> Structuring datasets to facilitate analysis (Wickham 2014)

So, you've sat down to analyze a new dataset. What do you do first?

In episode 11 of Not So Standard Deviations, Hilary and Roger discussed their typical approaches. I'm with Hilary on this one, you should make sure your data is tidy. Before you do any plots, filtering, transformations, summary statistics, regressions... Without a tidy dataset, you'll be fighting your tools to get the result you need. With a tidy dataset, it's relatively easy to do all of those.

Hadley Wickham kindly summarized tidiness as a dataset where

1. Each variable forms a column
2. Each observation forms a row
3. Each type of observational unit forms a table

And today we'll only concern ourselves with the first two. As quoted at the top, this really is about facilitating analysis: going as quickly as possible from question to answer.

NBA Data

This StackOverflow question asked about calculating the number of days of rest NBA teams have between games. The answer would have been difficult to compute with the raw data. After transforming the dataset to be tidy, we're able to quickly get the answer.

We'll grab some NBA game data from basketball-reference.com using pandas' `read_html` function, which returns a list of DataFrames.

```
In [2]: fp = 'nba.csv'
   ...:
   ...: if not os.path.exists(fp):
   ...:     tables = pd.read_html("http://www.basketball-reference.com/leagues/NBA_2016_game
   ...:     games = tables[0]
   ...:     games.to_csv(fp)
   ...: else:
   ...:     games = pd.read_csv(fp, index_col=0)
   ...: games.head()
```

	Date	Start (ET)	Unnamed: 2	Visitor/Neutral	PTS	Home/Neutral
0	October	NaN	NaN	NaN	NaN	NaN
1	Tue, Oct 27, 2015	8:00 pm	Box Score	Detroit Pistons	106.0	Atlanta Hawks
2	Tue, Oct 27, 2015	8:00 pm	Box Score	Cleveland Cavaliers	95.0	Chicago Bulls
3	Tue, Oct 27, 2015	10:30 pm	Box Score	New Orleans Pelicans	95.0	Golden State Warriors
4	Wed, Oct 28, 2015	7:30 pm	Box Score	Philadelphia 76ers	95.0	Boston Celtics

Side note: pandas' `read_html` is pretty good. On simple websites it almost always works. It provides a couple parameters for controlling what gets selected from the webpage if the defaults fail. I'll always use it first, before moving on to BeautifulSoup or lxml if the page is more complicated.

As you can see, we have a bit of general munging to do before tidying. Each month slips in an extra row of mostly NaNs, the column names aren't too useful, and we have some dtypes to fix up.

```
In [3]: column_names = {'Date': 'date', 'Start (ET)': 'start',
   ...:                 'Unamed: 2': 'box', 'Visitor/Neutral': 'away_team',
   ...:                 'PTS': 'away_points', 'Home/Neutral': 'home_team',
   ...:                 'PTS.1': 'home_points', 'Unamed: 7': 'n_ot'}
   ...:
   ...: games = (games.rename(columns=column_names)
   ...:     .dropna(thresh=4)
   ...:     [['date', 'away_team', 'away_points', 'home_team', 'home_points']]
   ...:     .assign(date=lambda x: pd.to_datetime(x['date'], format='%a, %b %d, %Y'))
   ...:     .set_index('date', append=True)
   ...:     .rename_axis(["game_id", "date"])
   ...:     .sort_index())
   ...: games.head()
```

		away_team	away_points	home_team	home_points
game_id	date				
1	2015-10-27	Detroit Pistons	106.0	Atlanta Hawks	94.0
2		Cleveland Cavaliers	95.0	Chicago Bulls	97.0
3		New Orleans Pelicans	95.0	Golden State Warriors	111.0
4	2015-10-28	Philadelphia 76ers	95.0	Boston Celtics	112.0
5		Chicago Bulls	115.0	Brooklyn Nets	100.0

A quick aside on that last block.

- `dropna` has a `thresh` argument. If at least `thresh` items are missing, the row is dropped. We used it to remove the "Month headers" that slipped into the table.
- `assign` can take a callable. This lets us refer to the DataFrame in the previous step of the chain. Otherwise we would have to assign `temp_df = games.dropna()...` And then do the `pd.to_datetime` on that.
- `set_index` has an `append` keyword. We keep the original index around since it will be our unique identifier per game.
- We use `.rename_axis` to set the index names (this behavior is new in pandas 0.18; before `.rename_axis` only took a mapping for changing labels).

The Question:

> **How many days of rest did each team get between each**

game?

Whether or not your dataset is tidy depends on your question. Given our question, what is an observation?

In this case, an observation is a `(team, game)` pair, which we don't have yet. Rather, we have two observations per row, one for home and one for away. We'll fix that with `pd.melt`.

`pd.melt` works by taking observations that are spread across columns (`away_team`, `home_team`), and melting them down into one column with multiple rows. However, we don't want to lose the metadata (like `game_id` and `date`) that is shared between the observations. By including those columns as `id_vars`, the values will be repeated as many times as needed to stay with their observations.

```
In [4]: tidy = pd.melt(games.reset_index(),
   ...:                id_vars=['game_id', 'date'], value_vars=['away_team', 'home_team'],
   ...:                value_name='team')
   ...: tidy.head()
```

	game_id	date	variable	team
0	1	2015-10-27	away_team	Detroit Pistons
1	2	2015-10-27	away_team	Cleveland Cavaliers
2	3	2015-10-27	away_team	New Orleans Pelicans
3	4	2015-10-28	away_team	Philadelphia 76ers
4	5	2015-10-28	away_team	Chicago Bulls

The DataFrame `tidy` meets our rules for tidiness: each variable is in a column, and each observation (`team`, `date` pair) is on its own row. Now the translation from question ("How many days of rest between games") to operation ("date of today's game - date of previous game - 1") is direct:

```
In [5]: # For each team... get number of days between games
   ...: tidy.groupby('team')['date'].diff().dt.days - 1
```

```
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN
       ...
2455    7.0
2456    1.0
2457    1.0
2458    3.0
2459    2.0
Name: date, dtype: float64
```

That's the essence of tidy data, the reason why it's worth considering what shape your data should be in. It's about setting yourself up for success so that the answers naturally flow from the data (just kidding, it's usually still difficult. But hopefully less so).

Let's assign that back into our DataFrame

```
In [6]: tidy['rest'] = tidy.sort_values('date').groupby('team').date.diff().dt.days - 1
   ...: tidy.dropna().head()
```

	game_id	date	variable	team	rest
4	5	2015-10-28	away_team	Chicago Bulls	0.0
8	9	2015-10-28	away_team	Cleveland Cavaliers	0.0
14	15	2015-10-28	away_team	New Orleans Pelicans	0.0
17	18	2015-10-29	away_team	Memphis Grizzlies	0.0
18	19	2015-10-29	away_team	Dallas Mavericks	0.0

To show the inverse of `melt`, let's take `rest` values we just calculated and place them back in the original DataFrame with a `pivot_table`.

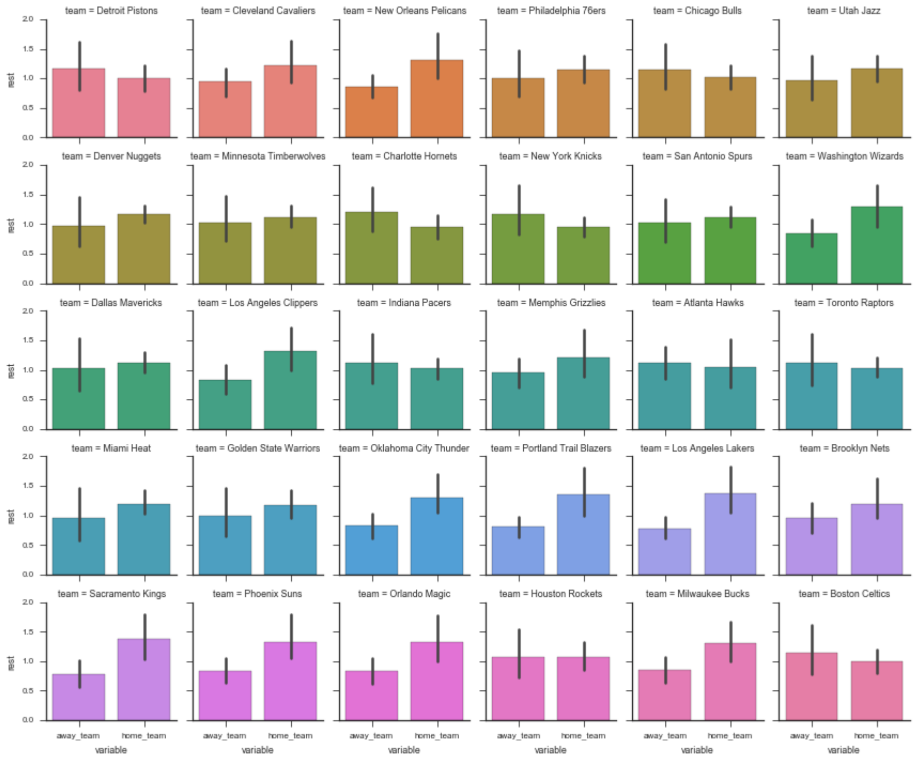
```
In [7]: by_game = (pd.pivot_table(tidy, values='rest',
   ...:                           index=['game_id', 'date'],
   ...:                           columns='variable')
   ...:              .rename(columns={'away_team': 'away_rest',
   ...:                               'home_team': 'home_rest'}))
   ...: df = pd.concat([games, by_game], axis=1)
   ...: df.dropna().head()
```

		away_team	away_points	home_team	home_points	away_r
game_id	date					
18	2015-10-29	Memphis Grizzlies	112.0	Indiana Pacers	103.0	
19		Dallas Mavericks	88.0	Los Angeles Clippers	104.0	
20		Atlanta Hawks	112.0	New York Knicks	101.0	
21	2015-10-30	Charlotte Hornets	94.0	Atlanta Hawks	97.0	
22		Toronto Raptors	113.0	Boston Celtics	103.0	

One somewhat subtle point: an "observation" depends on the question being asked. So really, we have two tidy datasets, `tidy` for answering team-level questions, and `df` for answering game-level questions.

One potentially interesting question is "what was each team's average days of rest, at home and on the road?" With a tidy dataset (the DataFrame `tidy`, since it's team-level), `seaborn` makes this easy (more on seaborn in a future post):

```
In [9]: g = sns.FacetGrid(tidy, col='team', col_wrap=6, hue='team', size=2)
   ...: g.map(sns.barplot, 'variable', 'rest');
```



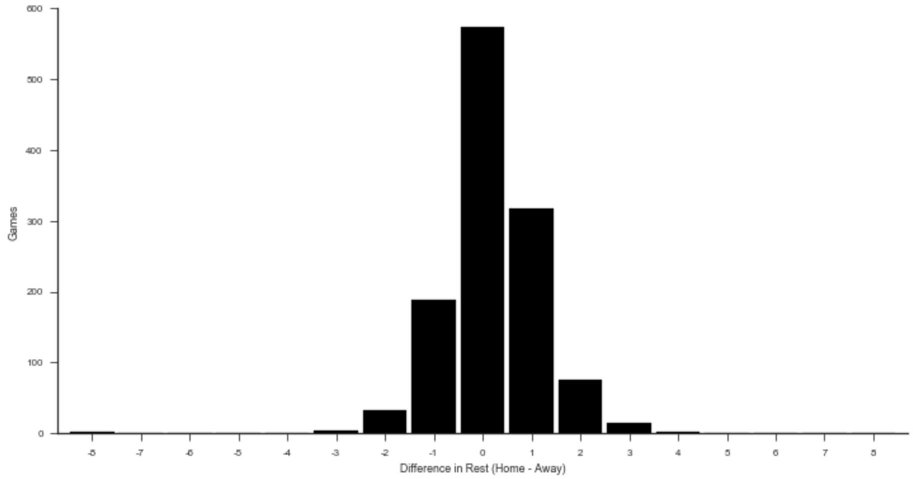
An example of a game-level statistic is the distribution of rest differences in games:

```
In [10]: df['home_win'] = df['home_points'] > df['away_points']
    ...: df['rest_spread'] = df['home_rest'] - df['away_rest']
    ...: df.dropna().head()
```

		away_team	away_points	home_team	home_points	away_
game_id	date					
18	2015-10-29	Memphis Grizzlies	112.0	Indiana Pacers	103.0	
19		Dallas Mavericks	88.0	Los Angeles Clippers	104.0	
20		Atlanta Hawks	112.0	New York Knicks	101.0	
21	2015-10-30	Charlotte Hornets	94.0	Atlanta Hawks	97.0	
22		Toronto Raptors	113.0	Boston Celtics	103.0	

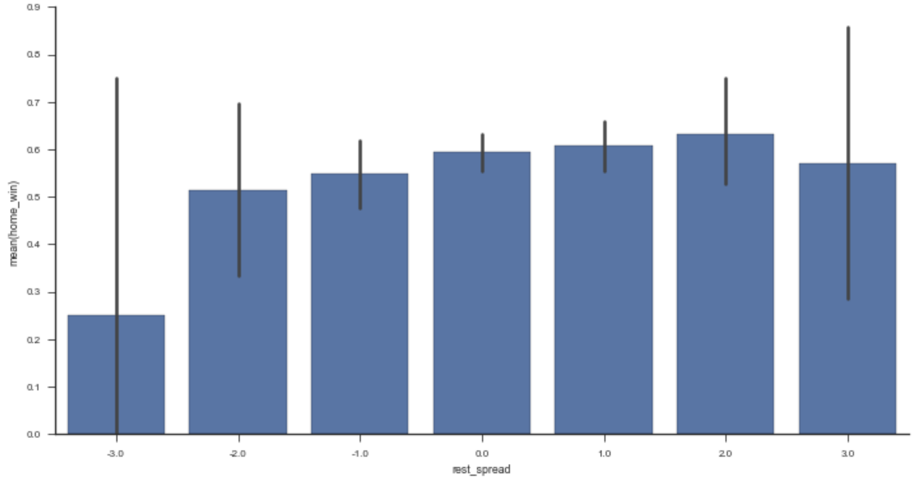
```
In [11]: delta = (by_game.home_rest - by_game.away_rest).dropna().astype(int)
    ...: ax = (delta.value_counts()
    ...:     .reindex(np.arange(delta.min(), delta.max() + 1), fill_value=0)
    ...:     .sort_index()
    ...:     .plot(kind='bar', color='k', width=.9, rot=0, figsize=(12, 6))
    ...: )
    ...: sns.despine()
```

```
   ...: ax.set(xlabel='Difference in Rest (Home - Away)', ylabel='Games');
```



Or the win percent by rest difference

```
In [12]: fig, ax = plt.subplots(figsize=(12, 6))
    ...: sns.barplot(x='rest_spread', y='home_win', data=df.query('-3 <= rest_spread <= 3'),
    ...:             color='#4c72b0', ax=ax)
    ...: sns.despine()
```



Stack / Unstack

Pandas has two useful methods for quickly converting from wide to long format (`stack`) and long to wide (`unstack`).

```
In [13]: rest = (tidy.groupby(['date', 'variable'])
    ...:             .rest.mean()
    ...:             .dropna())
    ...: rest.head()
```

```
date        variable
2015-10-28  away_team    0.000000
            home_team    0.000000
2015-10-29  away_team    0.333333
            home_team    0.000000
2015-10-30  away_team    1.083333
Name: rest, dtype: float64
```

`rest` is in a "long" form since we have a single column of data, with multiple "columns" of metadata (in the MultiIndex). We use `.unstack` to move from long to wide.

```
In [14]: rest.unstack().head()
```

variable	away_team	home_team
date		
2015-10-28	0.000000	0.000000
2015-10-29	0.333333	0.000000
2015-10-30	1.083333	0.916667
2015-10-31	0.166667	0.833333
2015-11-01	1.142857	1.000000

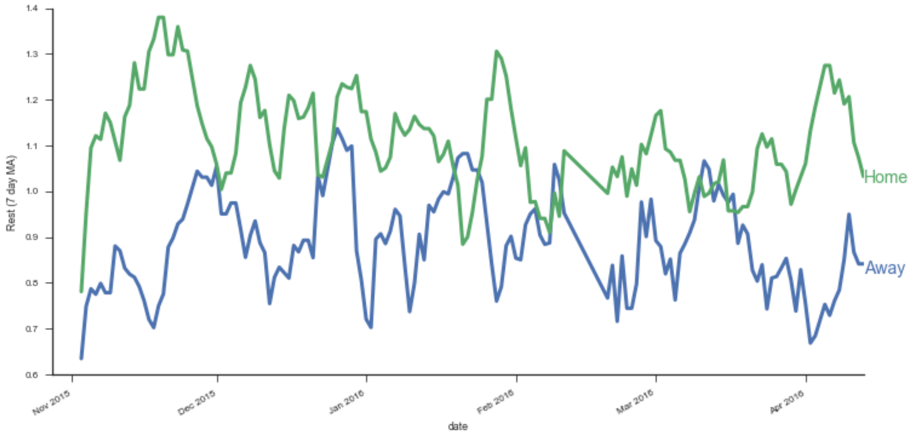
`unstack` moves a level of a MultiIndex (innermost by default) up to the columns. `stack` is the inverse.

```
In [15]: rest.unstack().stack()
```

```
date        variable
2015-10-28  away_team    0.000000
            home_team    0.000000
2015-10-29  away_team    0.333333
            home_team    0.000000
2015-10-30  away_team    1.083333
                           ...
2016-04-11  home_team    0.666667
2016-04-12  away_team    1.000000
            home_team    1.400000
2016-04-13  away_team    0.500000
            home_team    1.214286
dtype: float64
```

With `.unstack` you can move between those APIs that expect there data in long-format and those APIs that work with wide-format data. For example, `DataFrame.plot()`, works with wide-form data, one line per column.

```
In [16]: with sns.color_palette() as pal:
    ...:     b, g = pal.as_hex()[:2]
    ...:
    ...: ax=(rest.unstack()
    ...:         .query('away_team < 7')
    ...:         .rolling(7)
    ...:         .mean()
    ...:         .plot(figsize=(12, 6), linewidth=3, legend=False))
    ...: ax.set(ylabel='Rest (7 day MA)')
    ...: ax.annotate("Home", (rest.index[-1][0], 1.02), color=g, size=14)
    ...: ax.annotate("Away", (rest.index[-1][0], 0.82), color=b, size=14)
    ...: sns.despine()
```



The most convenient form will depend on exactly what you're doing. When interacting with databases you'll often deal with long form data. Pandas' DataFrame.plot often expects wide-form data, while seaborn often expect long-form data. Regressions will expect wide-form data. Either way, it's good to be comfortable with stack and unstack (and MultiIndexes) to quickly move between the two.

Mini Project: Home Court Advantage?

We've gone to all that work tidying our dataset, let's put it to use. What's the effect (in terms of probability to win) of being the home team?

Step 1: Create an outcome variable

We need to create an indicator for whether the home team won. Add it as a column called home_win in games.

```
In [17]: df['home_win'] = df.home_points > df.away_points
```

Step 2: Find the win percent for each team

In the 10-minute literature review I did on the topic, it seems like people include a team-strength variable in their regressions. I suppose that makes sense; if stronger teams happened to play against weaker teams at home more often than away, it'd look like the home-effect is stronger than it actually is. We'll do a terrible job of controlling for team strength by calculating each team's win percent and using that as a predictor. It'd be better to use some kind of independent measure of team strength, but this will do for now.

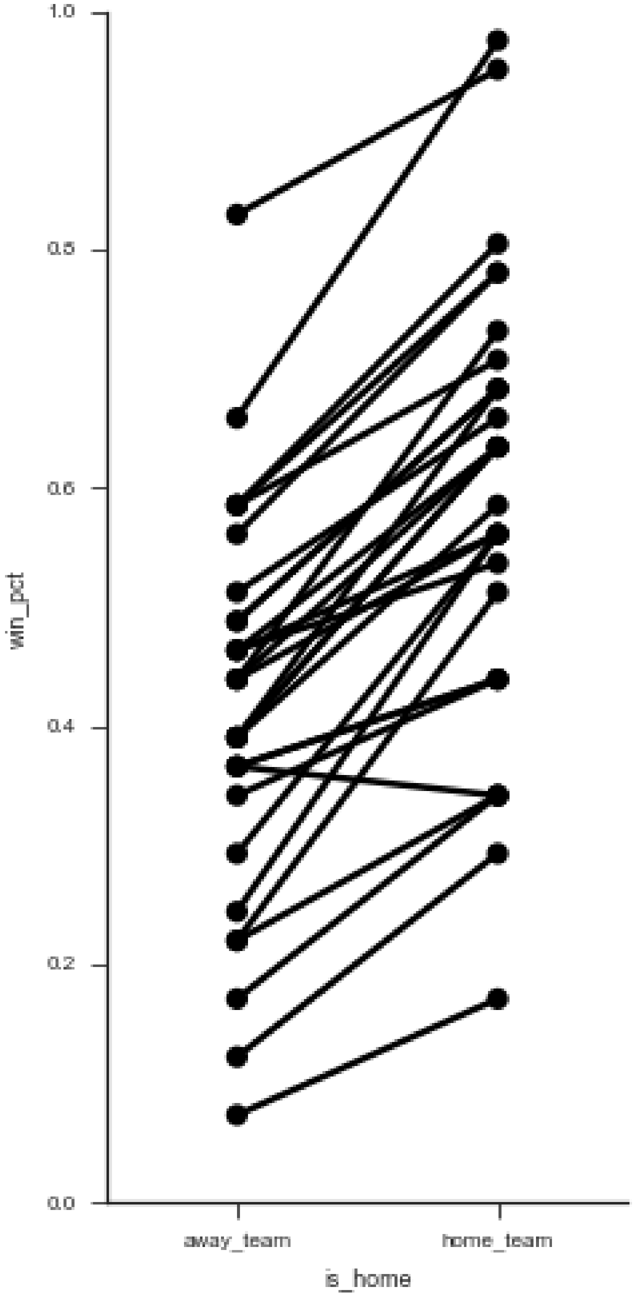
We'll use a similar `melt` operation as earlier, only now with the `home_win` variable we just created.

```
In [18]: wins = (
    ...:     pd.melt(df.reset_index(),
    ...:             id_vars=['game_id', 'date', 'home_win'],
    ...:             value_name='team', var_name='is_home',
    ...:             value_vars=['home_team', 'away_team'])
    ...:    .assign(win=lambda x: x.home_win == (x.is_home == 'home_team'))
    ...:    .groupby(['team', 'is_home'])
    ...:    .win
    ...:    .agg({'n_wins': 'sum', 'n_games': 'count', 'win_pct': 'mean'})
    ...: )
    ...: wins.head()
```

		n_wins	n_games	win_pct
team	is_home			
Atlanta Hawks	away_team	21.0	41	0.512195
	home_team	27.0	41	0.658537
Boston Celtics	away_team	20.0	41	0.487805
	home_team	28.0	41	0.682927
Brooklyn Nets	away_team	7.0	41	0.170732

Pause for visualization, because why not

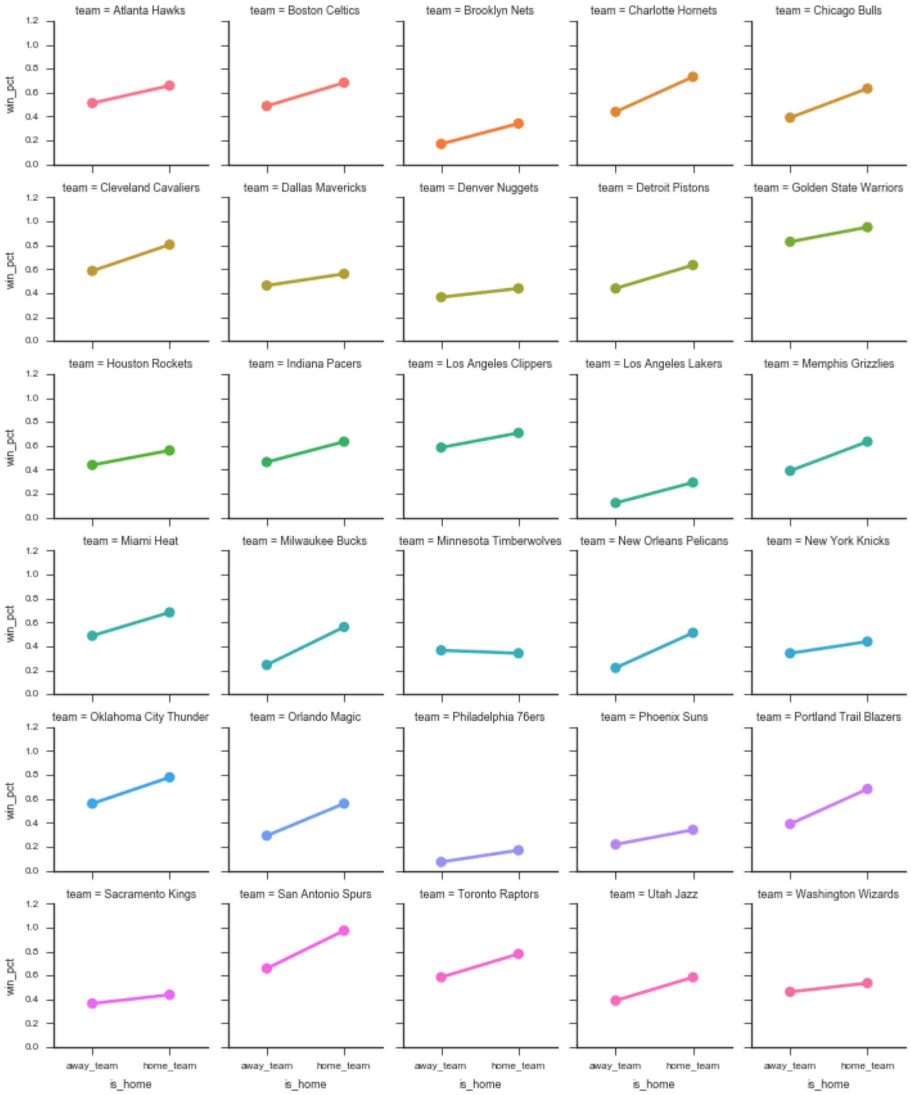
```
In [19]: g = sns.FacetGrid(wins.reset_index(), hue='team', size=7, aspect=.5, palette=['k'])
    ...: g.map(sns.pointplot, 'is_home', 'win_pct').set(ylim=(0, 1));
```



(It'd be great if there was a library built on top of matplotlib that auto-labeled each point decently well. Apparently this is a difficult problem to do in general).

```
In [20]: g = sns.FacetGrid(wins.reset_index(), col='team', hue='team', col_wrap=5, size=2)
```

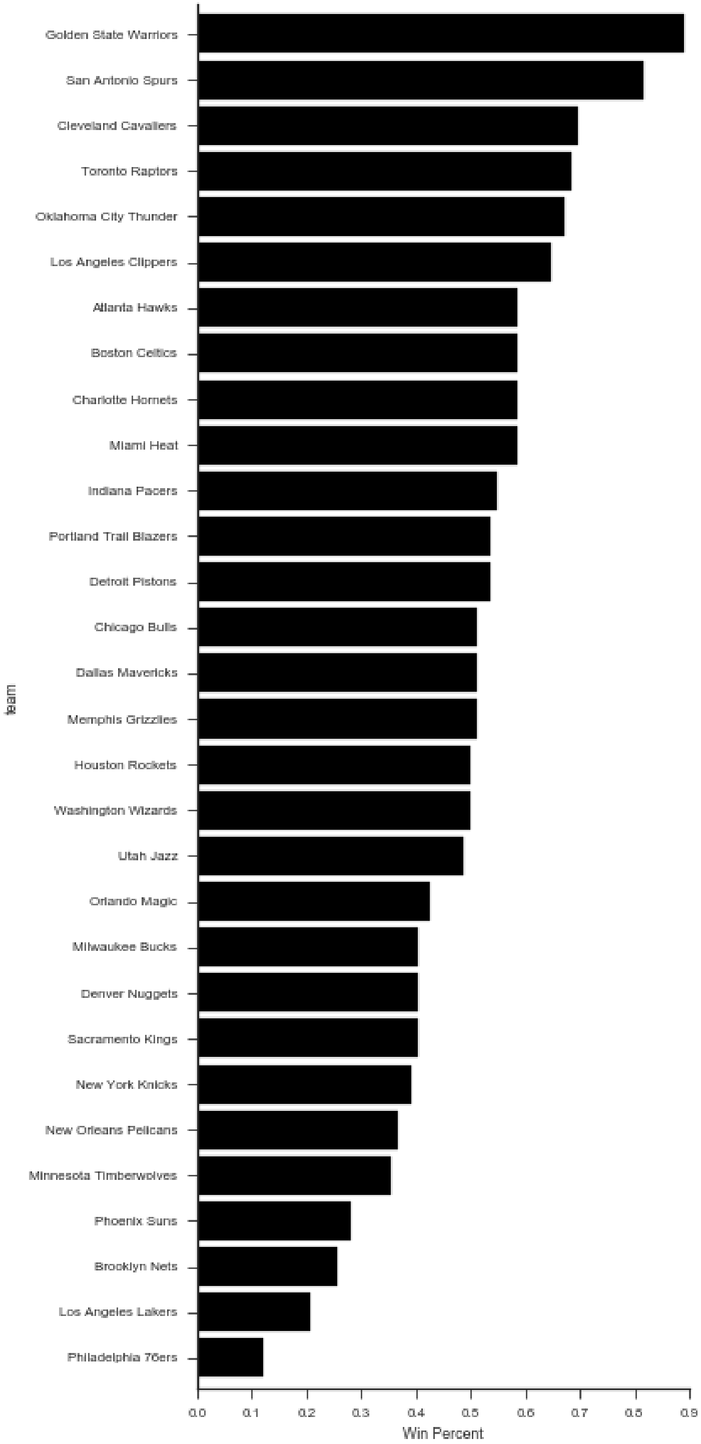
```
   ...: g.map(sns.pointplot, 'is_home', 'win_pct');
```



Those two graphs show that most teams have a higher win-percent at home than away. So we can continue to investigate. Let's aggregate over home / away to get an overall win percent per team.

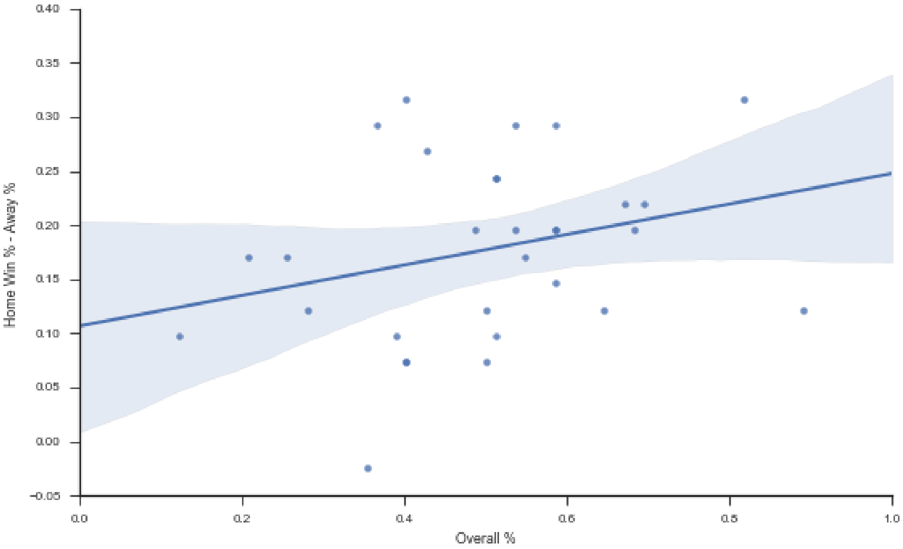
```
In [21]: win_percent = (
   ...:     # Use sum(games) / sum(games) instead of mean
   ...:     # since I don't know if teams play the same
   ...:     # number of games at home as away
   ...:     wins.groupby(level='team', as_index=True)
```

```
    ...:         .apply(lambda x: x.n_wins.sum() / x.n_games.sum())
    ...: )
    ...: win_percent.head()

team
Atlanta Hawks        0.585366
Boston Celtics       0.585366
Brooklyn Nets        0.256098
Charlotte Hornets    0.585366
Chicago Bulls        0.512195
dtype: float64

In [22]: win_percent.sort_values().plot.barh(figsize=(6, 12), width=.85, color='k')
    ...: plt.tight_layout()
    ...: sns.despine()
    ...: plt.xlabel("Win Percent");
```


Golden State Warriors
San Antonio Spurs
Cleveland Cavaliers
Toronto Raptors
Oklahoma City Thunder
Los Angeles Clippers
Atlanta Hawks
Boston Celtics
Charlotte Hornets
Miami Heat
Indiana Pacers
Portland Trail Blazers
Detroit Pistons
Chicago Bulls
Dallas Mavericks
Memphis Grizzlies
Houston Rockets
Washington Wizards
Utah Jazz
Orlando Magic
Milwaukee Bucks
Denver Nuggets
Sacramento Kings
New York Knicks
New Orleans Pelicans
Minnesota Timberwolves
Phoenix Suns
Brooklyn Nets
Los Angeles Lakers
Philadelphia 76ers
team
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Win Percent

Is there a relationship between overall team strength and their home-court advantage?

```
In [23]: plt.figure(figsize=(8, 5))
    ...: (wins.win_pct
    ...:     .unstack()
    ...:     .assign(**{'Home Win % - Away %': lambda x: x.home_team - x.away_team,
    ...:                'Overall %': lambda x: (x.home_team + x.away_team) / 2})
    ...:      .pipe((sns.regplot, 'data'), x='Overall %', y='Home Win % - Away %')
    ...: )
    ...: sns.despine()
    ...: plt.tight_layout()
```



Let's get the team strength back into `df`. You could you `pd.merge`, but I prefer `.map` when joining a `Series`.

```
In [24]: df = df.assign(away_strength=df['away_team'].map(win_percent),
    ...:                home_strength=df['home_team'].map(win_percent),
    ...:                point_diff=df['home_points'] - df['away_points'],
    ...:                rest_diff=df['home_rest'] - df['away_rest'])
    ...: df.head()
```

		away_team	away_points	home_team	home_points	aw
game_id	date					
1	2015-10-27	Detroit Pistons	106.0	Atlanta Hawks	94.0	
2		Cleveland Cavaliers	95.0	Chicago Bulls	97.0	
3		New Orleans Pelicans	95.0	Golden State Warriors	111.0	
4	2015-10-28	Philadelphia 76ers	95.0	Boston Celtics	112.0	
5		Chicago Bulls	115.0	Brooklyn Nets	100.0	

```
In [25]: import statsmodels.formula.api as sm
    ...:
    ...: df['home_win'] = df.home_win.astype(int)  # for statsmodels
```

```
In [27]: mod = sm.logit('home_win ~ home_strength + away_strength + home_rest + away_rest',
    ...: res = mod.fit()
    ...: res.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.552792
         Iterations 6
```

Dep. Variable:	home_win	**No. Observations:**	1213
Model:	Logit	**Df Residuals:**	1208
Method:	MLE	**Df Model:**	4
Date:	Wed, 31 Aug 2016	**Pseudo R-squ.:**	0.1832
Time:	11:05:39	**Log-Likelihood:**	-670.54
converged:	True	**LL-Null:**	-820.91

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	0.0707	0.314	0.225	0.822	-0.546	0.687
home_strength	5.4204	0.465	11.647	0.000	4.508	6.333
away_strength	-4.7445	0.452	-10.506	0.000	-5.630	-3.859
home_rest	0.0894	0.079	1.137	0.255	-0.065	0.243
away_rest	-0.0422	0.067	-0.629	0.529	-0.174	0.089

The strength variables both have large coefficients (really we should be using some independent measure of team strength here, `win_percent` is showing up on the left and right side of the equation). The rest variables don't seem to matter as much.

With `.assign` we can quickly explore variations in formula.

```
In [28]: (sm.Logit.from_formula('home_win ~ strength_diff + rest_spread',
    ...:                        df.assign(strength_diff=df.home_strength - df.away_strength)
    ...:     .fit().summary())
```

```
Optimization terminated successfully.
         Current function value: 0.553499
         Iterations 6
```

Dep. Variable:	home_win	**No. Observations:**	1213
Model:	Logit	**Df Residuals:**	1210
Method:	MLE	**Df Model:**	2
Date:	Wed, 31 Aug 2016	**Pseudo R-squ.:**	0.1821
Time:	11:05:39	**Log-Likelihood:**	-671.39
converged:	True	**LL-Null:**	-820.91

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	0.4610	0.068	6.756	0.000	0.327	0.595
strength_diff	5.0671	0.349	14.521	0.000	4.383	5.751
rest_spread	0.0566	0.062	0.912	0.362	-0.065	0.178

```
In [29]: mod = sm.Logit.from_formula('home_win ~ home_rest + away_rest', df)
    ...: res = mod.fit()
    ...: res.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.676549
         Iterations 4
```

Dep. Variable:	home_win	**No. Observations:**	1213
Model:	Logit	**Df Residuals:**	1210
Method:	MLE	**Df Model:**	2
Date:	Wed, 31 Aug 2016	**Pseudo R-squ.:**	0.0003107
Time:	11:05:39	**Log-Likelihood:**	-820.65
converged:	True	**LL-Null:**	-820.91

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	0.3667	0.094	3.889	0.000	0.182	0.552
home_rest	0.0338	0.069	0.486	0.627	-0.102	0.170
away_rest	-0.0420	0.061	-0.693	0.488	-0.161	0.077

Overall not seeing to much support for rest mattering, but we got to see some more tidy data.

That's it for today. Next time we'll look at data visualization.