Improving Data Quality

Learning Objectives

1. Resolve missing values
2. Convert the Date feature column to a datetime format
3. Rename a feature column, remove a value from a feature column
4. Create one-hot encoding features
5. Understand temporal feature conversions

Introduction

Recall that machine learning models can only consume numeric data, and that numeric data should be "1"s or "0"s. Data is said to be "messy" or "untidy" if it is missing attribute values, contains noise or outliers, has duplicates, wrong data, upper/lower case column names, and is essentially not ready for ingestion by a machine learning algorithm.

This notebook presents and solves some of the most common issues of "untidy" data. Note that different problems will require different methods, and they are beyond the scope of this notebook.

Each learning objective will correspond to a *#TODO* in this student lab notebook -- try to complete this notebook first and then review the solution notebook.

In [1]:
```
!sudo chown -R jupyter:jupyter /home/jupyter/training-data-analyst
```

In [2]:
```
# Ensure the right version of Tensorflow is installed.
!pip freeze | grep tensorflow==2.1 || pip install tensorflow==2.1
```

```
Collecting tensorflow==2.1
  Downloading tensorflow-2.1.0-cp37-cp37m-manylinux2010_x86_64.whl (421.8 MB)
     |████████████████████████████████| 421.8 MB 16 kB/s s eta 0:00:01MB/s eta 0:00:03     |██████████████████████████▏     | 344.7 MB 63.6 MB/s eta 0:00:02     |██████████████████████████████▏ | 399.7 MB 75.4 MB/s eta 0:00:01
Requirement already satisfied: six>=1.12.0 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (1.15.0)
Requirement already satisfied: grpcio>=1.8.6 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (1.36.0)
Collecting scipy==1.4.1
  Downloading scipy-1.4.1-cp37-cp37m-manylinux1_x86_64.whl (26.1 MB)
     |████████████████████████████████| 26.1 MB 49.0 MB/s eta 0:00:01
Collecting astor>=0.6.0
  Downloading astor-0.8.1-py2.py3-none-any.whl (27 kB)
Requirement already satisfied: wrapt>=1.11.1 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (1.12.1)
Collecting tensorflow-estimator<2.2.0,>=2.1.0rc0
  Downloading tensorflow_estimator-2.1.0-py2.py3-none-any.whl (448 kB)
     |████████████████████████████████| 448 kB 18.2 MB/s eta 0:00:01
Requirement already satisfied: absl-py>=0.7.0 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (0.10.0)
Collecting gast==0.2.2
  Downloading gast-0.2.2.tar.gz (10 kB)
Collecting tensorboard<2.2.0,>=2.1.0
  Downloading tensorboard-2.1.1-py3-none-any.whl (3.8 MB)
     |████████████████████████████████| 3.8 MB 56.6 MB/s eta 0:00:01
Requirement already satisfied: wheel>=0.26 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (0.36.2)
Collecting keras-applications>=1.0.8
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
     |████████████████████████████████| 50 kB 7.4 MB/s  eta 0:00:01
Requirement already satisfied: termcolor>=1.1.0 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (1.1.0)
Requirement already satisfied: keras-preprocessing>=1.1.0 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (1.1.2)
Requirement already satisfied: google-pasta>=0.1.6 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (0.2.0)
Requirement already satisfied: numpy<2.0,>=1.16.0 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (1.19.5)
Requirement already satisfied: protobuf>=3.8.0 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (3.15.3)
Requirement already satisfied: opt-einsum>=2.3.2 in /opt/conda/lib/python3.7/site-packages (from tensorflow==2.1) (3.3.0)
Requirement already satisfied: h5py in /opt/conda/lib/python3.7/site-packages (from keras-applications>=1.0.8->tensorflow==2.1) (2.1
0.0)
Requirement already satisfied: werkzeug>=0.11.15 in /opt/conda/lib/python3.7/site-packages (from tensorboard<2.2.0,>=2.1.0->tensorfl
ow==2.1) (1.0.1)
Requirement already satisfied: google-auth<2,>=1.6.3 in /opt/conda/lib/python3.7/site-packages (from tensorboard<2.2.0,>=2.1.0->tens
orflow==2.1) (1.27.0)
Requirement already satisfied: requests<3,>=2.21.0 in /opt/conda/lib/python3.7/site-packages (from tensorboard<2.2.0,>=2.1.0->tensor
flow==2.1) (2.25.1)
Requirement already satisfied: markdown>=2.6.8 in /opt/conda/lib/python3.7/site-packages (from tensorboard<2.2.0,>=2.1.0->tensorflow
==2.1) (3.3.4)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /opt/conda/lib/python3.7/site-packages (from tensorboard<2.2.0,>=
2.1.0->tensorflow==2.1) (0.4.2)
Requirement already satisfied: setuptools>=41.0.0 in /opt/conda/lib/python3.7/site-packages (from tensorboard<2.2.0,>=2.1.0->tensorf
low==2.1) (54.0.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /opt/conda/lib/python3.7/site-packages (from google-auth<2,>=1.6.3->tensorbo
ard<2.2.0,>=2.1.0->tensorflow==2.1) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4 in /opt/conda/lib/python3.7/site-packages (from google-auth<2,>=1.6.3->tensorboard<2.2.
0,>=2.1.0->tensorflow==2.1) (4.7.2)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /opt/conda/lib/python3.7/site-packages (from google-auth<2,>=1.6.3->tensorb
oard<2.2.0,>=2.1.0->tensorflow==2.1) (4.2.1)
```

```
Requirement already satisfied: requests-oauthlib>=0.7.0 in /opt/conda/lib/python3.7/site-packages (from google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (1.3.0)
Requirement already satisfied: importlib-metadata in /opt/conda/lib/python3.7/site-packages (from markdown>=2.6.8->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (3.7.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /opt/conda/lib/python3.7/site-packages (from pyasn1-modules>=0.2.1->google-auth<2,>=1.6.3->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (0.4.8)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.7/site-packages (from requests<3,>=2.21.0->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (2020.12.5)
Requirement already satisfied: chardet<5,>=3.0.2 in /opt/conda/lib/python3.7/site-packages (from requests<3,>=2.21.0->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (4.0.0)
Requirement already satisfied: idna<3,>=2.5 in /opt/conda/lib/python3.7/site-packages (from requests<3,>=2.21.0->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (2.10)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /opt/conda/lib/python3.7/site-packages (from requests<3,>=2.21.0->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (1.26.3)
Requirement already satisfied: oauthlib>=3.0.0 in /opt/conda/lib/python3.7/site-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (3.1.0)
Requirement already satisfied: zipp>=0.5 in /opt/conda/lib/python3.7/site-packages (from importlib-metadata->markdown>=2.6.8->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (3.4.0)
Requirement already satisfied: typing-extensions>=3.6.4 in /opt/conda/lib/python3.7/site-packages (from importlib-metadata->markdown>=2.6.8->tensorboard<2.2.0,>=2.1.0->tensorflow==2.1) (3.7.4.3)
Building wheels for collected packages: gast
  Building wheel for gast (setup.py) ... done
  Created wheel for gast: filename=gast-0.2.2-py3-none-any.whl size=7538 sha256=8109e59d170b1fd05e141174d77c53eabccf6ec32a2692797ae3b25e0768f0ce
  Stored in directory: /home/jupyter/.cache/pip/wheels/21/7f/02/420f32a803f7d0967b48dd823da3f558c5166991bfd204eef3
Successfully built gast
Installing collected packages: tensorflow-estimator, tensorboard, scipy, keras-applications, gast, astor, tensorflow
  Attempting uninstall: tensorflow-estimator
    Found existing installation: tensorflow-estimator 2.3.0
    Uninstalling tensorflow-estimator-2.3.0:
      Successfully uninstalled tensorflow-estimator-2.3.0
  Attempting uninstall: tensorboard
    Found existing installation: tensorboard 2.3.0
    Uninstalling tensorboard-2.3.0:
      Successfully uninstalled tensorboard-2.3.0
  Attempting uninstall: scipy
    Found existing installation: scipy 1.6.0
    Uninstalling scipy-1.6.0:
      Successfully uninstalled scipy-1.6.0
  Attempting uninstall: gast
    Found existing installation: gast 0.3.3
    Uninstalling gast-0.3.3:
      Successfully uninstalled gast-0.3.3
  Attempting uninstall: tensorflow
    Found existing installation: tensorflow 2.3.2
    Uninstalling tensorflow-2.3.2:
      Successfully uninstalled tensorflow-2.3.2
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts.
explainable-ai-sdk 1.2.0 requires xai-tabular-widget, which is not installed.
tfx 0.26.1 requires kubernetes<12,>=10.0.1, but you have kubernetes 12.0.1 which is incompatible.
tfx 0.26.1 requires pyarrow<0.18,>=0.17, but you have pyarrow 3.0.0 which is incompatible.
tfx 0.26.1 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,!=2.4.*,<3,>=1.15.2, but you have tensorflow 2.1.0 which is incompatible.
tfx-bsl 0.26.1 requires pyarrow<0.18,>=0.17, but you have pyarrow 3.0.0 which is incompatible.
tfx-bsl 0.26.1 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,!=2.4.*,<3,>=1.15.2, but you have tensorflow 2.1.0 which is incompatible.
tensorflow-transform 0.26.0 requires pyarrow<0.18,>=0.17, but you have pyarrow 3.0.0 which is incompatible.
tensorflow-transform 0.26.0 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,<2.4,>=1.15.2, but you have tensorflow 2.1.0 which is incompatible.
tensorflow-serving-api 2.3.0 requires tensorflow<3,>=2.3, but you have tensorflow 2.1.0 which is incompatible.
tensorflow-probability 0.11.0 requires cloudpickle==1.3, but you have cloudpickle 1.6.0 which is incompatible.
tensorflow-probability 0.11.0 requires gast>=0.3.2, but you have gast 0.2.2 which is incompatible.
tensorflow-model-analysis 0.26.0 requires pyarrow<0.18,>=0.17, but you have pyarrow 3.0.0 which is incompatible.
tensorflow-model-analysis 0.26.0 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,!=2.4.*,<3,>=1.15.2, but you have tensorflow 2.1.0 which is incompatible.
tensorflow-io 0.15.0 requires tensorflow<2.4.0,>=2.3.0, but you have tensorflow 2.1.0 which is incompatible.
tensorflow-data-validation 0.26.0 requires joblib<0.15,>=0.12, but you have joblib 1.0.1 which is incompatible.
tensorflow-data-validation 0.26.0 requires pyarrow<0.18,>=0.17, but you have pyarrow 3.0.0 which is incompatible.
tensorflow-data-validation 0.26.0 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,!=2.4.*,<3,>=1.15.2, but you have tensorflow 2.1.0 which is incompatible.
tensorflow-cloud 0.1.13 requires tensorboard>=2.3.0, but you have tensorboard 2.1.1 which is incompatible.
keras 2.4.0 requires tensorflow>=2.2.0, but you have tensorflow 2.1.0 which is incompatible.
fairness-indicators 0.26.0 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,!=2.4.*,<3,>=1.15.2, but you have tensorflow 2.1.0 which is incompatible.
explainable-ai-sdk 1.2.0 requires numpy<1.19.0, but you have numpy 1.19.5 which is incompatible.
Successfully installed astor-0.8.1 gast-0.2.2 keras-applications-1.0.8 scipy-1.4.1 tensorboard-2.1.1 tensorflow-2.1.0 tensorflow-estimator-2.1.0
```

Please ignore any incompatibility warnings and errors and re-run the cell to view the installed tensorflow version.

Start by importing the necessary libraries for this lab.

Import Libraries

In [3]:

```
import os
import pandas as pd  # First, we'll import Pandas, a data processing and CSV file I/O library
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Load the Dataset

The dataset is based on California's Vehicle Fuel Type Count by Zip Code report. The dataset has been modified to make the data "untidy" and is thus a synthetic representation that can be used for learning purposes.

Let's download the raw .csv data by copying the data from a cloud storage bucket.

In [4]:
```
if not os.path.isdir("../data/transport"):
    os.makedirs("../data/transport")
```

In [5]:
```
!gsutil cp gs://cloud-training-demos/feat_eng/transport/untidy_vehicle_data.csv ../data/transport
```

```
Copying gs://cloud-training-demos/feat_eng/transport/untidy_vehicle_data.csv...
/ [1 files][ 47.2 KiB/ 47.2 KiB]
Operation completed over 1 objects/47.2 KiB.
```

In [6]:
```
!ls -l ../data/transport
```

```
total 48
-rw-r--r-- 1 jupyter jupyter 48343 Mar 30 08:32 untidy_vehicle_data.csv
```

Read Dataset into a Pandas DataFrame

Next, let's read in the dataset just copied from the cloud storage bucket and create a Pandas DataFrame. We also add a Pandas .head() function to show you the top 5 rows of data in the DataFrame. Head() and Tail() are "best-practice" functions used to investigate datasets.

In [7]:
```
df_transport = pd.read_csv('../data/transport/untidy_vehicle_data.csv')
df_transport.head() # Output the first five rows.
```

Out[7]:

	Date	Zip Code	Model Year	Fuel	Make	Light_Duty	Vehicles
0	10/1/2018	90000	2006	Gasoline	OTHER/UNK	NaN	1.0
1	10/1/2018	NaN	2014	Gasoline	NaN	Yes	1.0
2	NaN	90000	NaN	Gasoline	OTHER/UNK	Yes	NaN
3	10/1/2018	90000	2017	Gasoline	OTHER/UNK	Yes	1.0
4	10/1/2018	90000	<2006	Diesel and Diesel Hybrid	OTHER/UNK	No	55.0

DataFrame Column Data Types

DataFrames may have heterogenous or "mixed" data types, that is, some columns are numbers, some are strings, and some are dates etc. Because CSV files do not contain information on what data types are contained in each column, Pandas infers the data types when loading the data, e.g. if a column contains only numbers, Pandas will set that column’s data type to numeric: integer or float.

Run the next cell to see information on the DataFrame.

In [8]:
```
df_transport.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Date        997 non-null    object 
 1   Zip Code    997 non-null    object 
 2   Model Year  997 non-null    object 
 3   Fuel        996 non-null    object 
 4   Make        996 non-null    object 
 5   Light_Duty  996 non-null    object 
 6   Vehicles    996 non-null    float64
dtypes: float64(1), object(6)
memory usage: 54.8+ KB
```

From what the .info() function shows us, we have six string objects and one float object. Let's print out the first and last five rows of each column. We can definitely see more of the "string" object values now!

In [9]:
```
print(df_transport,5)
```

```
          Date Zip Code Model Year                      Fuel       Make  \
0    10/1/2018    90000       2006                  Gasoline  OTHER/UNK   
1    10/1/2018      NaN       2014                  Gasoline        NaN   
2          NaN    90000        NaN                  Gasoline  OTHER/UNK   
3    10/1/2018    90000       2017                  Gasoline  OTHER/UNK   
4    10/1/2018    90000      <2006  Diesel and Diesel Hybrid  OTHER/UNK   
..         ...      ...        ...                       ...        ...   
994   6/7/2019    90003       2012                  Gasoline     Type_R   
995   6/8/2019    90003       2012           Hybrid Gasoline  OTHER/UNK   
```

```
996   6/9/2019    90003       2012           Hybrid Gasoline     Type_Q
997  6/10/2019    90003       2012               Natural Gas  OTHER/UNK
998  6/11/2019    90003       2012            Plug-in Hybrid  OTHER/UNK

    Light_Duty  Vehicles
0          NaN       1.0
1          Yes       1.0
2          Yes       NaN
3          Yes       1.0
4           No      55.0
..         ...       ...
994        Yes      26.0
995        Yes       4.0
996        Yes      25.0
997        Yes       1.0
998        Yes       3.0

[999 rows x 7 columns] 5
```

Summary Statistics

At this point, we have only one column which contains a numerical value (e.g. Vehicles). For features which contain numerical values, we are often interested in various statistical measures relating to those values. We can use .describe() to see some summary statistics for the numeric fields in our dataframe. Note, that because we only have one numeric feature, we see only one summary stastic - for now.

In [10]:
```
df_transport.describe()
```

Out[10]:

	Vehicles
count	996.000000
mean	72.878514
std	229.696895
min	1.000000
25%	13.000000
50%	23.000000
75%	57.250000
max	3178.000000

Let's investigate a bit more of our data by using the .groupby() function.

In [11]:
```
grouped_data = df_transport.groupby(['Zip Code','Model Year','Fuel','Make','Light_Duty','Vehicles'])
df_transport.groupby('Fuel').first() # Get the first entry for each month.
```

Out[11]:

	Date	Zip Code	Model Year	Make	Light_Duty	Vehicles
Fuel						
Battery Electric	10/1/2018	90000	<2006	OTHER/UNK	No	4.0
Diesel and Diesel Hybrid	10/1/2018	90000	<2006	OTHER/UNK	No	55.0
Flex-Fuel	10/14/2018	90001	2007	Type_A	Yes	78.0
Gasoline	10/1/2018	90000	2006	OTHER/UNK	Yes	1.0
Hybrid Gasoline	10/24/2018	90001	2009	OTHER/UNK	Yes	18.0
Natural Gas	10/25/2018	90001	2009	OTHER/UNK	No	2.0
Other	10/8/2018	90000	<2006	OTHER/UNK	Yes	6.0
Plug-in Hybrid	11/2/2018	90001	2012	OTHER/UNK	Yes	1.0

Checking for Missing Values

Missing values adversely impact data quality, as they can lead the machine learning model to make inaccurate inferences about the data. Missing values can be the result of numerous factors, e.g. "bits" lost during streaming transmission, data entry, or perhaps a user forgot to fill in a field. Note that Pandas recognizes both empty cells and “NaN” types as missing values.

Let's show the null values for all features in the DataFrame.

In [12]:
```
df_transport.isnull().sum()
```

Out[12]:
```
Date          2
Zip Code      2
Model Year    2
Fuel          3
Make          3
```

```
Light_Duty    3
Vehicles      3
dtype: int64
```

To see a sampling of which values are missing, enter the feature column name. You'll notice that "False" and "True" correpond to the presence or abscence of a value by index number.

In [13]:

```python
print (df_transport['Date'])
print (df_transport['Date'].isnull())
```

```
0      10/1/2018
1      10/1/2018
2            NaN
3      10/1/2018
4      10/1/2018
         ...
994     6/7/2019
995     6/8/2019
996     6/9/2019
997    6/10/2019
998    6/11/2019
Name: Date, Length: 999, dtype: object
0      False
1      False
2       True
3      False
4      False
       ...
994    False
995    False
996    False
997    False
998    False
Name: Date, Length: 999, dtype: bool
```

In [14]:

```python
print (df_transport['Make'])
print (df_transport['Make'].isnull())
```

```
0      OTHER/UNK
1            NaN
2      OTHER/UNK
3      OTHER/UNK
4      OTHER/UNK
         ...
994       Type_R
995    OTHER/UNK
996       Type_Q
997    OTHER/UNK
998    OTHER/UNK
Name: Make, Length: 999, dtype: object
0      False
1       True
2      False
3      False
4      False
       ...
994    False
995    False
996    False
997    False
998    False
Name: Make, Length: 999, dtype: bool
```

In [15]:

```python
print (df_transport['Model Year'])
print (df_transport['Model Year'].isnull())
```

```
0       2006
1       2014
2        NaN
3       2017
4      <2006
       ...
994     2012
995     2012
996     2012
997     2012
998     2012
Name: Model Year, Length: 999, dtype: object
0      False
1      False
2       True
3      False
4      False
       ...
994    False
995    False
996    False
997    False
```

```
998    False
Name: Model Year, Length: 999, dtype: bool
```

What can we deduce about the data at this point?

First, let's summarize our data by row, column, features, unique, and missing values,

In [16]:

```
print ("Rows     : " ,df_transport.shape[0])
print ("Columns  : " ,df_transport.shape[1])
print ("\nFeatures : \n" ,df_transport.columns.tolist())
print ("\nUnique values :  \n",df_transport.nunique())
print ("\nMissing values :  ", df_transport.isnull().sum().values.sum())
```

```
Rows     :  999
Columns  :  7

Features :
 ['Date', 'Zip Code', 'Model Year', 'Fuel', 'Make', 'Light_Duty', 'Vehicles']

Unique values :
 Date          248
Zip Code        6
Model Year     15
Fuel            8
Make           43
Light_Duty      3
Vehicles      210
dtype: int64

Missing values :   18
```

Let's see the data again -- this time the last five rows in the dataset.

In [17]:

```
df_transport.tail()
```

Out[17]:

	Date	Zip Code	Model Year	Fuel	Make	Light_Duty	Vehicles
994	6/7/2019	90003	2012	Gasoline	Type_R	Yes	26.0
995	6/8/2019	90003	2012	Hybrid Gasoline	OTHER/UNK	Yes	4.0
996	6/9/2019	90003	2012	Hybrid Gasoline	Type_Q	Yes	25.0
997	6/10/2019	90003	2012	Natural Gas	OTHER/UNK	Yes	1.0
998	6/11/2019	90003	2012	Plug-in Hybrid	OTHER/UNK	Yes	3.0

What Are Our Data Quality Issues?

1. **Data Quality Issue #1**:

    > **Missing Values**: Each feature column has multiple missing values. In fact, we have a total of 18 missing values.

2. **Data Quality Issue #2**:

    > **Date DataType**: Date is shown as an "object" datatype and should be a datetime. In addition, Date is in one column. Our business requirement is to see the Date parsed out to year, month, and day.

3. **Data Quality Issue #3**:

    > **Model Year**: We are only interested in years greater than 2006, not "<2006".

4. **Data Quality Issue #4**:

    > **Categorical Columns**: The feature column "Light_Duty" is categorical and has a "Yes/No" choice. We cannot feed values like this into a machine learning model. In addition, we need to "one-hot encode the remaining "string"/"object" columns.

5. **Data Quality Issue #5**:

    > **Temporal Features**: How do we handle year, month, and day?

Data Quality Issue #1:

Resolving Missing Values

Most algorithms do not accept missing values. Yet, when we see missing values in our dataset, there is always a tendency to just "drop all the rows" with missing values. Although Pandas will fill in the blank space with “NaN", we should "handle" them in some way.

While all the methods to handle missing values is beyond the scope of this lab, there are a few methods you should consider. For numeric columns, use the "mean" values to fill in the missing numeric values. For categorical columns, use the "mode" (or most frequent values) to fill in missing categorical values.

In this lab, we use the .apply and Lambda functions to fill every column with its own most frequent value. You'll learn more about Lambda functions later in the lab.

Let's check again for missing values by showing how many rows contain NaN values for each feature column.

Lab Task #1a: Check for missing values by showing how many rows contain NaN values for each feature column.

In [18]:

```
# TODO 1a
# TODO -- Your code here.
df_transport.isnull().sum()
```

Out[18]:

```
Date          2
Zip Code      2
Model Year    2
Fuel          3
Make          3
Light_Duty    3
Vehicles      3
dtype: int64
```

Lab Task #1b: Apply the lambda function.

In [22]:

```
# TODO 1b
# TODO -- Your code here.
df_transport = df_transport.apply(lambda x:x.fillna(x.value_counts().index[0]))
```

Lab Task #1c: Check again for missing values.

In [23]:

```
# TODO 1c
# TODO -- Your code here.
df_transport.isnull().sum()
```

Out[23]:

```
Date          0
Zip Code      0
Model Year    0
Fuel          0
Make          0
Light_Duty    0
Vehicles      0
dtype: int64
```

Data Quality Issue #2:

Convert the Date Feature Column to a Datetime Format

The date column is indeed shown as a string object.

Lab Task #2a: Convert the datetime datatype with the to_datetime() function in Pandas.

In [24]:

```
# TODO 2a
# TODO -- Your code here.
df_transport['Date'] =  pd.to_datetime(df_transport['Date'], format='%m/%d/%Y')
```

Lab Task #2b: Show the converted Date.

In [25]:

```
# TODO 2b
# TODO -- Your code here.
df_transport.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Date        999 non-null    datetime64[ns]
 1   Zip Code    999 non-null    object
 2   Model Year  999 non-null    object
 3   Fuel        999 non-null    object
 4   Make        999 non-null    object
 5   Light_Duty  999 non-null    object
 6   Vehicles    999 non-null    float64
dtypes: datetime64[ns](1), float64(1), object(5)
memory usage: 54.8+ KB
```

Let's parse Date into three columns, e.g. year, month, and day.

In [26]:

```
df_transport['year'] = df_transport['Date'].dt.year
df_transport['month'] = df_transport['Date'].dt.month
df_transport['day'] = df_transport['Date'].dt.day
#df['hour'] = df['date'].dt.hour - you could use this if your date format included hour.
#df['minute'] = df['date'].dt.minute - you could use this if your date format included minute.
df_transport.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Date        999 non-null    datetime64[ns]
 1   Zip Code    999 non-null    object
 2   Model Year  999 non-null    object
 3   Fuel        999 non-null    object
 4   Make        999 non-null    object
 5   Light_Duty  999 non-null    object
 6   Vehicles    999 non-null    float64
 7   year        999 non-null    int64
 8   month       999 non-null    int64
 9   day         999 non-null    int64
dtypes: datetime64[ns](1), float64(1), int64(3), object(5)
memory usage: 78.2+ KB
```

Next, let's confirm the Date parsing. This will also give us a another visualization of the data.

In [27]:

```
# Here, we are creating a new dataframe called "grouped_data" and grouping by on the column "Make"
grouped_data = df_transport.groupby(['Make'])

# Get the first entry for each month.
df_transport.groupby('month').first()
```

Out[27]:

	Date	Zip Code	Model Year	Fuel	Make	Light_Duty	Vehicles	year	day
month									
1	2019-01-01	90001	2016	Gasoline	Type_G	Yes	18.0	2019	1
2	2019-02-01	90001	2017	Gasoline	Type_D	Yes	13.0	2019	1
3	2019-03-01	90001	2018	Gasoline	Type_C	Yes	32.0	2019	1
4	2019-04-01	90003	2006	Gasoline	Type_U	Yes	13.0	2019	1
5	2019-05-01	90003	2007	Gasoline	Type_GG	Yes	13.0	2019	1
6	2019-06-01	90003	2008	Gasoline	Type_J	Yes	15.0	2019	1
7	2019-07-01	90003	2009	Gasoline	Type_J	Yes	141.0	2019	1
10	2018-10-01	90000	2006	Gasoline	OTHER/UNK	Yes	1.0	2018	1
11	2018-11-01	90001	2007	Gasoline	Type_M	Yes	15.0	2018	1
12	2018-12-02	90001	2015	Gasoline	Type_G	Yes	19.0	2018	2

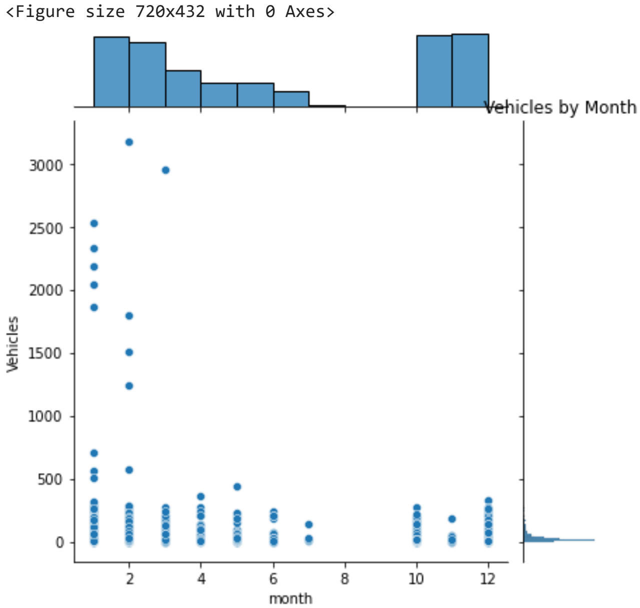
Now that we have Dates as a integers, let's do some additional plotting.

In [29]:

```
plt.figure(figsize=(10,6))
sns.jointplot(x='month',y='Vehicles',data=df_transport)
plt.title('Vehicles by Month')
```

Out[29]: Text(0.5, 1.0, 'Vehicles by Month')

<Figure size 720x432 with 0 Axes>



Data Quality Issue #3:

Rename a Feature Column and Remove a Value.

Our feature columns have different "capitalizations" in their names, e.g. both upper and lower "case". In addition, there are "spaces" in some of the column names. In addition, we are only interested in years greater than 2006, not "<2006".

Lab Task #3a: Remove all the spaces for feature columns by renaming them.

In [34]:
```
# TODO 3a
# TODO -- Your code here.
new_columns = [x.replace(' ','').replace('_','').lower() for x in df_transport.columns]
df_transport.columns = new_columns
df_transport.head(2)
```

Out[34]:

	date	zipcode	modelyear	fuel	make	lightduty	vehicles	year	month	day
0	2018-10-01	90000	2006	Gasoline	OTHER/UNK	Yes	1.0	2018	10	1
1	2018-10-01	90002	2014	Gasoline	OTHER/UNK	Yes	1.0	2018	10	1

Note: Next we create a copy of the dataframe to avoid the "SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame" warning. Run the cell to remove the value '<2006' from the modelyear feature column.

Lab Task #3b: Create a copy of the dataframe to avoid copy warning issues.

In [40]:
```
# TODO 3b
# TODO -- Your code here.
df = df_transport[df_transport['modelyear'] != '<2006'].copy()
```

Next, confirm that the modelyear value '<2006' has been removed by doing a value count.

In [41]:
```
df['modelyear'].value_counts()
```

Out[41]:
```
2007    87
2012    81
2008    79
2011    77
2010    71
2006    70
2015    61
2014    59
2016    57
2017    57
2009    53
2013    52
2018    42
2019     6
Name: modelyear, dtype: int64
```

Data Quality Issue #4:

Handling Categorical Columns

The feature column "lightduty" is categorical and has a "Yes/No" choice. We cannot feed values like this into a machine learning model. We need to convert the binary answers from strings of yes/no to integers of 1/0. There are various methods to achieve this. We will use the "apply" method with a lambda expression. Pandas. apply() takes a function and applies it to all values of a Pandas series.

What is a Lambda Function?

Typically, Python requires that you define a function using the def keyword. However, lambda functions are anonymous -- which means there is no need to name them. The most common use case for lambda functions is in code that requires a simple one-line function (e.g. lambdas only have a single expression).

As you progress through the Course Specialization, you will see many examples where lambda functions are being used. Now is a good time to become familiar with them.

First, lets count the number of "Yes" and"No's" in the 'lightduty' feature column.

In [43]:
```
df['lightduty'].value_counts(0)
```

Out[43]:
```
Yes    771
No      80
--       1
Name: lightduty, dtype: int64
```

Let's convert the Yes to 1 and No to 0. Pandas. apply() . apply takes a function and applies it to all values of a Pandas series (e.g. lightduty).

In [44]:
```
df.loc[:,'lightduty'] = df['lightduty'].apply(lambda x: 0 if x=='No' else 1)
df['lightduty'].value_counts(0)
```

Out[44]:
```
1    772
```

```
0     80
Name: lightduty, dtype: int64
```

In [45]:

```
# Confirm that "lightduty" has been converted.

df.head()
```

Out[45]:

	date	zipcode	modelyear	fuel	make	lightduty	vehicles	year	month	day
0	2018-10-01	90000	2006	Gasoline	OTHER/UNK	1	1.0	2018	10	1
1	2018-10-01	90002	2014	Gasoline	OTHER/UNK	1	1.0	2018	10	1
3	2018-10-01	90000	2017	Gasoline	OTHER/UNK	1	1.0	2018	10	1
16	2018-10-09	90001	2006	Diesel and Diesel Hybrid	Type_C	0	16.0	2018	10	9
17	2018-10-10	90001	2006	Diesel and Diesel Hybrid	OTHER/UNK	0	23.0	2018	10	10

One-Hot Encoding Categorical Feature Columns

Machine learning algorithms expect input vectors and not categorical features. Specifically, they cannot handle text or string values. Thus, it is often useful to transform categorical features into vectors.

One transformation method is to create dummy variables for our categorical features. Dummy variables are a set of binary (0 or 1) variables that each represent a single class from a categorical feature. We simply encode the categorical variable as a one-hot vector, i.e. a vector where only one element is non-zero, or hot. With one-hot encoding, a categorical feature becomes an array whose size is the number of possible choices for that feature.

Panda provides a function called "get_dummies" to convert a categorical variable into dummy/indicator variables.

In [46]:

```
# Making dummy variables for categorical data with more inputs.

data_dummy = pd.get_dummies(df[['zipcode','modelyear', 'fuel', 'make']], drop_first=True)
data_dummy.head()
```

Out[46]:

	zipcode_90001	zipcode_90002	zipcode_90003	zipcode_9001	zipcode_na	modelyear_2007	modelyear_2008	modelyear_2009	modelyear_2010	modelye
0	0	0	0	0	0	0	0	0	0	
1	0	1	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
16	1	0	0	0	0	0	0	0	0	
17	1	0	0	0	0	0	0	0	0	

5 rows × 56 columns

Lab Task #4a: Merge (concatenate) original data frame with 'dummy' dataframe.

In [47]:

```
# TODO 4a
# TODO -- Your code here.
df = pd.concat([df,data_dummy], axis=1)
df.head()
```

Out[47]:

	date	zipcode	modelyear	fuel	make	lightduty	vehicles	year	month	day	...	make_Type_Q	make_Type_R	make_Type_S	make_Type_T
0	2018-10-01	90000	2006	Gasoline	OTHER/UNK	1	1.0	2018	10	1	...	0	0	0	0
1	2018-10-01	90002	2014	Gasoline	OTHER/UNK	1	1.0	2018	10	1	...	0	0	0	0
3	2018-10-01	90000	2017	Gasoline	OTHER/UNK	1	1.0	2018	10	1	...	0	0	0	0
16	2018-10-09	90001	2006	Diesel and Diesel Hybrid	Type_C	0	16.0	2018	10	9	...	0	0	0	0
17	2018-10-10	90001	2006	Diesel and Diesel Hybrid	OTHER/UNK	0	23.0	2018	10	10	...	0	0	0	0

5 rows × 66 columns

Lab Task #4b: Drop attributes for which we made dummy variables.

In [51]:
```
# TODO 4b
# TODO -- Your code here.
df.drop(columns = ['date', 'zipcode','modelyear', 'fuel', 'make'], inplace = True)
```

In [52]:
```
# Confirm that 'zipcode','modelyear', 'fuel', and 'make' have been dropped.

df.head()
```

Out[52]:

	lightduty	vehicles	year	month	day	zipcode_90001	zipcode_90002	zipcode_90003	zipcode_9001	zipcode_na	...	make_Type_Q	make_Type_R	mak
0	1	1.0	2018	10	1	0	0	0	0	0	...	0	0	
1	1	1.0	2018	10	1	0	1	0	0	0	...	0	0	
3	1	1.0	2018	10	1	0	0	0	0	0	...	0	0	
16	0	16.0	2018	10	9	1	0	0	0	0	...	0	0	
17	0	23.0	2018	10	10	1	0	0	0	0	...	0	0	

5 rows × 61 columns

Data Quality Issue #5:

Temporal Feature Columns

Our dataset now contains year, month, and day feature columns. Let's convert the month and day feature columns to meaningful representations as a way to get us thinking about changing temporal features -- as they are sometimes overlooked.

Note that the Feature Engineering course in this Specialization will provide more depth on methods to handle year, month, day, and hour feature columns.

First, let's print the unique values for "month" and "day" in our dataset.

In [53]:
```
print ('Unique values of month:',df.month.unique())
print ('Unique values of day:',df.day.unique())
print ('Unique values of year:',df.year.unique())
```

```
Unique values of month: [10 11 12  1  2  3  4  5  6  7]
Unique values of day: [ 1  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31
  2  3  4  5  6  7  8]
Unique values of year: [2018 2019]
```

Next, we map each temporal variable onto a circle such that the lowest value for that variable appears right next to the largest value. We compute the x- and y- component of that point using sin and cos trigonometric functions. Don't worry, this is the last time we will use this code, as you can develop an input pipeline to address these temporal feature columns in TensorFlow and Keras - and it is much easier! But, sometimes you need to appreciate what you're not going to encounter as you move through the course!

Run the cell to view the output.

Lab Task #5: Drop month, and day

In [54]:
```
df['day_sin'] = np.sin(df.day*(2.*np.pi/31))
df['day_cos'] = np.cos(df.day*(2.*np.pi/31))
df['month_sin'] = np.sin((df.month-1)*(2.*np.pi/12))
df['month_cos'] = np.cos((df.month-1)*(2.*np.pi/12))

# TODO 5
# TODO -- Your code here.
df.drop(columns = ['month','day','year'], inplace = True)
```

In [55]:
```
# scroll left to see the converted month and day coluumns.
df.tail(4)
```

Out[55]:

	lightduty	vehicles	zipcode_90001	zipcode_90002	zipcode_90003	zipcode_9001	zipcode_na	modelyear_2007	modelyear_2008	modelyear_2009	...
995	1	4.0	0	0	1	0	0	0	0	0	...
996	1	25.0	0	0	1	0	0	0	0	0	...
997	1	1.0	0	0	1	0	0	0	0	0	...
998	1	3.0	0	0	1	0	0	0	0	0	...

4 rows × 62 columns

Conclusion

This notebook introduced a few concepts to improve data quality. We resolved missing values, converted the Date feature column to a datetime format, renamed feature columns, removed a value from a feature column, created one-hot encoding features, and converted temporal features to meaningful representations. By the end of our lab, we gained an understanding as to why data should be "cleaned" and "pre-processed" before input into a machine learning model.