DELAWARE OH 43015	500	1.638	1.638A 1479	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	2/25/2019 12:00:00 AM	0	MILLER AARON P TRUSTEE	UNAVAILABLE	UNAVAILABLE

In [41]:
```
pd.set_option('display.max_column', 200)
morrow.head()
```

Out[41]:

	Parcel	Owner	PropertyAddress	MailingAddress	LegalDescription	TaxDistrict	SchoolDistrict	City	Township	NeighborhoodNumber	AnnualTax	LandUs
0	A02-001-00-061-01	MCKENZIE GLORIA	5378 TWP 211 RD	5378 TOWNSHIP ROAD 211 MARENGO OH 43334	TWP LOT 19 MOHO REG #162 ...	A02 BENNINGTON CEM HIGHLAND	HIGHLAND LSD	UNINCORPORATED	BENNINGTON TOWNSHIP	1700	643.92	59
1	A02-001-00-161-02	STIFFLER ROBERT D & ROBYN	5585 CO 21 RD	5585 TOWNSHIP ROAD 21 MARENGO OH 43334	E1/2 TWP LOT 11 ...	A02 BENNINGTON CEM HIGHLAND	HIGHLAND LSD	UNINCORPORATED	BENNINGTON TOWNSHIP	1700	2613.08	51
2	A02-001-00-180-02	CLEMONS DOUGLAS M & MAE D	4958 TWP 191 RD	11813 WINCHESTER ROAD ASHVILLE OH 43103	E 1/2 TWP LOT 40 ...	A02 BENNINGTON CEM HIGHLAND	HIGHLAND LSD	UNINCORPORATED	BENNINGTON TOWNSHIP	1700	1040.78	59
3	B06-001-00-273-00	MURRAY BARBARA A	7346 TWP 62 RD	7346 TOWNSHIP ROAD 62 CALEDONIA OH 43314	NEPT WPT NE 1/4 ...	B06 CANAAN RIVER VALLEY	RIVER VALLEY LSD	UNINCORPORATED	CANAAN TOWNSHIP	400	2267.02	51
4	B06-001-00-323-00	COLLINS LYLE G & ERIN A	1371 RT 309 ST	1371 ST RT 309 CALEDONIA OH 43314	E1/2 NW1/4 ...	B06 CANAAN RIVER VALLEY	RIVER VALLEY LSD	UNINCORPORATED	CANAAN TOWNSHIP	400	1868.03	51

```
In [42]: #Look at columns for each county's data
         madison.columns.tolist()
```

```
Out[42]: ['Parcel',
          'Owner',
          'PropertyAddress',
          'MailingAddress',
          'LandUse',
          'Acres',
          'LegalDescription',
          'NeighborhoodCode',
          'SaleDate',
          'SalePrice',
          'Seller',
          'YearBuilt',
          'Style',
          'NumberOfStories',
          'FinishedArea',
          'NumberOfRooms',
          'NumberOfBedrooms',
          'NumberOfFamilyRooms',
          'NumberOfDiningRooms',
          'NumberOfFullBaths',
          'NumberOfHalfBaths',
          'AppraisedLandValue',
          'AppraisedImprovementValue',
          'AppraisedTotalValue',
          'AssessedLandValue',
          'AssessedImprovementValue',
          'AssessedTotalValue',
          'TaxableValue',
          'Unnamed: 28']
```

```
In [43]: morrow.columns.tolist()
```

```
Out[43]: ['Parcel',
          'Owner',
          'PropertyAddress',
          'MailingAddress',
          'LegalDescription',
          'TaxDistrict',
          'SchoolDistrict',
          'City',
          'Township',
          'NeighborhoodNumber',
          'AnnualTax',
          'LandUse',
          'Acres',
          'TransferNumber',
          'TransferDate',
          'TransferTypeCode',
          'TransferTypeDescription',
          'Buyer',
          'Seller',
          'Price',
          'LandOnlySale',
          'ValidSale',
          'NumberOfPropertiesInSale',
          'YearBuilt',
          'YearRemodeled',
          'Stories',
          'NumberOfRooms',
          'NumberOfBedrooms',
          'NumberOfFamilyRooms',
          'NumberOfDiningRooms',
          'NumberOfFullBaths',
          'NumberOfHalfBaths',
          'FinishedLivingArea',
          'HomesteadReduction',
          'Reduction25',
          'Foreclosed',
          'NewConstruction',
          'BoardOfRevision',
          'DividedProperty',
          'Unnamed: 39']
```

In [44]:
```
franklin.columns.tolist()
```

Out[44]:
```
['ParcelNumber',
 'PID',
 'AEXMLND',
 'AEXMBLD',
 'AEXMTOT',
 'APPRLND',
 'APPRBLD',
 'APPRTOT',
 'AudMap',
 'AudRtg',
 'LandUse',
 'Cauv',
 'SCHOOL',
 'HOMESTD',
 'MAILAD1',
 'MAILAD2',
 'MAILAD3',
 'MAILAD4',
 'TRANDT',
 'TRANYR',
 'NAME1',
 'NAME2',
 'OWNER_ADD1',
 'OWNER_ADD2',
 'NBRHD',
 'PCLASS',
 'NOCARDS',
 'ACREA',
 'PRICE',
 'ANN_TAX',
 'STADDR',
 'USPS_CITY',
 'STATE',
 'ZIPCODE',
 'DESCR1',
 'DESCR2',
 'DESCR3',
 'TAXDESI',
 'AREA2',
 'DWELTYP',
 'ROOMS',
 'BATHS',
 'HBATHS',
 'BEDRMS',
 'AIRCOND',
 'COND',
 'FIREPLC',
 'Grade',
 'HEIGHT',
 'NOSTORY',
 'YEARBLT',
 'WALL']
```

We will use the original documentation about the Franklin County dataset to understand the data and compare the columns in the doc to what is actually in the file.

In [45]:
```python
# display auditor documentation in the notebook (NOTE: May not work properly in all browsers)
from IPython.display import IFrame
IFrame(src="../data/county_auditor/OH-Franklin/documentation/ParcelDataReadme.pdf", height=800, width=1024)
```

Out[45]:

Decide which columns are common across Franklin, Madison and Morrow Data

To do this, we put the column names for each in an Excel workbook.
Based on name and content, we made decisions about which columns were common across each.

Along the way, we took notes about whether we needed to clean any of the data (ex., like merging address fields).

Please see ../data/Column mapping.xls for these details.

Now we will create a list of the columns that we identified as common across these counties. We copied the list from the output of the madison.columns.tolist() command we ran above and removed those that we did not need. We also added a County field since we would want to know which data came from which county.

In [46]:
```python
columns = ["Parcel",
"Owner",
"PropertyAddress",
"MailingAddress",
"LandUse",
"Acres",
"LegalDescription",
"NeighborhoodCode",
"SaleDate",
"SalePrice",
"YearBuilt",
"NumberOfStories",
"FinishedArea",
"NumberOfRooms",
"NumberOfBedrooms",
"NumberOfFullBaths",
"NumberOfHalfBaths",]
```

Merge the counties

To do this, will create a dataset, starting with Madison that filters on our defined columns.

For Morrow and Madison, we will have to rename some of the columns and the create subset of those based on our defined columns Then, merge!

We will create 'merge' files for each county. Since we are using Madison column names, we won't have to do any column renaming

Create Merge files for each county

These will be a copy of the original file, with columns renamed for Morrow and Franklin as needed and a Cunty column added.

Madison merge file

These will be a copy of the original file, adding County column.

In [47]:
```
madison_merge = madison[columns].copy()
madison_merge['County'] = 'Madison'
```

Morrow merge file

Rename columns for Morrow and add a County column.

In [48]:
```
morrow.rename(
    {'TransferDate': 'SaleDate',
     'Price': 'SalePrice',
     'Stories': 'NumberOfStories',
     'FinishedLivingArea': 'FinishedArea',
     'NeighborhoodNumber': 'NeighborhoodCode'
    },
    axis=1 ,
    inplace=True
)
```

In [49]:
```
morrow.head()
```

1	A02-001-00-161-02	STIFFLER ROBERT D & ROBYN	5585 CO 21 RD	5585 TOWNSHIP ROAD 21 MARENGO OH 43334	E1/2 TWP LOT 11 ...	A02 BENNINGTON CEM HIGHLAND	HIGHLAND LSD	UNINCORPORATED	BENNINGTON TOWNSHIP	1700	2613.08	511
2	A02-001-00-180-02	CLEMONS DOUGLAS M & MAE D	4958 TWP 191 RD	11813 WINCHESTER ROAD ASHVILLE OH 43103	E 1/2 TWP LOT 40 ...	A02 BENNINGTON CEM HIGHLAND	HIGHLAND LSD	UNINCORPORATED	BENNINGTON TOWNSHIP	1700	1040.78	599
3	B06-001-00-273-00	MURRAY BARBARA A	7346 TWP 62 RD	7346 TOWNSHIP ROAD 62 CALEDONIA OH 43314	NEPT WPT NE 1/4 ...	B06 CANAAN RIVER VALLEY	RIVER VALLEY LSD	UNINCORPORATED	CANAAN TOWNSHIP	400	2267.02	511
4	B06-001-00-323-00	COLLINS LYLE G & ERIN A	1371 RT 309 ST	1371 ST RT 309 CALEDONIA OH 43314	E1/2 NW1/4 ...	B06 CANAAN RIVER VALLEY	RIVER VALLEY LSD	UNINCORPORATED	CANAAN TOWNSHIP	400	1868.03	511

In [50]:
```
morrow_merge = morrow[columns].copy()
morrow_merge['County'] = 'Morrow'
```

In [51]:
```
morrow_merge.head()
```

Out[51]:

	Parcel	Owner	PropertyAddress	MailingAddress	LandUse	Acres	LegalDescription	NeighborhoodCode	SaleDate	SalePrice	YearBuilt	NumberOfStories	FinishedArea	Nu
0	A02-001-00-061-01	MCKENZIE GLORIA	5378 TWP 211 RD	5378 TOWNSHIP ROAD 211 MARENGO OH 43334	599	3.380	TWP LOT 19 MOHO REG #162 ...	1700	2/26/2019 12:33:00 PM	0	NaN	NaN	NaN	
1	A02-001-00-161-02	STIFFLER ROBERT D & ROBYN	5585 CO 21 RD	5585 TOWNSHIP ROAD 21 MARENGO OH 43334	511	2.000	E1/2 TWP LOT 11 ...	1700	2/28/2019 1:42:00 PM	0	2003.0	1.0	1474.0	
2	A02-001-00-180-02	CLEMONS DOUGLAS M & MAE D	4958 TWP 191 RD	11813 WINCHESTER ROAD ASHVILLE OH 43103	599	13.020	E 1/2 TWP LOT 40 ...	1700	2/22/2019 12:11:00 PM	0	NaN	NaN	NaN	
3	B06-001-00-273-00	MURRAY BARBARA A	7346 TWP 62 RD	7346 TOWNSHIP ROAD 62 CALEDONIA OH 43314	511	0.980	NEPT WPT NE 1/4 ...	400	2/25/2019 12:26:00 PM	0	1974.0	1.0	1692.0	
4	B06-001-00-323-00	COLLINS LYLE G & ERIN A	1371 RT 309 ST	1371 ST RT 309 CALEDONIA OH 43314	511	0.767	E1/2 NW1/4 ...	400	2/21/2019 10:17:00 AM	95000	1969.0	1.0	1500.0	

Franklin merge file

Next we will rename columns for Franklin that did not match Madison. However, before we do that, we have to mer MAILAD3 and MAILAD4 so that address will include city, state and zip. (NOTE: We identified this in our cross-column analysis)

In [52]:
```
#franklin['MAILAD3'] = (franklin['MAILAD3'] + ", " + franklin['MAILAD4'])
franklin.head()
```

Out[52]:

	ParcelNumber	PID	AEXMLND	AEXMBLD	AEXMTOT	APPRLND	APPRBLD	APPRTOT	AudMap	AudRtg	LandUse	Cauv	SCHOOL	HOMESTD	MAILAD1	MAI
0	010-000045	10000045.0	0	17700	17700	22600	40300	62900	D021	43.0	510.0	0.0	COLUMBUS CSD	NaN	SUSANNA K WARREN	
1	010-000061	10000061.0	0	19600	19600	6800	26400	33200	J010	48.0	510.0	0.0	COLUMBUS CSD	NaN	QUIGLEY ENTERPRISES LLC	
2	010-000103	10000103.0	0	3300	3300	3200	6500	9700	F039	36.0	599.0	0.0	COLUMBUS CSD	NaN	INNOCENT HARSHAW	
3	010-000129	10000129.0	0	569600	569600	196200	765800	962000	A030	1.0	401.0	0.0	COLUMBUS CSD	NaN	JASON BOWERS	
4	010-000004	10000004.0	0	62500	62500	14500	77000	91500	I017	80.0	520.0	0.0	COLUMBUS CSD	NaN	CENTRAL OHIO COMMUNITY IMPROVEMENT CORP	

In [53]:
```
franklin.rename(
    {'ParcelNumber': 'Parcel',
     'MAILAD3': 'MailingAddress',
     'Stories': 'NumberOfStories',
     'TRANDT': 'SaleDate',
     'NAME1': 'Owner',
     'NBRHD': 'NeighborhoodCode',
     'ACREA': 'Acres',
     'PRICE': 'SalePrice',
     'STADDR': 'PropertyAddress',
     'DESCR3': 'LegalDescription',
     'AREA2': 'FinishedArea',
     'ROOMS': 'NumberOfRooms',
     'BATHS': 'NumberOfFullBaths',
     'HBATHS': 'NumberOfHalfBaths',
     'BEDRMS': 'NumberOfBedrooms',
     'NOSTORY': 'NumberOfStories',
     'YEARBLT': 'YearBuilt',
    },
    axis=1 ,
    inplace=True
)
```

In [54]:
```
#Preview the data to ensure the column names changed accordingly
franklin.head()
```

0	010-000045	10000045.0	0	17700	17700	22600	40300	62900	D021	43.0	510.0	0.0	COLUMBUS CSD	NaN	SUSANNA K WARREN	NaN
1	010-000061	10000061.0	0	19600	19600	6800	26400	33200	J010	48.0	510.0	0.0	COLUMBUS CSD	NaN	QUIGLEY ENTERPRISES LLC	NaN
2	010-000103	10000103.0	0	3300	3300	3200	6500	9700	F039	36.0	599.0	0.0	COLUMBUS CSD	NaN	INNOCENT HARSHAW	NaN
3	010-000129	10000129.0	0	569600	569600	196200	765800	962000	A030	1.0	401.0	0.0	COLUMBUS CSD	NaN	JASON BOWERS	NaN
4	010-000004	10000004.0	0	62500	62500	14500	77000	91500	I017	80.0	520.0	0.0	COLUMBUS CSD	NaN	CENTRAL OHIO COMMUNITY IMPROVEMENT CORP	NaN

In [55]:
```
# Look at more of the data
display(franklin)
```

	Parcel	PID	AEXMLND	AEXMBLD	AEXMTOT	APPRLND	APPRBLD	APPRTOT	AudMap	AudRtg	LandUse	Cauv	SCHOOL	HOMESTD	MAILAD1
0	010-000045	10000045.0	0	17700	17700	22600	40300	62900	D021	43.0	510.0	0.0	COLUMBUS CSD	NaN	SUSANNA K WARREN
1	010-000061	10000061.0	0	19600	19600	6800	26400	33200	J010	48.0	510.0	0.0	COLUMBUS CSD	NaN	QUIGLEY ENTERPRISES LLC
2	010-000103	10000103.0	0	3300	3300	3200	6500	9700	F039	36.0	599.0	0.0	COLUMBUS CSD	NaN	INNOCENT HARSHAW
3	010-000129	10000129.0	0	569600	569600	196200	765800	962000	A030	1.0	401.0	0.0	COLUMBUS CSD	NaN	JASON BOWERS
4	010-000004	10000004.0	0	62500	62500	14500	77000	91500	I017	80.0	520.0	0.0	COLUMBUS CSD	NaN	CENTRAL OHIO COMMUNITY IMPROVEMENT CORP

```
In [56]: franklin_merge = franklin[columns].copy()
         #do I use .copy() at the end?
         franklin_merge['County'] = 'Franklin'
         franklin_merge.head()
```

Out[56]:

	Parcel	Owner	PropertyAddress	MailingAddress	LandUse	Acres	LegalDescription	NeighborhoodCode	SaleDate	SalePrice	YearBuilt	NumberOfStories	FinishedArea
0	010-000045	WARREN SUSANNA K	145 N EUREKA AV	PO BOX 44221	510.0	0.0	LOTS 27 & 28	9400.0	7/28/2011	0.0	1903.0	2.0	1848.0
1	010-000061	QUIGLEY ENTERPRISES LLC	801 MILLER AV	7069 VAN GORDON CT	510.0	0.0	LOT 149-50-51	1500.0	1/14/2015	55000.0	1913.0	2.0	1184.0
2	010-000103	HARSHAW INNOCENT C	THOMAS AV	79 BREHL AVE	599.0	0.0	LOT 173	9100.0	12/4/2008	15000.0	NaN	NaN	NaN
3	010-000129	BOWERS JASON A	1431 NEIL AV	4211 WOODBRIDGE RD	401.0	0.0	LOTS 1-2-3	1305.0	1/3/2002	825000.0	NaN	NaN	NaN
4	010-000004	CENTRAL OHIO COMMUNITY IM	1570 FRANKLIN AV	373 S HIGH ST FL 15	520.0	0.0	LOT 4	1201.0	4/13/2015	0.0	1900.0	2.0	2186.0

Validate Columns for All Merge Files

Before trying to merge, we should confirm that the columns across datasets are the same using the Series eq() method. Any differences will have to be corrected before merging the data

```
In [57]: cols1 = pd.Series(madison_merge.columns.sort_values())
         cols2 = pd.Series(morrow_merge.columns.sort_values())
         cols1.eq(cols2)
```

```
Out[57]: 0     True
         1     True
         2     True
         3     True
         4     True
         5     True
         6     True
         7     True
         8     True
         9     True
         10    True
         11    True
         12    True
         13    True
         14    True
         15    True
         16    True
         17    True
         dtype: bool
```

```
In [58]: cols1 = pd.Series(madison_merge.columns.sort_values())
         cols2 = pd.Series(franklin_merge.columns.sort_values())
         cols1.eq(cols2)
```

```
Out[58]: 0     True
         1     True
         2     True
         3     True
         4     True
         5     True
         6     True
         7     True
         8     True
         9     True
         10    True
         11    True
         12    True
         13    True
         14    True
         15    True
         16    True
         17    True
         dtype: bool
```

We will take a last look at the columns for all the merge files

In [59]:
```
display(madison_merge.columns.sort_values())
display(morrow_merge.columns.sort_values())
display(franklin_merge.columns.sort_values())
```

```
Index(['Acres', 'County', 'FinishedArea', 'LandUse', 'LegalDescription',
       'MailingAddress', 'NeighborhoodCode', 'NumberOfBedrooms',
       'NumberOfFullBaths', 'NumberOfHalfBaths', 'NumberOfRooms',
       'NumberOfStories', 'Owner', 'Parcel', 'PropertyAddress', 'SaleDate',
       'SalePrice', 'YearBuilt'],
      dtype='object')

Index(['Acres', 'County', 'FinishedArea', 'LandUse', 'LegalDescription',
       'MailingAddress', 'NeighborhoodCode', 'NumberOfBedrooms',
       'NumberOfFullBaths', 'NumberOfHalfBaths', 'NumberOfRooms',
       'NumberOfStories', 'Owner', 'Parcel', 'PropertyAddress', 'SaleDate',
       'SalePrice', 'YearBuilt'],
      dtype='object')

Index(['Acres', 'County', 'FinishedArea', 'LandUse', 'LegalDescription',
       'MailingAddress', 'NeighborhoodCode', 'NumberOfBedrooms',
       'NumberOfFullBaths', 'NumberOfHalfBaths', 'NumberOfRooms',
       'NumberOfStories', 'Owner', 'Parcel', 'PropertyAddress', 'SaleDate',
       'SalePrice', 'YearBuilt'],
      dtype='object')
```

Merge files into one (using APPEND)

Since all of the columns of the 3 files match, we can use APPEND.
NOTE: **Pandas concat Vs append Vs join Vs merge**

- **Concat** gives the flexibility to join based on the axis(all rows or all columns)
- **Append** is the specific case(axis=0, join='outer') of concat
- **Join** is based on the indexes (set by set_index) on how variable =['left','right','inner','couter']
- **Merge** is based on any particular column each of the two dataframes, this columns are variables on like 'left_on', 'right_on', 'on'

NOTE: Came across a thread about Concat being faster than Append, would like to investigate this further

In [60]:
```
all_data = madison_merge.append([morrow_merge,franklin_merge], ignore_index=True, sort=True)
all_data.head()
```

Out[60]:

	Acres	County	FinishedArea	LandUse	LegalDescription	MailingAddress	NeighborhoodCode	NumberOfBedrooms	NumberOfFullBaths	NumberOfHalfBaths	NumberOfRooms
0	80.000	Madison	2114.0	111.0	80.00A 7791	5155 PRICE HILLIARDS ROAD PLAIN CITY OH 43064	1111102 - DARBY-PLAINCITY-CANAAN-N JEFF AG	3.0	2.0	0.0	6.0
1	2.453	Madison	0.0	100.0	2.4532A 1479	154 BEECH DR DELAWARE OH 43015	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	0.0	0.0	0.0	0.0
2	2.453	Madison	0.0	100.0	2.4532A 1479	154 BEECH DR DELAWARE OH 43015	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	0.0	0.0	0.0	0.0
3	1.638	Madison	0.0	500.0	1.638A 1479	154 BEECH DR DELAWARE OH 43015	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	0.0	0.0	0.0	0.0
4	1.638	Madison	0.0	500.0	1.638A 1479	154 BEECH DR DELAWARE OH 43015	0159015 - CANAAN TWP JONATHAN ALDER SD BASE	0.0	0.0	0.0	0.0

Validate all 3 Counties are in the merged file

In [61]:
```
all_data.County.value_counts()
```

Out[61]:
```
Franklin    42871
Madison       156
Morrow         85
Name: County, dtype: int64
```

In [62]:
```
all_data.to_csv ('../data/county_auditor/all_data.csv', index = None, header=True)
```

```
<a name="Explore-data"></a>
## Explore Data
We will use functions to explore the data a little more and seek opportunities to clean the data
```

```
<a name="Check-dtypes"></a>
### Get dtypes for each Column
<hr>

First, we will look at the data types of each column to know what will apprear when we use the `describe()` method. NOTE:
 `describe()` only shows numerics

<hr>
```

In [83]:
```
all_data.dtypes
```

Out[83]:
```
Acres                 float64
County                 object
FinishedArea          float64
LandUse               float64
LegalDescription       object
MailingAddress         object
NeighborhoodCode       object
NumberOfBedrooms      float64
NumberOfFullBaths     float64
NumberOfHalfBaths     float64
NumberOfRooms         float64
NumberOfStories       float64
Owner                  object
Parcel                 object
PropertyAddress        object
SaleDate               object
SalePrice             float64
YearBuilt              object
dtype: object
```

```
<a name="Describe"></a>
### Describe Data
<hr>

We can use the DataFrame `describe()` method to quickly calculate some discriptive statistics for each of the numeric columns in the dataframe.

<hr>
```

In [63]:
```
all_data.describe()
```

Out[63]:

	Acres	FinishedArea	LandUse	NumberOfBedrooms	NumberOfFullBaths	NumberOfHalfBaths	NumberOfRooms	NumberOfStories	SalePrice
count	43111.000000	35944.000000	42219.000000	35910.000000	35919.000000	19034.000000	35944.000000	35944.000000	4.300300e+04
mean	0.407542	1609.864289	512.478339	3.110109	1.650324	1.049438	6.313682	1.476806	2.264483e+05
std	6.515603	757.999185	48.827793	0.908076	0.676091	0.270289	1.707536	0.501866	1.455031e+06
min	0.000000	0.000000	100.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000e+00
25%	0.000000	1080.000000	510.000000	3.000000	1.000000	1.000000	5.000000	1.000000	0.000000e+00
50%	0.000000	1404.000000	510.000000	3.000000	2.000000	1.000000	6.000000	1.000000	6.850000e+04
75%	0.000000	1967.000000	510.000000	4.000000	2.000000	1.000000	7.000000	2.000000	1.563125e+05
max	550.300000	30000.000000	900.000000	15.000000	9.000000	7.000000	24.000000	3.000000	1.342410e+08

```
<a name="Get-value-counts"></a>
### Get Value Counts
<hr>

We can we iterate through the columns of the DataFrame and display the column name with the output from the value_counts() method.

Primarily, we are interested in the numeric columns to get more insight on those.
YearBuilt is one we want to see values on as well (at a glance, there are 'UNAVAILABLE' values) and this is non-numeric as shown in our .dtypes() result above

The non-numeric columns are:  LegalDescription, MailingAddress, NeighborhoodCode, Owner, Parcel, PropertyAddress
<hr>
```

In [67]:
```python
import numpy as np

for column in all_data.columns:
    if np.issubdtype(all_data[column].dtype, np.number):
        display(column, all_data[column].value_counts())
```

```
3790.0      1
4852.0      1
2119.0      1
5476.0      1
3846.0      1
4337.0      1
3550.0      1
4718.0      1
30000.0     1
923.0       1
4198.0      1
336.0       1
3488.0      1
5345.0      1
5144.0      1
3037.0      1
614.0       1
3521.0      1
3598.0      1
```

In [82]:
```
all_data.YearBuilt.value_counts()
```

Out[82]:
```
1900.0    1185
1959.0     759
2001.0     695
1972.0     642
2003.0     633
1999.0     625
1998.0     623
2002.0     612
1994.0     604
2004.0     598
2000.0     592
1997.0     583
1953.0     581
1962.0     577
1996.0     562
2005.0     561
1954.0     556
1987.0     554
1955.0     551
1964.0     548
1960.0     528
1956.0     527
1963.0     522
1957.0     520
1970.0     510
1988.0     504
1973.0     478
1920.0     467
1965.0     467
1989.0     466
          ...
1960         1
1936         1
1953         1
1865.0       1
1992         1
1847         1
1967         1
1951         1
1996         1
1979         1
1976         1
1961         1
1977         1
1966         1
1887         1
2009         1
2008         1
1867.0       1
1920         1
1978         1
1959         1
1956         1
1916         1
1888.0       1
1886.0       1
1883.0       1
1881.0       1
1878.0       1
1873.0       1
1986         1
Name: YearBuilt, Length: 207, dtype: int64
```

In [102]:
```
all_data.YearBuilt.unique()
```

Out[102]:
```
array(['1977', 'UNAVAILABLE', '1930', '2001', '1958', '1975', '1967',
       '1916', '1969', '2005', '1997', '1972', '1960', '2008', '2002',
       '1994', '1992', '1982', '1966', '1945', '1950', '1987', '1956',
       '1961', '1984', '2003', 1969.0, 1870.0, 1958.0, 2007.0, 1979.0,
       1999.0, 1906.0, 2001.0, 2000.0, 1972.0, 1954.0, 1977.0, 1913.0,
       1952.0, 1920.0, 1919.0, 1900.0, 1884.0, 1904.0, 1957.0, 2011.0,
       1923.0, 1928.0, 1910.0, 1925.0, 1987.0, 1940.0, 1909.0, 1899.0,
       1912.0, 1894.0, 1941.0, 1924.0, 1949.0, 1915.0, 2004.0, 1971.0,
       1890.0, 1911.0, 1951.0, 2005.0, 1950.0, 1914.0, 2003.0, 1945.0,
       1898.0, 1895.0, 1922.0, 1930.0, 1948.0, 1939.0, 1926.0, 1991.0,
       1937.0, 1974.0, 1918.0, 1905.0, 1908.0, 1938.0, 1880.0, 1967.0,
       1989.0, 1973.0, 2002.0, 1953.0, 1943.0, 1867.0, 1929.0, 1921.0,
       1901.0, 1936.0, 1985.0, 1927.0, 1962.0, 1946.0, 1887.0, 1907.0,
       1942.0, 1878.0, 1902.0, 1931.0, 1959.0, 1917.0, 1968.0, 1980.0,
       1889.0, 1964.0, 1956.0, 1893.0, 1988.0, 1885.0, 2012.0, 1935.0,
       1993.0, 1963.0, 1916.0, 1932.0, 1877.0, 1961.0, 1934.0, 2006.0,
       1888.0, 1860.0, 2009.0, 1850.0, 1995.0, 1992.0, 1891.0, 1975.0,
       1990.0, 2010.0, 1997.0, 1871.0, 1800.0, 1965.0, 1903.0, 1960.0,
       1983.0, 1981.0, 1944.0, 1998.0, 1966.0, 1955.0, 1892.0, 1881.0,
       1897.0, 1978.0, 1896.0, 1970.0, 1994.0, 1947.0, 1882.0, 1879.0,
       1996.0, 1976.0, 1933.0, 2013.0, 1986.0, 1984.0, 1982.0, 2008.0,
       1868.0, 1840.0, 1873.0, 1857.0, 1875.0, 1865.0, 1837.0, 1855.0,
       1863.0, 1874.0], dtype=object)
```

```
<a name="Check-duplicates"></a>
### Check for Duplicates
```

```
In [78]: temp = all_data
         display("all_data")
         display(len(temp))
         display(len(temp.drop_duplicates()))
         display(len(temp.drop_duplicates())/len(temp))

         #Curious to see which counties represent the duplicates
         temp = franklin_merge
         display("franklin_merge")
         display(len(temp))
         display(len(temp.drop_duplicates()))
         display(len(temp.drop_duplicates())/len(temp))

         temp = madison_merge
         display("madison_merge")
         display(len(temp))
         display(len(temp.drop_duplicates()))
         display(len(temp.drop_duplicates())/len(temp))

         temp = morrow_merge
         display("morrow_merge")
         display(len(temp))
         display(len(temp.drop_duplicates()))
         display(len(temp.drop_duplicates())/len(temp))
```

```
'all_data'

43112

43099

0.9996984598255706

'franklin_merge'

42871

42871

1.0

'madison_merge'

156

143

0.9166666666666666

'morrow_merge'

85

85

1.0
```

```
<a name="Check-isna"></a>
### Check for NaN values
```

```
In [85]: all_data.isna().sum()
```

```
Out[85]: Acres                    1
         County                   0
         FinishedArea          7168
         LandUse                893
         LegalDescription      3192
         MailingAddress         378
         NeighborhoodCode         1
         NumberOfBedrooms      7202
         NumberOfFullBaths     7193
         NumberOfHalfBaths    24078
         NumberOfRooms         7168
         NumberOfStories       7168
         Owner                    1
         Parcel                   1
         PropertyAddress        387
         SaleDate               141
         SalePrice              109
         YearBuilt             7168
         dtype: int64
```

Note that Finished Area and NumberOf... values are all roughly the same (close to 7168). I wonder if this is because these are land plots vs. homes? We can cross-check the land use code (http://codes.ohio.gov/oac/5703-25-10) with these to see if this is the case.

```
In [90]: temp = all_data[all_data.FinishedArea.isna()]
         temp.head(20)
         temp.LandUse.value_counts()
```

```
Out[90]: 500.0    1118
         510.0     499
         401.0     397
         400.0     276
         640.0     265
         501.0     264
         685.0     232
         447.0     172
         403.0     155
         450.0     134
         599.0     121
         499.0     118
         480.0     112
         456.0     111
         559.0     108
         420.0     106
         455.0     105
         660.0     101
         553.0      98
         680.0      96
         610.0      89
         670.0      89
         511.0      86
         350.0      84
         429.0      64
         435.0      60
         650.0      58
         404.0      57
         550.0      54
         442.0      53
                  ...
         419.0       3
         437.0       3
         124.0       3
         560.0       3
         446.0       3
         341.0       3
         423.0       3
         342.0       3
         488.0       3
         464.0       2
         302.0       2
         438.0       2
         305.0       2
         304.0       2
         123.0       2
         424.0       2
         451.0       2
         541.0       1
         112.0       1
         462.0       1
         485.0       1
         460.0       1
         585.0       1
         432.0       1
         434.0       1
         504.0       1
         681.0       1
         466.0       1
         555.0       1
         513.0       1
         Name: LandUse, Length: 146, dtype: int64
```

```
With the exception of 510.0 - 530.0 (Single family dwelling), the others would make sense not to have Finished areas as they are
agricultural or unplatted lots or other structures.
```

```
<a name="Clean-data"></a>
## Clean Data
Now that we can see some of the values in more detail, we can clean up some of the data
```

```
<a name="Clean-data-approach"></a>
### Clean Data Approach
* For Half bath, make the NaN = 0
    * We do not wish to eliminate all rows with HalfBaths hainv NaN, that would be more than 1/2 of the rows
    * Instead, we will assume a value of 0 for those that are NaN
    * Make sure we do this before removing rows that have NaN
* Eliminate all rows that have NaN values for
    * Acres
    * Finished Area
    * Land Use
    * NeighborhoodCode
    * NumberOf fields (Bedrooms, Bathrooms, Roooms, Stories)
    * Owner, Parcel,
    * PropertyAddress (Could be valid, ex., no assigned address, just GIS coordinates or LOT#, but we are choosing not to look at
these in our analysis)
    * SaleDate
    * SalePrice
* Eliminate duplicates
* For SalePrice, only use values > 0 and eliminate the 4th quartile to eliminate the anomolies
* For YearBuilt, eliminate 'UNAVAILABLE' rows, only use values > 0 and not blanks (NOTE:  In Excel, this is 7,168)
    * Make this and integer data type

**Team Decision:  Do we eliminate Acreage = 0?  That will just leave us with roughly 2000 recs.
*** Eliminate all rows that have zero values for
    * Finished Area
    * NumberOf fields (Bedrooms, FullBath, HalBaths, Rooms, Stories)?
*** Or maybe hone on on specific Land Use Codes?
```

```
<a name="Half-bath"></a>
```
### Half Bath NaN = 0

In [92]:
```
# Display first rows of our data where NumberOfHalfBaths isna()
all_data[all_data.NumberOfHalfBaths.isna()].head()
```

In [ ]:
```
all_data.NumberOfHalfBaths = all_data.NumberOfHalfBaths.fillna(value=0)
```

In [93]:
```
# Display again, should get no rows
all_data[all_data.NumberOfHalfBaths.isna()].head()
```

Out[93]:

Acres	County	FinishedArea	LandUse	LegalDescription	MailingAddress	NeighborhoodCode	NumberOfBedrooms	NumberOfFullBaths	NumberOfHalfBaths	NumberOfRooms	Nu

```
<a name="Eliminate-nan"></a>
```
### Eliminate NaN

In [94]:
```
all_data = all_data[all_data.Acres.notna()]
all_data = all_data[all_data.FinishedArea.notna()]
all_data = all_data[all_data.LandUse.notna()]
all_data = all_data[all_data.NeighborhoodCode.notna()]
all_data = all_data[all_data.NumberOfBedrooms.notna()]
all_data = all_data[all_data.NumberOfFullBaths.notna()]
all_data = all_data[all_data.NumberOfHalfBaths.notna()]
all_data = all_data[all_data.NumberOfRooms.notna()]
all_data = all_data[all_data.NumberOfStories.notna()]
all_data = all_data[all_data.Owner.notna()]
all_data = all_data[all_data.Parcel.notna()]
all_data = all_data[all_data.PropertyAddress.notna()]
all_data = all_data[all_data.SaleDate.notna()]
all_data = all_data[all_data.SalePrice.notna()]
# Check the number of NaN values again
all_data.isna().sum()
```

Out[94]:
```
Acres                   0
County                  0
FinishedArea            0
LandUse                 0
LegalDescription     2480
MailingAddress        166
NeighborhoodCode        0
NumberOfBedrooms        0
NumberOfFullBaths       0
NumberOfHalfBaths       0
NumberOfRooms           0
NumberOfStories         0
Owner                   0
Parcel                  0
PropertyAddress         0
SaleDate                0
SalePrice               0
YearBuilt               0
dtype: int64
```

In [95]:
```
# Look at how this impacted counts
all_data.County.value_counts()
```

Out[95]:
```
Franklin    35325
Madison       156
Morrow         32
Name: County, dtype: int64
```

```
<a name="Eliminate-dups"></a>
```
### Eliminate Duplicates

```
In [96]: all_data.drop_duplicates()
```

13	2.438	Madison	1260.0	510.0	2.4384A 7059 ETC	%CORELOGIC 3001 HACKBERRY IRVING TX 75063	0259025 - DARBY TWP JONATHAN ALDER SD BASE	3.0	1.0	0.0
14	4.950	Madison	2111.0	510.0	4.947A 3685	%WELLS FARGO 1 HOME CAMPUS ST DES MOINES IA 50328	0259025 - DARBY TWP JONATHAN ALDER SD BASE	3.0	2.0	0.0
16	1.000	Madison	2847.0	510.0	1.00A 8539	10500 CONVERSE CHAPEL RD PLAIN CITY OH 43064	0259025 - DARBY TWP JONATHAN ALDER SD BASE	3.0	2.0	0.0
17	0.460	Madison	0.0	500.0	.4583A 8539	10500 CONVERSE CHAPEL RD PLAIN CITY OH 43064	0259025 - DARBY TWP JONATHAN ALDER SD BASE	0.0	0.0	0.0
18	0.600	Madison	0.0	447.0	.600A 7074	16432 GRAND BASIN CT WILDWOOD MO	4444402 - DARBY-PLAINCITY-CANAAN-N JEFF	0.0	0.0	0.0

```
In [97]: # Look at how this impacted counts
         all_data.County.value_counts()

Out[97]: Franklin    35325
         Madison       156
         Morrow         32
         Name: County, dtype: int64
```

```
<a name="Saleprice-drop"></a>
### Drop 1st and 4th quartile SalesPrices
```

```
In [100]: all_data = all_data[all_data.SalePrice > 0.0]
          all_data = all_data[all_data.SalePrice < 1500000]
          display(all_data.SalePrice.describe())
          all_data.County.value_counts()

          count    2.351500e+04
          mean     1.546939e+05
          std      1.321078e+05
          min      5.000000e+00
          25%      7.790000e+04
          50%      1.277000e+05
          75%      1.875075e+05
          max      1.474000e+06
          Name: SalePrice, dtype: float64

Out[100]: Franklin    23432
          Madison        69
          Morrow         14
          Name: County, dtype: int64
```

```
<a name="YearBuilt-cleanup"></a>
### Filter YearBuilt
```

```
In [103]: all_data = all_data[all_data.YearBuilt != 'UNAVAILABLE']
          all_data.YearBuilt.unique()
          #all_data.County.value_counts()

Out[103]: array(['1977', '1930', '2001', '1958', '1975', '1967', '1916', '1969',
                 '2005', '1997', '1972', '1960', '2008', '2002', '1994', '1992',
                 '1982', '1966', '1945', '1950', '1987', '1956', '1961', '1984',
                 '2003', 1969.0, 1870.0, 1958.0, 2007.0, 1979.0, 1999.0, 1906.0,
                 2001.0, 2000.0, 1972.0, 1954.0, 1977.0, 1913.0, 1952.0, 1920.0,
                 1919.0, 1900.0, 1884.0, 1904.0, 1957.0, 2011.0, 1923.0, 1928.0,
                 1910.0, 1925.0, 1987.0, 1940.0, 1909.0, 1899.0, 1912.0, 1894.0,
                 1941.0, 1924.0, 1949.0, 1915.0, 2004.0, 1971.0, 1890.0, 1911.0,
                 1951.0, 2005.0, 1950.0, 1914.0, 2003.0, 1945.0, 1898.0, 1895.0,
                 1922.0, 1930.0, 1948.0, 1939.0, 1926.0, 1991.0, 1937.0, 1974.0,
                 1918.0, 1905.0, 1908.0, 1938.0, 1880.0, 1967.0, 1989.0, 1973.0,
                 2002.0, 1953.0, 1943.0, 1867.0, 1929.0, 1921.0, 1901.0, 1936.0,
                 1985.0, 1927.0, 1962.0, 1946.0, 1887.0, 1907.0, 1942.0, 1878.0,
                 1902.0, 1931.0, 1959.0, 1917.0, 1968.0, 1980.0, 1889.0, 1964.0,
                 1956.0, 1893.0, 1988.0, 1885.0, 2012.0, 1935.0, 1993.0, 1963.0,
                 1916.0, 1932.0, 1877.0, 1961.0, 1934.0, 2006.0, 1888.0, 1860.0,
                 2009.0, 1850.0, 1995.0, 1992.0, 1891.0, 1975.0, 1990.0, 2010.0,
                 1997.0, 1871.0, 1800.0, 1965.0, 1903.0, 1960.0, 1983.0, 1981.0,
                 1944.0, 1998.0, 1966.0, 1955.0, 1892.0, 1881.0, 1897.0, 1978.0,
                 1896.0, 1970.0, 1994.0, 1947.0, 1882.0, 1879.0, 1996.0, 1976.0,
                 1933.0, 2013.0, 1986.0, 1984.0, 1982.0, 2008.0, 1868.0, 1840.0,
                 1873.0, 1857.0, 1875.0, 1865.0, 1837.0, 1855.0, 1863.0, 1874.0],
                dtype=object)
```

In [104]:
```
all_data.YearBuilt.value_counts()
```

Out[104]:
```
1900.0    690
2003.0    489
2004.0    469
1994.0    464
2001.0    463
2005.0    462
1998.0    444
1999.0    436
2002.0    430
1987.0    415
2000.0    410
1997.0    409
1959.0    407
1996.0    398
1972.0    391
1988.0    382
1992.0    371
2006.0    359
1989.0    345
1953.0    334
1991.0    329
1954.0    328
1993.0    326
1986.0    324
1995.0    324
1985.0    320
1962.0    316
1956.0    315
1955.0    314
1957.0    307
         ...
1960        1
1975        1
1966        1
1987        1
1882.0      1
1945        1
1958        1
1961        1
2001        1
2008        1
1992        1
2005        1
2002        1
1840.0      1
1837.0      1
1881.0      1
1855.0      1
1857.0      1
1956        1
1863.0      1
1865.0      1
1867.0      1
1868.0      1
1967        1
1873.0      1
1896.0      1
1889.0      1
1878.0      1
1888.0      1
1916        1
Name: YearBuilt, Length: 176, dtype: int64
```

In [112]:
```
for index, row in all_data.iterrows():
    new_value = str(row.YearBuilt)
    new_value = new_value.replace('.0', '')
    new_value = int(new_value)
    all_data.loc[index, 'YearBuilt'] = new_value
#NOTE:  Look for a more efficient way to do this!  This took a while and machine was running hot!
```

In [113]:
```
all_data.YearBuilt.unique()
```

Out[113]:
```
array([1977, 1930, 2001, 1958, 1975, 1967, 1916, 1969, 2005, 1997, 1972,
       1960, 2008, 2002, 1994, 1992, 1982, 1966, 1945, 1950, 1987, 1956,
       1961, 1984, 2003, 1870, 2007, 1979, 1999, 1906, 2000, 1954, 1913,
       1952, 1920, 1919, 1900, 1884, 1904, 1957, 2011, 1923, 1928, 1910,
       1925, 1940, 1909, 1899, 1912, 1894, 1941, 1924, 1949, 1915, 2004,
       1971, 1890, 1911, 1951, 1914, 1898, 1895, 1922, 1948, 1939, 1926,
       1991, 1937, 1974, 1918, 1905, 1908, 1938, 1880, 1989, 1973, 1953,
       1943, 1867, 1929, 1921, 1901, 1936, 1985, 1927, 1962, 1946, 1887,
       1907, 1942, 1878, 1902, 1931, 1959, 1917, 1968, 1980, 1889, 1964,
       1893, 1988, 1885, 2012, 1935, 1993, 1963, 1932, 1877, 1934, 2006,
       1888, 1860, 2009, 1850, 1995, 1891, 1990, 2010, 1871, 1800, 1965,
       1903, 1983, 1981, 1944, 1998, 1955, 1892, 1881, 1897, 1978, 1896,
       1970, 1947, 1882, 1879, 1996, 1976, 1933, 2013, 1986, 1868, 1840,
       1873, 1857, 1875, 1865, 1837, 1855, 1863, 1874])
```

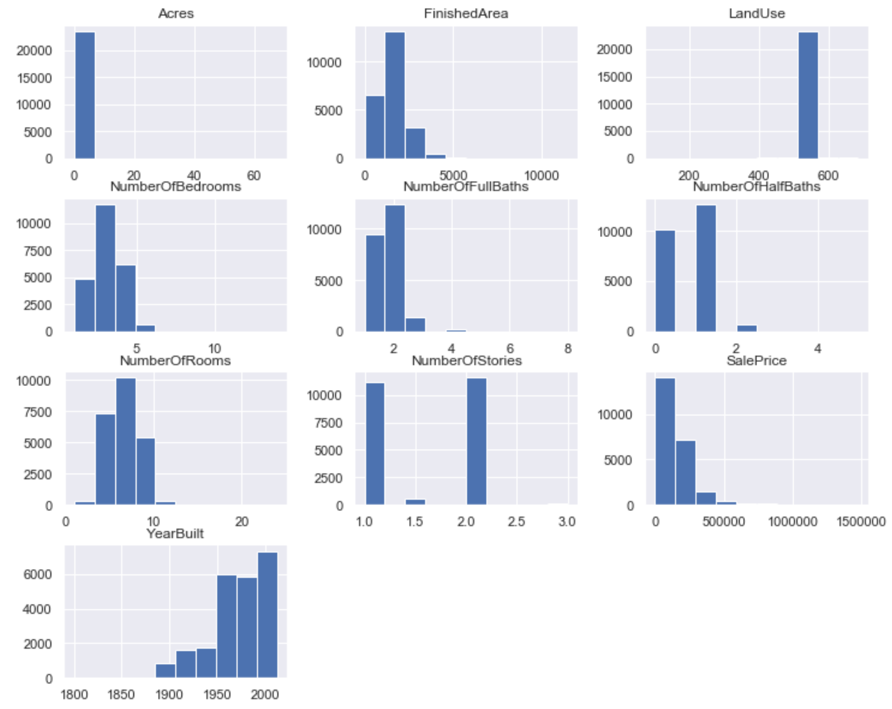
```
<a name="Explore-data-2"></a>
## Explore Data II
We will use charts and graphs to explore the data a little more and also seek opportunities to clean the data further
```

```
In [116]: %matplotlib inline
          import seaborn as sns

          pd.set_option("display.max_columns", 100)
          sns.set(rc={'figure.figsize': (12, 10), "lines.markeredgewidth": 0.5 })
```

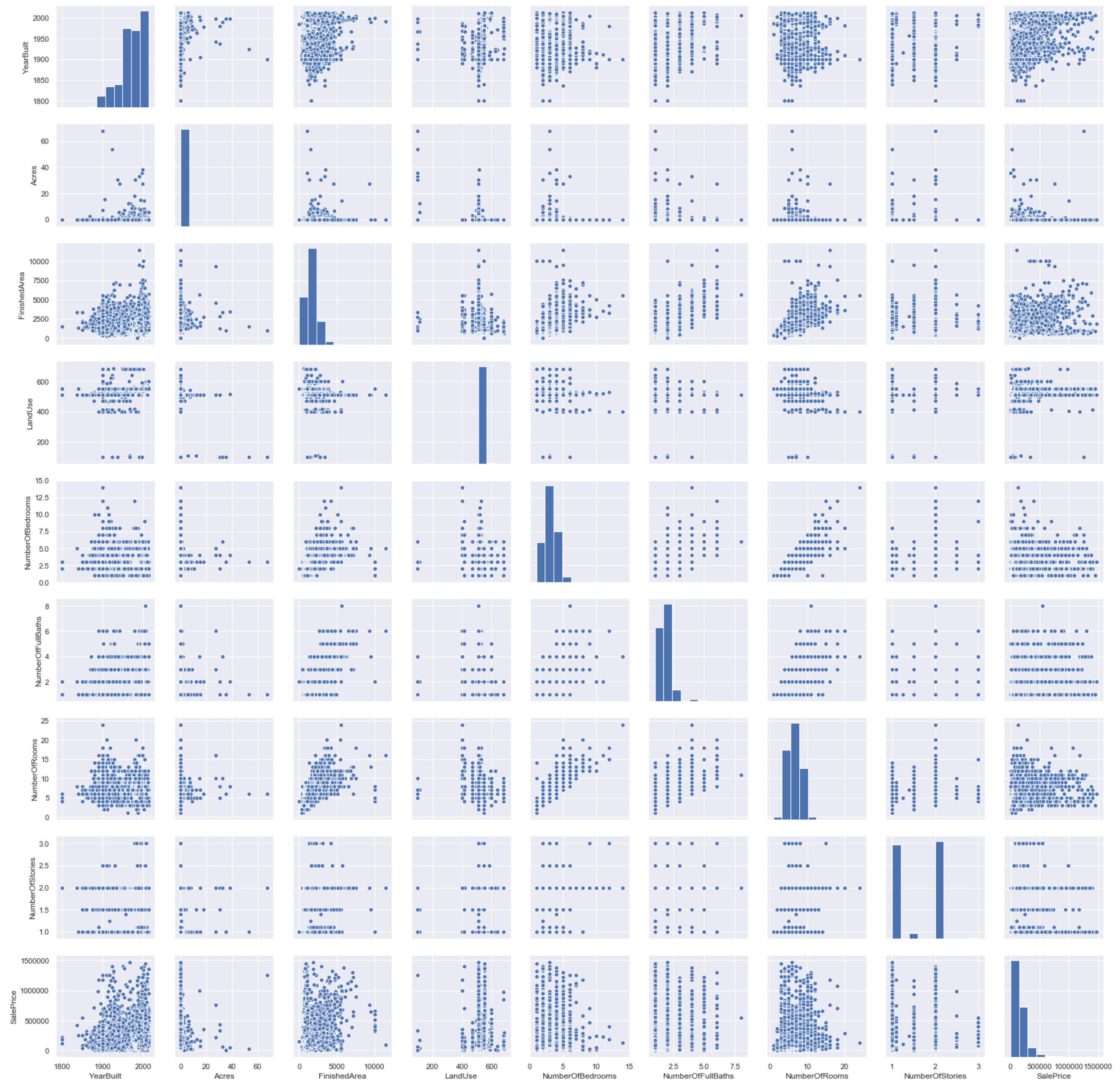
```
In [117]: all_data.hist()
```

```
Out[117]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1346a1a58>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x12e0dd048>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x134cc9390>],
                 [<matplotlib.axes._subplots.AxesSubplot object at 0x12bca0c50>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x12bc86cc0>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x1348c4f28>],
                 [<matplotlib.axes._subplots.AxesSubplot object at 0x13246f7b8>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x1324819b0>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x1324819e8>],
                 [<matplotlib.axes._subplots.AxesSubplot object at 0x123ea0390>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x123e78630>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x131c40f98>]],
                dtype=object)
```



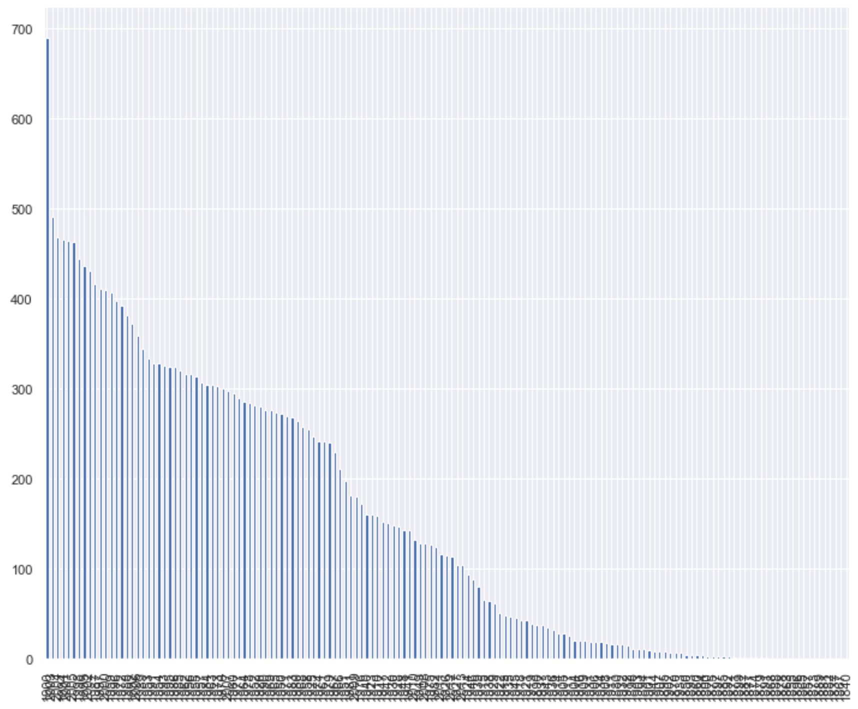
```
In [118]: columns = [ "YearBuilt", "Acres", "FinishedArea", "LandUse", "NumberOfBedrooms", "NumberOfFullBaths", "NumberOfRooms", "NumberOfStorie
          sns.pairplot(all_data[columns])

Out[118]: <seaborn.axisgrid.PairGrid at 0x134be3cf8>
```



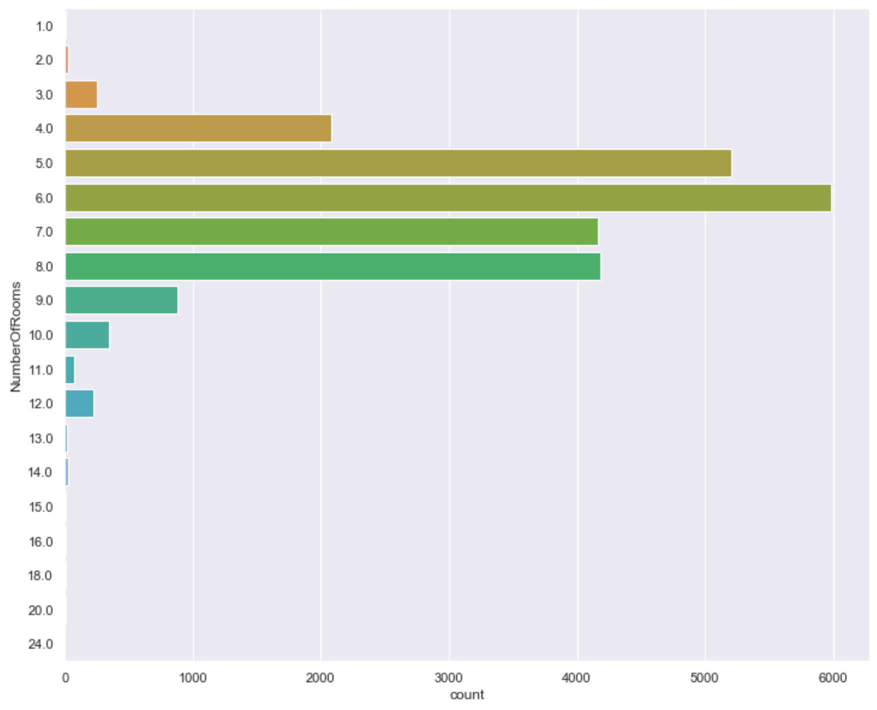
```
In [120]: all_data['YearBuilt'].value_counts().plot(kind="bar")
```

```
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x12ba882e8>
```



```
In [122]: sns.countplot(y=all_data['NumberOfRooms'])
```

```
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x1259585f8>
```



```
In [123]: all_data.groupby(["County", "LandUse"]).size()
```

```
Out[123]: County    LandUse
          Franklin  101.0          6
                    111.0          1
                    401.0         23
                    402.0          1
                    403.0          3
                    404.0          1
                    414.0          7
                    415.0          2
                    419.0          2
                    467.0          1
                    470.0         29
                    471.0          6
                    472.0          1
                    499.0          5
                    510.0      18213
                    511.0        601
                    512.0         13
                    513.0          3
                    514.0          1
                    520.0        640
                    530.0         37
                    550.0       3341
                    551.0        233
                    552.0         82
                    553.0         67
                    559.0          1
                    560.0          3
                    585.0          2
                    591.0         30
                    592.0          1
                    599.0         29
                    624.0          2
                    640.0          4
                    680.0         37
                    685.0          4
          Madison   111.0          1
                    510.0         36
                    550.0          2
          Morrow    510.0          6
                    511.0          4
                    512.0          1
                    540.0          1
                    541.0          2
          dtype: int64
```

```
In [ ]: sns.pairplot(all_data[columns], hue="FinishedArea")
```

```
/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:140: RuntimeWarning: Degrees of freedom <= 0 for slice
  keepdims=keepdims)
/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:132: RuntimeWarning: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kde.py:488: RuntimeWarning: invalid value encountered in true_divid
e
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kdetools.py:34: RuntimeWarning: invalid value encountered in double
_scalars
  FAC1 = 2*(np.pi*bw/RANGE)**2
```

```
In [ ]: sns.boxplot(x="SalePrice", y="YearBuilt", data=df_redux)
```