

# seaborn.Implot

**seaborn. Implot** (*x*, *y*, *data*, *hue*=None, *col*=None, *row*=None, *palette*=None, *col\_wrap*=None, *size*=5, *aspect*=1, *markers*='o', *sharex*=True, *sharey*=True, *hue\_order*=None, *col\_order*=None, *row\_order*=None, *legend*=True, *legend\_out*=True, *x\_estimator*=None, *x\_bins*=None, *x\_ci*='ci', *scatter*=True, *fit\_reg*=True, *ci*=95, *n\_boot*=1000, *units*=None, *order*=1, *logistic*=False, *lowess*=False, *robust*=False, *logx*=False, *x\_partial*=None, *y\_partial*=None, *truncate*=False, *x\_jitter*=None, *y\_jitter*=None, *scatter\_kws*=None, *line\_kws*=None)

Plot data and regression model fits across a FacetGrid.

This function combines `regplot()` (seaborn.regplot.html#seaborn.regplot) and `FacetGrid` (seaborn.FacetGrid.html#seaborn.FacetGrid). It is intended as a convenient interface to fit regression models across conditional subsets of a dataset.

When thinking about how to assign variables to different facets, a general rule is that it makes sense to use `hue` for the most important comparison, followed by `col` and `row`. However, always think about your particular dataset and the goals of the visualization you are creating.

There are a number of mutually exclusive options for estimating the regression model: `order`, `logistic`, `lowess`, `robust`, and `logx`. See the parameter docs for more information on these options.

The parameters to this function span most of the options in `FacetGrid` (seaborn.FacetGrid.html#seaborn.FacetGrid), although there may be occasional cases where you will want to use that class and `regplot()` (seaborn.regplot.html#seaborn.regplot) directly.

**Parameters:** `x`, `y` : strings, optional

Input variables; these should be column names in `data`.

**data** : DataFrame

Tidy (“long-form”) dataframe where each column is a variable and each row is an observation.

**hue, col, row** : strings

Variables that define subsets of the data, which will be drawn on separate facets in the grid. See the `*_order` parameters to control the order of levels of this variable.

**palette** : seaborn color palette or dict, optional

Colors to use for the different levels of the `hue` variable. Should be something that can be interpreted by `color_palette()` ([seaborn.color\\_palette.html#seaborn.color\\_palette](http://seaborn.color_palette.html#seaborn.color_palette)), or a dictionary mapping hue levels to matplotlib colors.

**col\_wrap** : int, optional

“Wrap” the column variable at this width, so that the column facets span multiple rows. Incompatible with a `row` facet.

**size** : scalar, optional

Height (in inches) of each facet. See also: `aspect`.

**aspect** : scalar, optional

Aspect ratio of each facet, so that `aspect * size` gives the width of each facet in inches.

**markers** : matplotlib marker code or list of marker codes, optional

Markers for the scatterplot. If a list, each marker in the list will be used for each level of the `hue` variable.

**share{x,y}** : bool, optional

If true, the facets will share y axes across columns and/or x axes across rows.

**{hue,col,row}\_order** : lists, optional

Order for the levels of the faceting variables. By default, this will be the order that the levels appear in `data` or, if the variables are pandas categoricals, the category order.

**legend** : bool, optional

If `True` and there is a `hue` variable, add a legend.

**legend\_out** : bool, optional

If `True`, the figure size will be extended, and the legend will be drawn outside the plot on the center right.

**x\_estimator** : callable that maps vector -> scalar, optional

Apply this function to each unique value of `x` and plot the resulting estimate. This is useful when `x` is a discrete variable. If `x_ci` is not `None`, this estimate will be bootstrapped and a confidence interval will be drawn.

**x\_bins** : int or vector, optional

Bin the `x` variable into discrete bins and then estimate the central tendency and a confidence interval. This binning only influences how the scatterplot is drawn; the regression is still fit to the original data. This parameter is interpreted either as the number of evenly-sized (not necessary spaced) bins or the positions of the bin centers. When this parameter is used, it implies that the default of `x_estimator` is `numpy.mean`.

**x\_ci** : "ci", int in [0, 100] or `None`, optional

Size of the confidence interval used when plotting a central tendency for discrete values of `x`. If "ci", defer to the value of the `ci` parameter.

**scatter** : bool, optional

If `True`, draw a scatterplot with the underlying observations (or the `x_estimator` values).

**fit\_reg** : bool, optional

If `True`, estimate and plot a regression model relating the `x` and `y` variables.

**ci** : int in [0, 100] or `None`, optional

Size of the confidence interval for the regression estimate. This will be drawn using translucent bands around the regression line. The confidence interval is estimated using a bootstrap; for large datasets, it may be advisable to avoid that computation by setting this parameter to `None`.

**n\_boot** : int, optional

Number of bootstrap resamples used to estimate the `ci`. The default value attempts to balance time and stability; you may want to increase this value for “final” versions of plots.

**units** : variable name in `data`, optional

If the `x` and `y` observations are nested within sampling units, those can be specified here. This will be taken into account when computing the confidence intervals by performing a multilevel bootstrap that resamples both units and observations (within unit). This does not otherwise influence how the regression is estimated or drawn.

**order** : int, optional

If `order` is greater than 1, use `numpy.polyfit` to estimate a polynomial regression.

**logistic** : bool, optional

If `True`, assume that `y` is a binary variable and use `statsmodels` to estimate a logistic regression model. Note that this is substantially more computationally intensive than linear regression, so you may wish to decrease the number of bootstrap resamples (`n_boot`) or set `ci` to `None`.

**lowess** : bool, optional

If `True`, use `statsmodels` to estimate a nonparametric lowess model (locally weighted linear regression). Note that confidence intervals cannot currently be drawn for this kind of model.

**robust** : bool, optional

If `True`, use `statsmodels` to estimate a robust regression. This will de-weight outliers. Note that this is substantially more computationally intensive than standard linear regression, so you may wish to decrease the number of bootstrap resamples ( `n_boot` ) or set `ci` to `None`.

**logx** : bool, optional

If `True`, estimate a linear regression of the form  $y \sim \log(x)$ , but plot the scatterplot and regression model in the input space. Note that `x` must be positive for this to work.

**{x,y}\_partial** : strings in `data` or matrices

Confounding variables to regress out of the `x` or `y` variables before plotting.

**truncate** : bool, optional

By default, the regression line is drawn to fill the `x` axis limits after the scatterplot is drawn. If `truncate` is `True`, it will instead be bounded by the data limits.

**{x,y}\_jitter** : floats, optional

Add uniform random noise of this size to either the `x` or `y` variables. The noise is added to a copy of the data after fitting the regression, and only influences the look of the scatterplot. This can be helpful when plotting variables that take discrete values.

**{scatter,line}\_kws** : dictionaries

Additional keyword arguments to pass to `plt.scatter` and `plt.plot`.

**See also****regplot** ([seaborn.regplot.html#seaborn.regplot](#))

Plot data and a conditional model fit.

**FacetGrid** ([seaborn.FacetGrid.html#seaborn.FacetGrid](#))

Subplot grid for plotting conditional relationships.

**pairplot** ([seaborn.pairplot.html#seaborn.pairplot](#))Combine **regplot()** ([seaborn.regplot.html#seaborn.regplot](#)) and **PairGrid** ([seaborn.PairGrid.html#seaborn.PairGrid](#)) (when used with `kind="reg"`).**Notes**

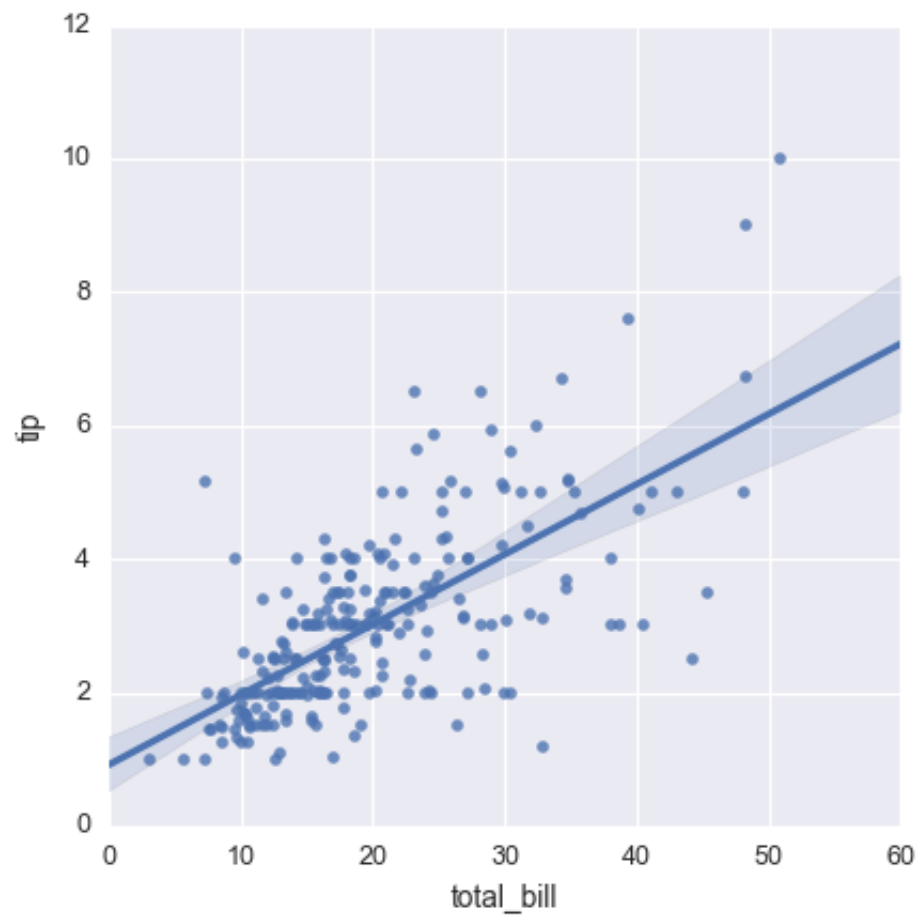
Understanding the difference between **regplot()** ([seaborn.regplot.html#seaborn.regplot](#)) and **lmplot()** can be a bit tricky. In fact, they are closely related, as **lmplot()** uses **regplot()** ([seaborn.regplot.html#seaborn.regplot](#)) internally and takes most of its parameters. However, **regplot()** ([seaborn.regplot.html#seaborn.regplot](#)) is an axes-level function, so it draws directly onto an axes (either the currently active axes or the one provided by the `ax` parameter), while **lmplot()** is a figure-level function and creates its own figure, which is managed through a **FacetGrid** ([seaborn.FacetGrid.html#seaborn.FacetGrid](#)). This has a few consequences, namely that **regplot()** ([seaborn.regplot.html#seaborn.regplot](#)) can happily coexist in a figure with other kinds of plots and will follow the global matplotlib color cycle. In contrast, **lmplot()** needs to occupy an entire figure, and the size and color cycle are controlled through function parameters, ignoring the global defaults.

**Examples**

These examples focus on basic regression model plots to exhibit the various faceting options; see the **regplot()** ([seaborn.regplot.html#seaborn.regplot](#)) docs for demonstrations of the other options for plotting the data and models. There are also other examples for how to manipulate plot using the returned object on the **FacetGrid** ([seaborn.FacetGrid.html#seaborn.FacetGrid](#)) docs.

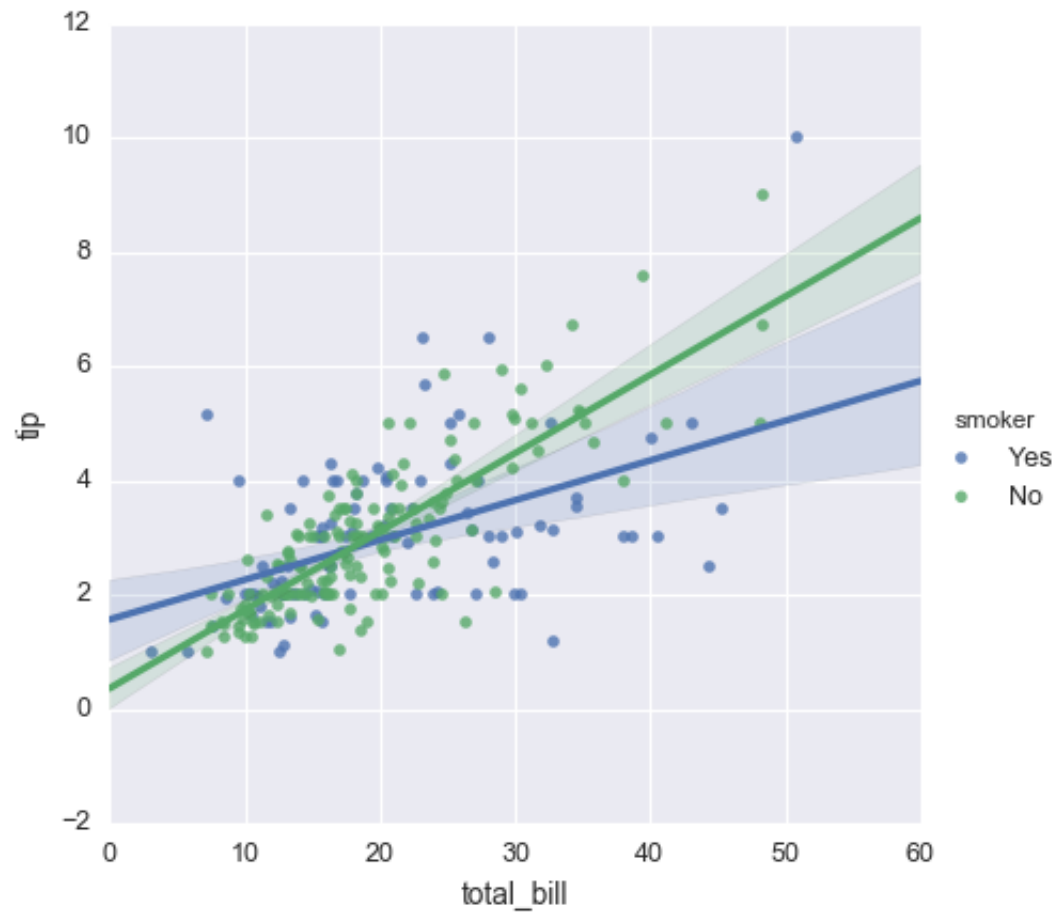
Plot a simple linear relationship between two variables:

```
>>> import seaborn as sns; sns.set(color_codes=True)
>>> tips = sns.load_dataset("tips")
>>> g = sns.lmplot(x="total_bill", y="tip", data=tips)
```



Condition on a third variable and plot the levels in different colors:

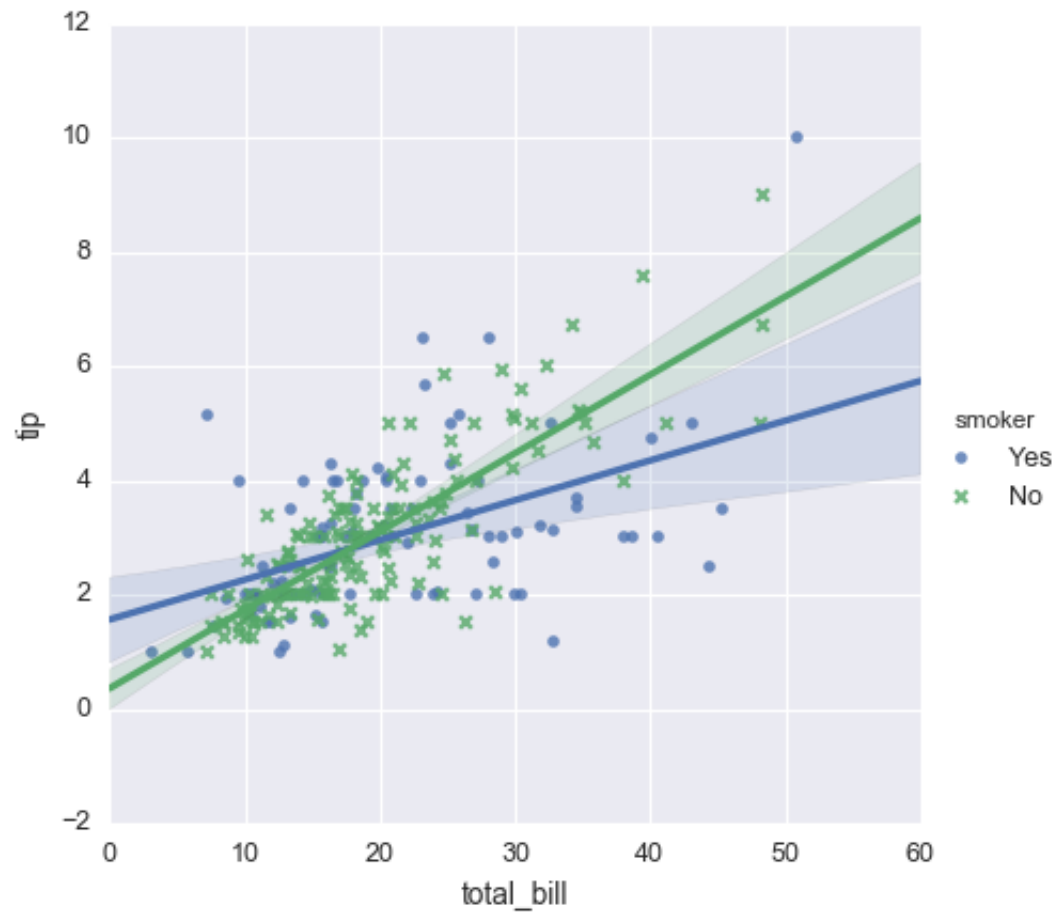
```
>>> g = sns.lmplot(x="total_bill", y="tip", hue="smoker", data=tips)
```



Use different markers as well as colors so the plot will reproduce to black-and-white more easily:

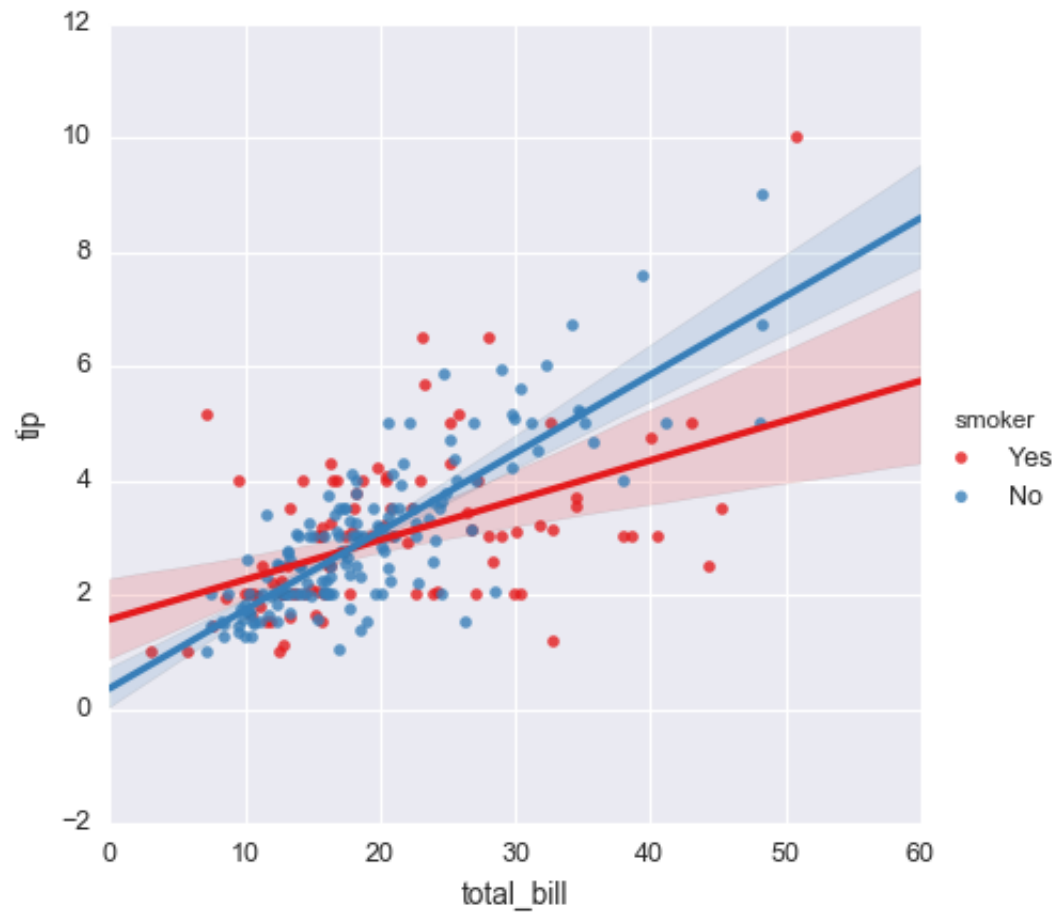
```
>>> g = sns.lmplot(x="total_bill", y="tip", hue="smoker", data=tips,  
...               markers=["o", "x"])
```





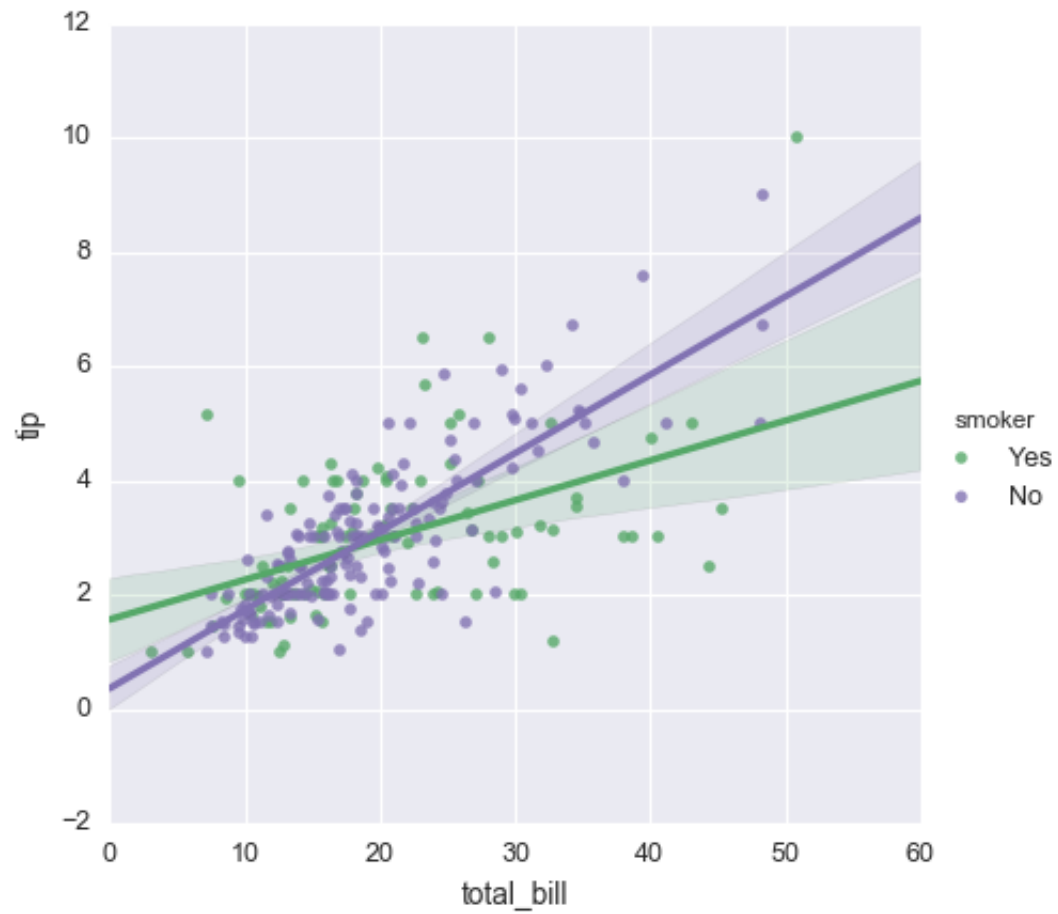
Use a different color palette:

```
>>> g = sns.lmplot(x="total_bill", y="tip", hue="smoker", data=tips,  
...                palette="Set1")
```



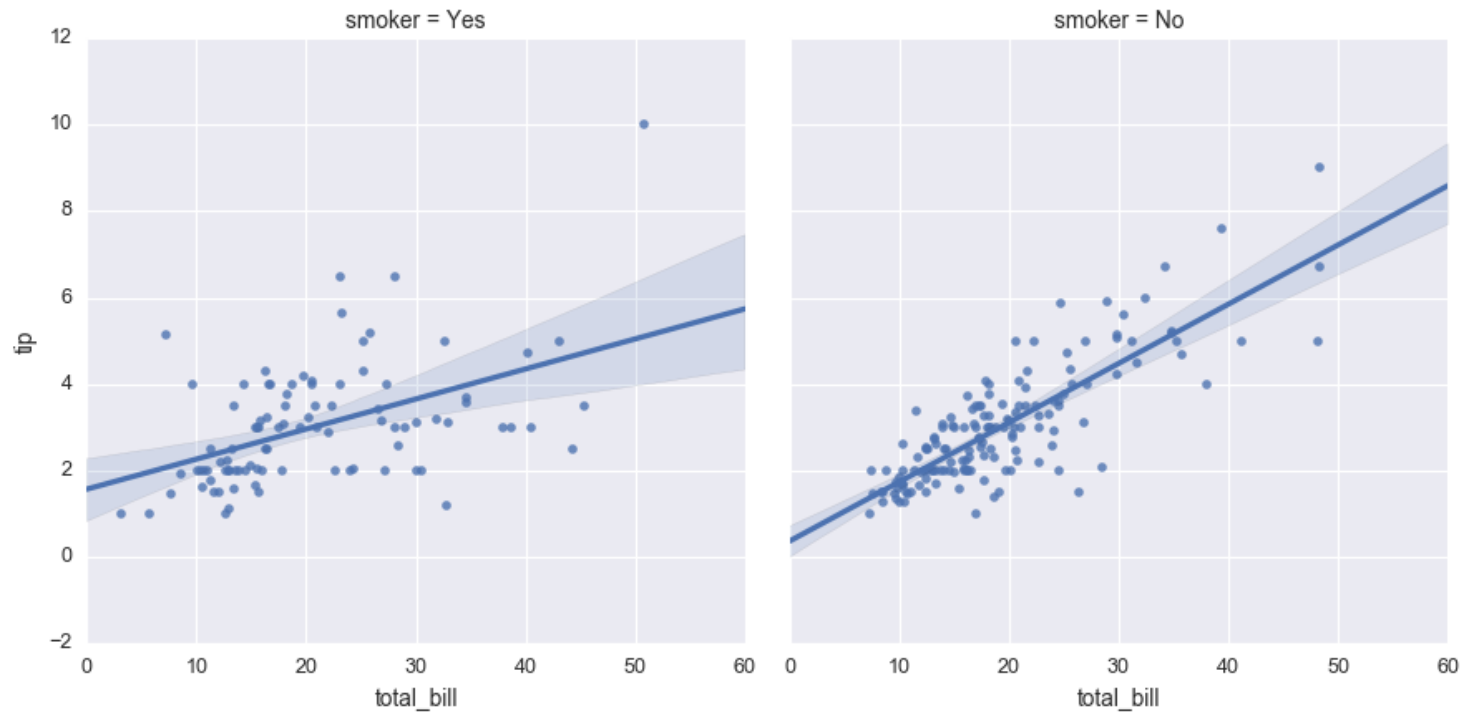
Map hue levels to colors with a dictionary:

```
>>> g = sns.lmplot(x="total_bill", y="tip", hue="smoker", data=tips,  
...                palette=dict(Yes="g", No="m"))
```



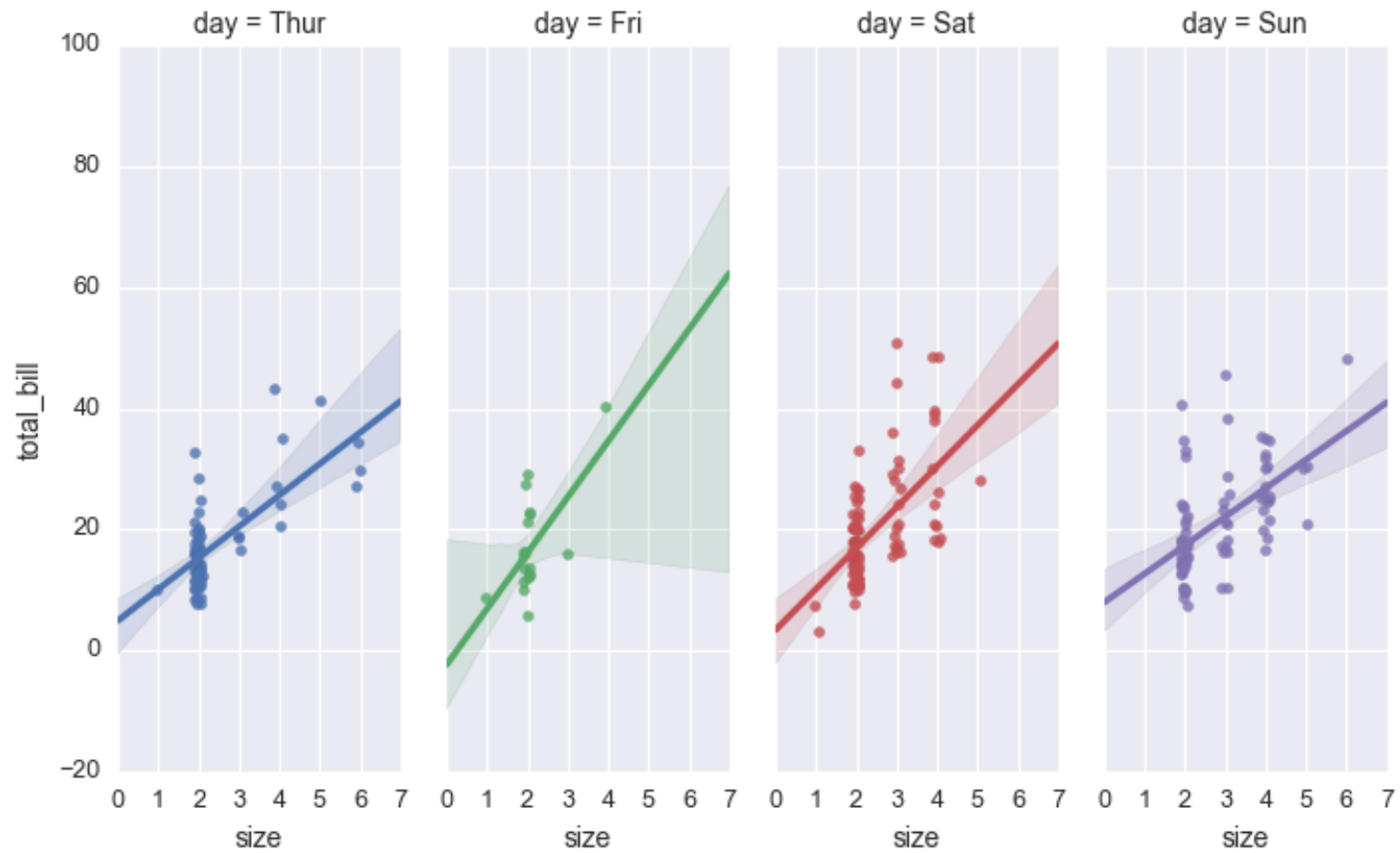
Plot the levels of the third variable across different columns:

```
>>> g = sns.lmplot(x="total_bill", y="tip", col="smoker", data=tips)
```



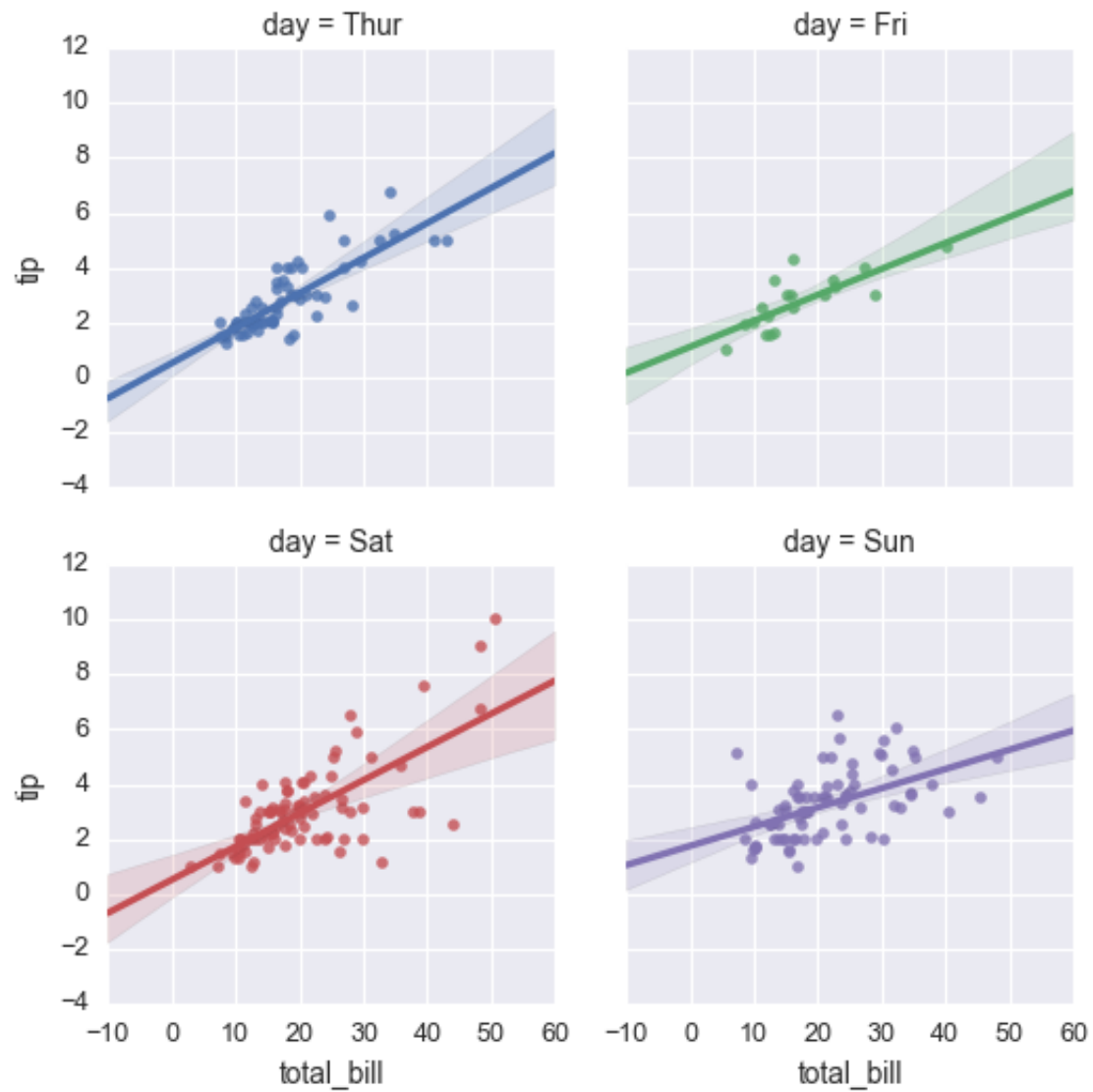
Change the size and aspect ratio of the facets:

```
>>> g = sns.lmplot(x="size", y="total_bill", hue="day", col="day",  
...                data=tips, aspect=.4, x_jitter=.1)
```



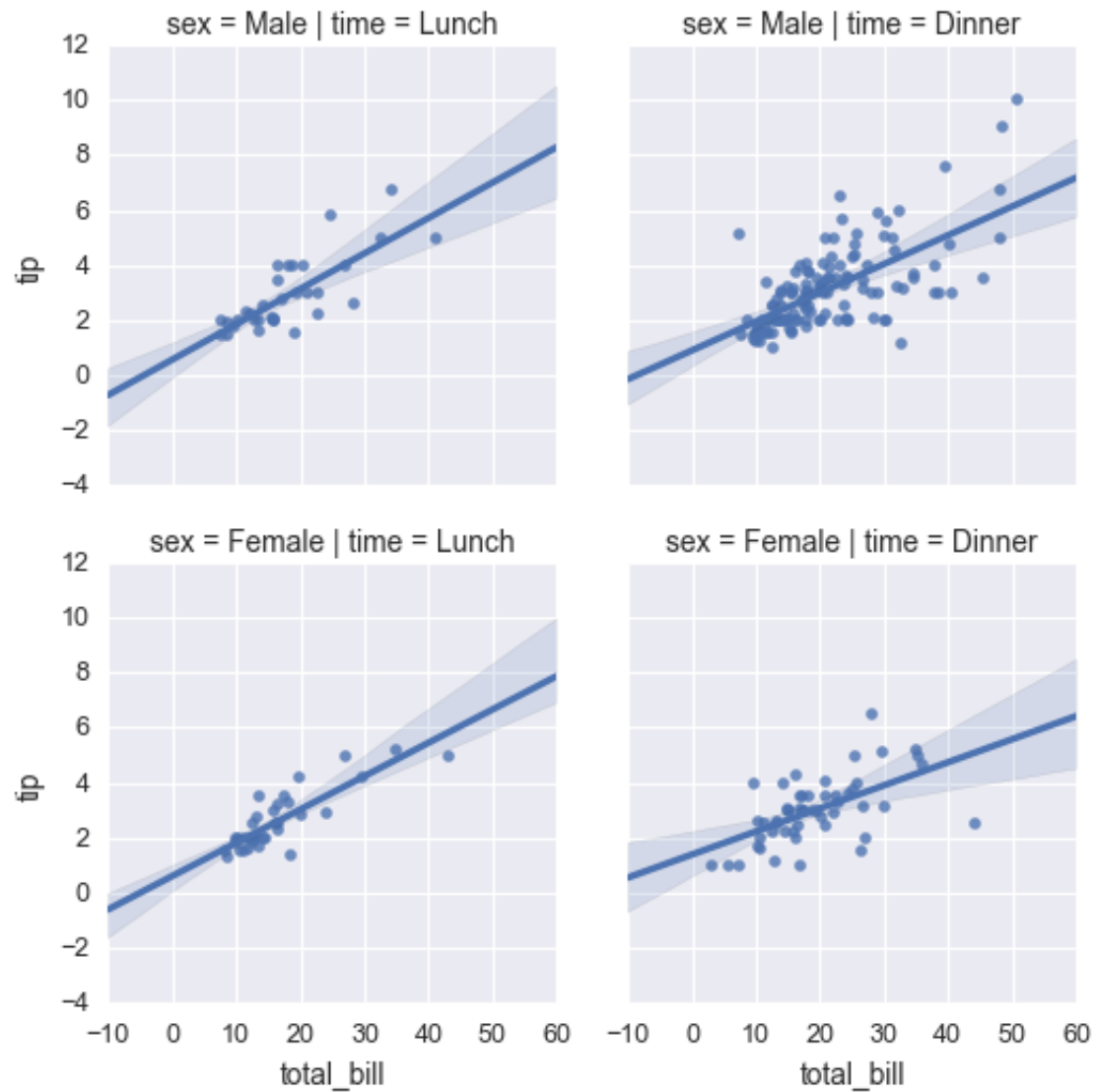
Wrap the levels of the column variable into multiple rows:

```
>>> g = sns.lmplot(x="total_bill", y="tip", col="day", hue="day",  
...               data=tips, col_wrap=2, size=3)
```



Condition on two variables to make a full grid:

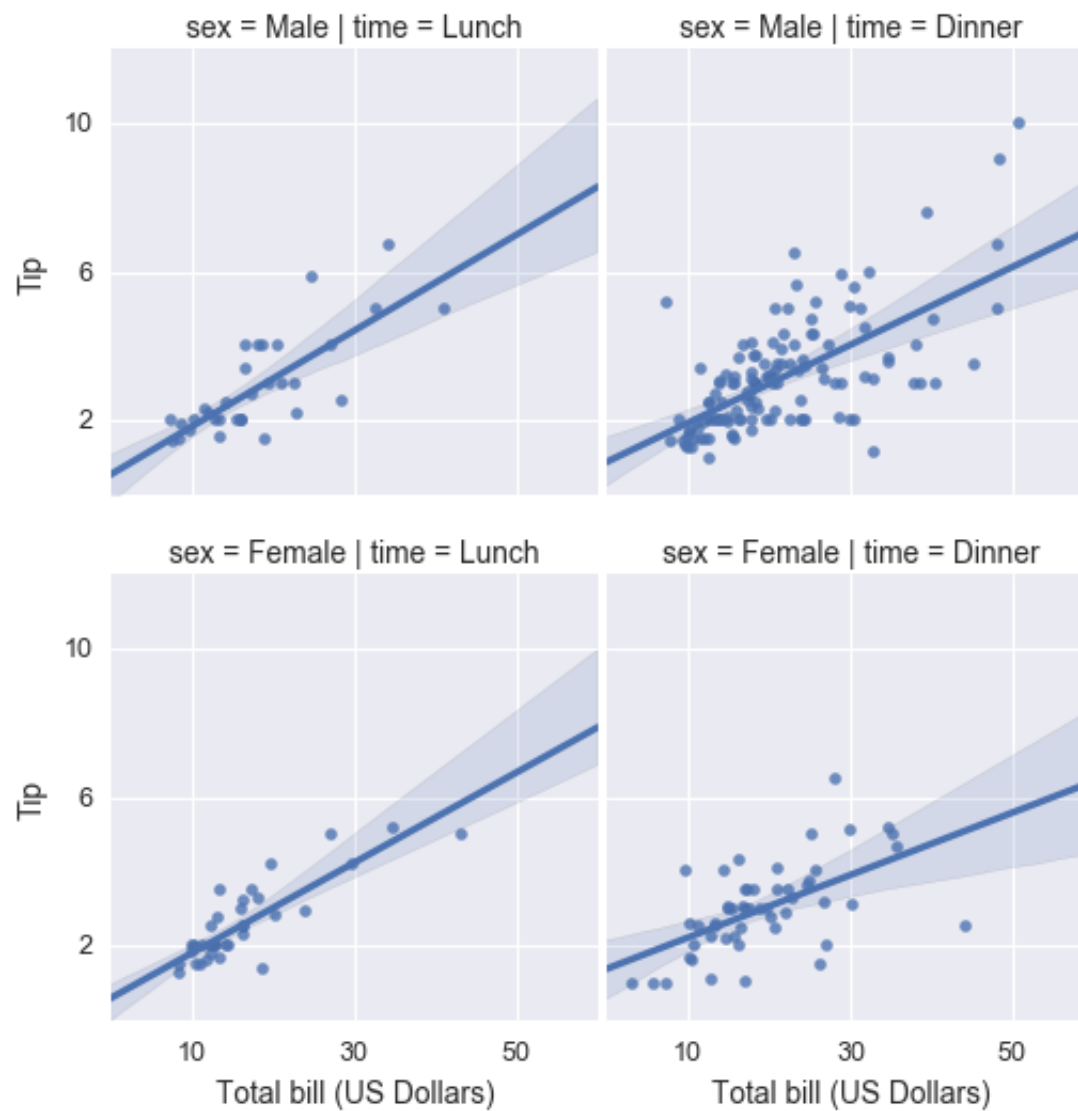
```
>>> g = sns.lmplot(x="total_bill", y="tip", row="sex", col="time",  
...                 data=tips, size=3)
```



Use methods on the returned **FacetGrid** ([seaborn.FacetGrid.html#seaborn.FacetGrid](https://seaborn.pydata.org/seaborn.pydata.org/seaborn.FacetGrid.html#seaborn.FacetGrid)) instance to further tweak the plot:

```
>>> g = sns.lmplot(x="total_bill", y="tip", row="sex", col="time",  
...               data=tips, size=3)  
>>> g = (g.set_axis_labels("Total bill (US Dollars)", "Tip")  
...      .set(xlim=(0, 60), ylim=(0, 12),  
...           xticks=[10, 30, 50], yticks=[2, 6, 10])  
...      .fig.subplots_adjust(wspace=.02))
```





Source ([../\\_sources/generated/seaborn.Implot.txt](#))

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