

A flight of craft beer samples consisting of ten small, identical glasses arranged in two rows on a dark wooden tray. The glasses contain various styles of beer, including dark ales, light lagers, and a reddish-pink brew. Each glass is topped with a thick, white head of foam. The background is a blurred wooden surface.

# **Hypothesis Testing With Beer:**

A Statistical Exploration of Craft Beer in the  
United States

# Data Selection and Initial Analysis

- Data was originally in two sets-- they were joined by brewery ID

## Loading the Dataset and Understanding the Data

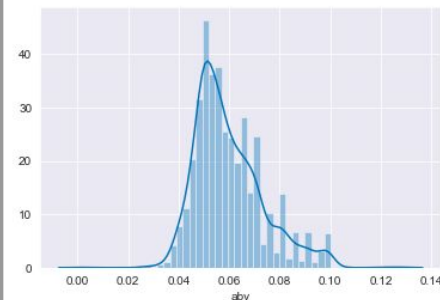
```
In [5]: brewery = pd.read_csv('data/beer_and_brewery.csv')  
brewery.head()
```

```
Out[5]:
```

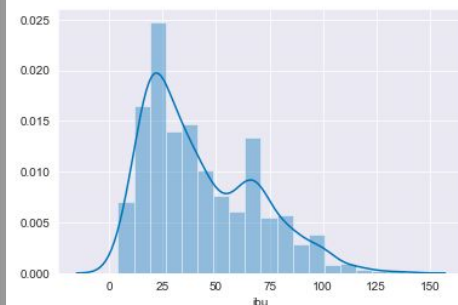
	Unnamed: 0	beer_id	abv	ibu	id	beer_name	style	brewery_id	ounces	brewery_name	city	state
0	0	0	0.050	NaN	1436	Pub Beer	American Pale Lager	408	12.0	10 Barrel Brewing Company	Bend	OR
1	1	1	0.066	NaN	2265	Devil's Cup	American Pale Ale (APA)	177	12.0	18th Street Brewery	Gary	IN
2	2	2	0.071	NaN	2264	Rise of the Phoenix	American IPA	177	12.0	18th Street Brewery	Gary	IN
3	3	3	0.090	NaN	2263	Sinister	American Double / Imperial IPA	177	12.0	18th Street Brewery	Gary	IN
4	4	4	0.075	NaN	2262	Sex and Candy	American IPA	177	12.0	18th Street Brewery	Gary	IN

- Here we see distribution plots of **ABV** and **IBU** and value counts of beers from the top 10 states:

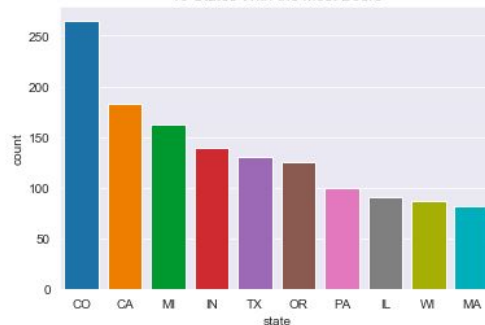
There are 2348 ABV values in the dataset.



There are 1405 IBU values in the dataset.

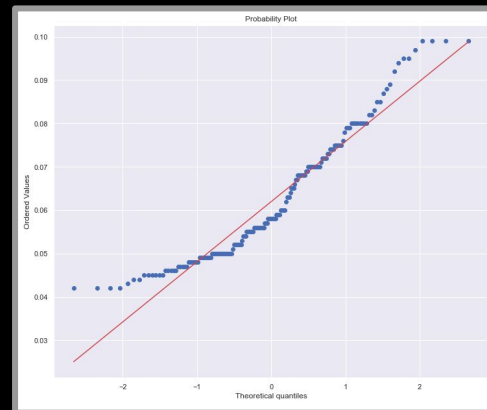
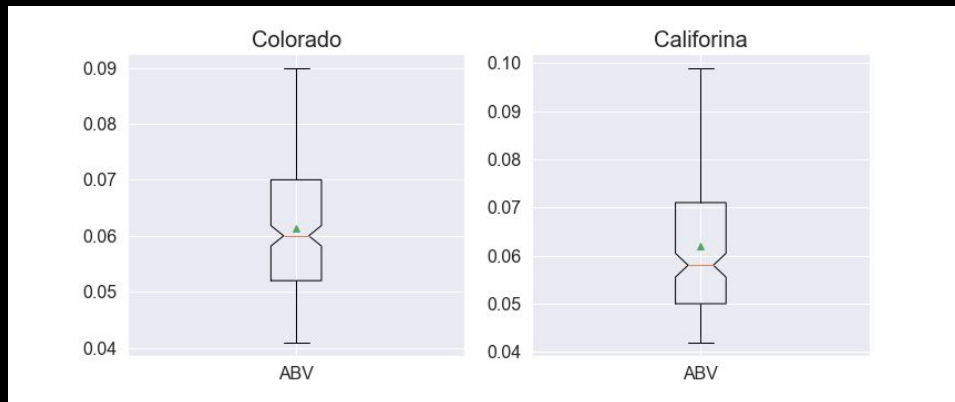


10 States With the Most Beers



# Test 1: Comparing ABV from Colorado and California

- Is there a difference in ABV between beers brewed in Colorado and California?
  - We examine the box-plot and QQ plot to get a sense of the data:



- We set our **Null and Alternative Hypothesis**:

**Null Hypothesis:**

$$H_0: \mu_1 = \mu_2$$

**Alternative hypothesis**

$$H_a: \mu_1 \neq \mu_2$$

# Test 1: Comparing Beers from Colorado and California

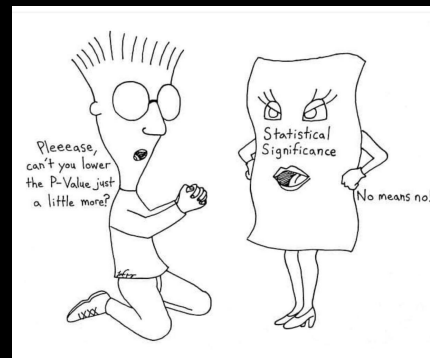
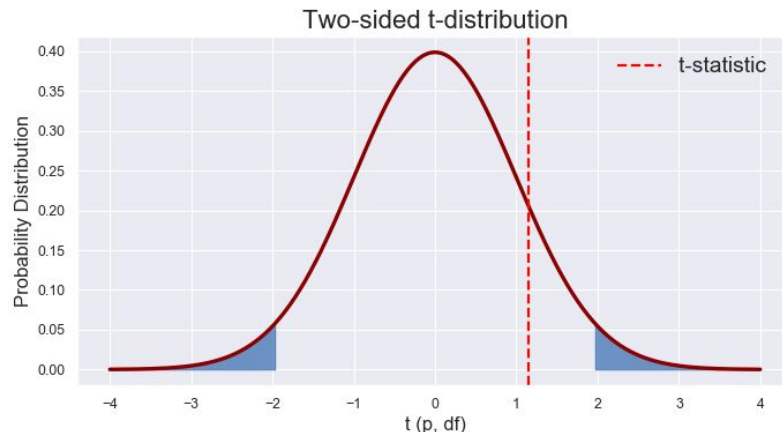
- We run a user-generated function to determine the t-statistic, critical t-values, and p-value

```
In [32]: 1 import test_moduls as test
          2 t_stat = test.twosample_tstatistic(CA_brewery, CO_brewery, alpha=0.05)

Null hypothesis is True with t-statistic = 1.149 , critical t-value = 1.9701 and p-value = 0.2517

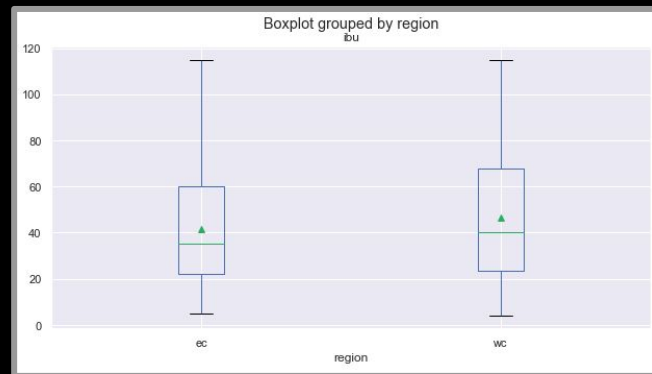
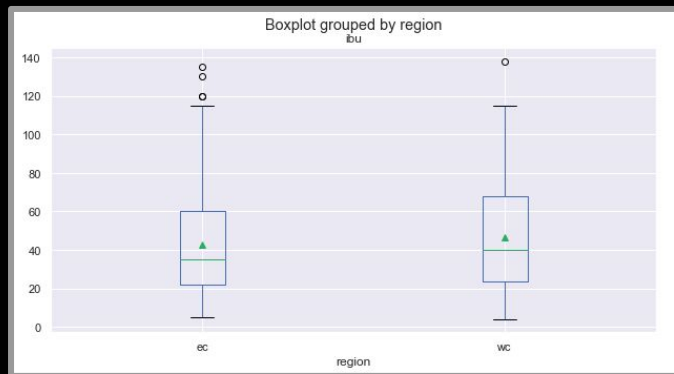
-----group info-----
The groups contain 113 and 125 observations. Means are: 0.065 and 0.063 respectively
```

- We run a user-generated function to generate and view a visualization



# Test 2: Comparing IBU from East Coast and West Coast

- Is there a difference in IBU between beers brewed on the East Coast and West Coast?
  - Outliers are removed from the set; we examine the box-plots



- We set our **null-hypothesis** and **alternative hypothesis**

## 2.1. Set Null Hypotheses

The null hypothesis is there is no difference in IBU between beers brewed on the East Coast and beers brewed on the West Coast.

$H_0$ : The mean IBU difference between East Coast beers and West Coast beers is zero. i.e.  $H_0 = H_1$

## 2.2. Set Alternate Hypothesis

$H_1$  (2-tailed): The mean difference between East Coast and West Coast beers is different.

# Test 2: Comparing IBU from East Coast and West Coast

- We run user-generated functions to determine the t-statistic, critical t-values, and p-value
  - Two-tailed t-test and Welch's t-test

```
In [41]: t_stat = test.twosample_tstatistic(wc_ibu, ec_ibu)

Null hypothesis rejected. Results are statistically significant          with t-statistic= 2.585 , critical t-val
ue=  1.9631 and p-value =  0.005

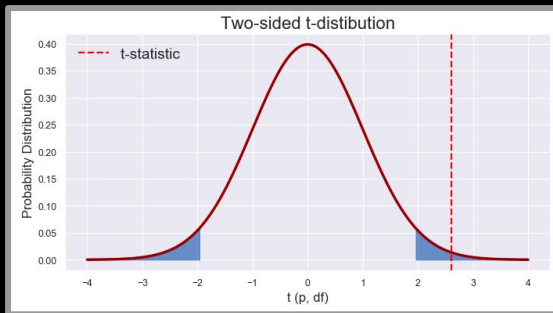
-----group info-----
The groups contain 427 and 329 observations. Means are:  46.452 and 41.6717 respectively

In [23]: welch_t = test.welch_t(wc_ibu, ec_ibu)
print("Welch's t-statistic is: ", round(welch_t,4))
welch_df = test.welch_df(wc_ibu, ec_ibu)
print("Welch's degrees of freedom (df):", round(welch_df,4))

# converting this to p_value
p_welch = test.p_value_welch_ttest(wc_ibu, ec_ibu, two_sided=True)

Welch's t-statistic is:  2.6058
Welch's degrees of freedom (df): 724.9698
Null hypothesis rejected. Results are statistically significant
with t-value =  2.6058 , critical t-value =  1.647 , and p-value =  0.0047
```

- We see that the t-statistic is 2.585 in the two-tailed t-test and 2.606 in the Welch's t-test
  - Using both tests, we reject the null hypothesis



	Sample Mean	Sample Size	Sample Variance
East Coast	42.69	333	25.88
West Coast	46.67	428	26.22

# Test 3: ANOVA test

- Is there a difference in IBU between beers brewed in DC/MD/VA, MA, MN, TX, and CO?

	Sample Size	Sample Mean	Sample Variance
Washington State	41	41.66	356.42
Minnesota	44	49.27	543.20
DMV	44	45.32	594.35
Texas	83	42.60	658.70
Colorado	136	49.93	632.40

- We set our **null-hypothesis** and **alternative hypothesis**

**Null Hypothesis:**

$$H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$$

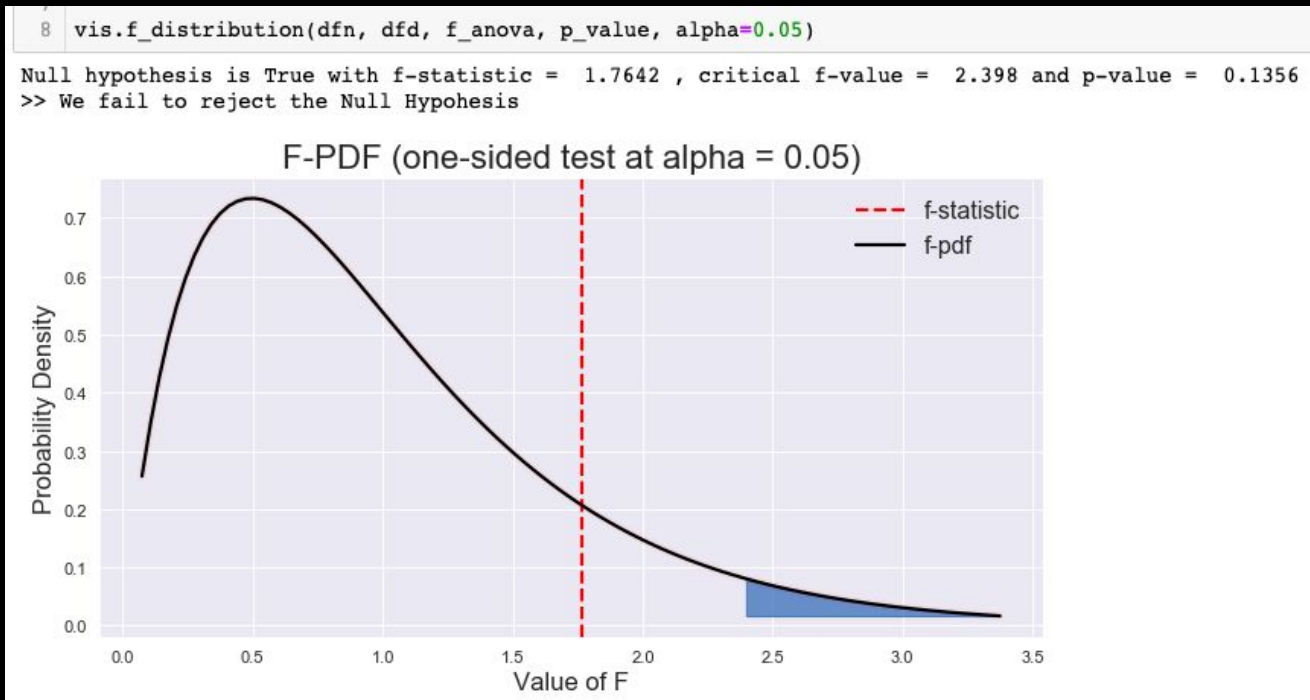
**Alternative Hypothesis:**

$H_a:$  not all means are equal



# Test 3: Comparing IBU from Five States

- We fail to reject the Null Hypothesis with  $f\_statistic = 1.6114$ , and  $p\_value = 0.1777$ .
  - We say the mean IBU is the same in WA, MN, CO, TX , DMV area:





# Conclusions

- There is no mean ABV difference between beers from Colorado and beers from Californias
- There is a significant mean IBU difference between beers from the East Coast and West Coast
  - West Coast beers are more bitter!
- There is no mean IBU difference among beers from CO, WA, MN, DMV, TX

# Next Steps

- Data
  - Collect more US data
  - Collect data that includes foreign beers
  - Collect time-series data to explore changes to the industry over time
- Tests
  - Explore the relationship between ABV and IBU using two-way ANOVA

**Q&A**