

```
# remove all the rows that contain a missing value
nfl_data.dropna()
```

remove all the rows that contain a missing value but it did remove all rows becuse all rows contant miss value

```
# remove all columns with at least one missing value
columns_with_na_dropped = nfl_data.dropna(axis=1)
columns_with_na_dropped.head()
```

remove all columns with at least one missing value

```
# just how much data did we lose?
print("Columns in original dataset: %d \n" % nfl_data.shape[1])
print("Columns with na's dropped: %d" % columns_with_na_dropped.shape[1])
```

```
Columns in original dataset: 102
Columns with na's dropped: 41
```

just how much data did we lose?

This is the point at which we get into the part of data science that I like to call "data intuition", by which I mean "really looking at your data and trying to figure out why it is the way it is and how that will affect your analysis". It can be a frustrating part of data science, especially if you're newer to the field and don't have a lot of experience. For dealing with missing values, you'll need to use your intuition to figure out why the value is missing. One of the most important question you can ask yourself to help figure this out is this:

Is this value missing because it wasn't recorded or because it doesn't exist?

If a value is missing because it doesn't exist (like the height of the oldest child of someone who doesn't have any children) then it doesn't make sense to try and guess what it might be. These values you probably do want to keep as NaN. On the other hand, if a value is missing because it wasn't recorded, then you can try to guess what it might have been based on the other values in that column and row. (This is called "imputation" and we'll learn how to do it next!)

Let's work through an example. Looking at the number of missing values in the nfl_data dataframe, I notice that the column "timeSec" has a lot of missing values in it:

By looking at the documentation, I can see that this column has information on the number of seconds left in the game when the play was made. This means that these values are probably missing because they were not recorded, rather than because they don't exist. So, it would make sense for us to try and guess what they should be rather than just leaving them as NAs.

On the other hand, there are other fields, like "renalizedTeam" that also have lot of missing fields. In this case, though, the field is missing because if there was no penalty then it doesn't make sense to say which team was penalized. For this column, it would make more sense to either leave it empty or to add a third value like "neither" and use that to replace the NAs.

Tip: This is a great place to read over the dataset documentation if you haven't already! If you're working with a dataset that you've gotten from another person, you can also try reaching out to them to get more information.

If you're doing very careful data analysis, this is the point at which you'd look at each column individually to figure out the best strategy for filling those missing values. For the rest of this notebook, we'll cover some "quick and dirty" techniques that can help you with missing values but will probably also end up removing some useful information or adding some noise to your data.

```
# get a small subset of the NFL dataset
subset_nfl_data = nfl_data.loc[:, 'EPA':'Season'].head()
subset_nfl_data
```

get a small subset of the NFL dataset

```
# replace all NA's with 0
subset_nfl_data.fillna(0)
```

replace all NA's with 0

```
# replace all NA's the value that comes directly after it in the same column,
# then replace all the remaining na's with 0
subset_nfl_data.fillna(method = 'bfill', axis=0).fillna("0")
```

replace all NA's the value that comes directly after it in the same column,
then replace all the reamining na's with 0

3. Drop missing values

3. Figure out why the data is missing

4. Filling in missing values automatically

Day1 Missing Values

1. Take a first look at the data

#set up modules and read in all our data

```
# modules we'll use
import pandas as pd
import numpy as np

# read in all our data
nfl_data = pd.read_csv("../input/nflplaybyplay2009to2016/NFL Play by Play 2009-2017 (v4).csv")
sf_permits = pd.read_csv("../input/building-permit-applications-data/Building Permits.csv")

# set seed for reproducibility
np.random.seed(0)
```

```
/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2698: DtypeWarning: Columns (25,51) have mixed types. Specify dtype option on import or set low_memory=False.
interactivity=interactivity, compiler=compiler, result=result)
/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2698: DtypeWarning: Columns (22,32) have mixed types. Specify dtype option on import or set low_memory=False.
interactivity=interactivity, compiler=compiler, result=result)
```

```
# look at a few rows of the nfl_data file. I can see a handful of missing data al ready!
nfl_data.sample(5)
```

look at a few rows of the nfl_data file. I can see a handful of missing data already!

```
# get the number of missing data points per column
missing_values_count = nfl_data.isnull().sum()
```

```
# look at the # of missing points in the first ten columns
missing_values_count[0:10]
```

```
Date          0
GameID         0
Drive          0
qtr            0
down          61154
time           224
TimeUnder      0
TimeSecs       224
PlayTimeDiff   444
SideofField    528
dtype: int64
```

how many total missing values do we have?
look at the # of missing points in the first ten columns

```
# how many total missing values do we have?
total_cells = np.product(nfl_data.shape)
print(nfl_data.shape)
total_missing = missing_values_count.sum()
```

```
# percent of data that is missing
(total_missing/total_cells) * 100
```

```
(407688, 102)
24.87214126835169
```

how many total missing values do we have?
percent of data that is missing