Learn

Part 1: Hypothesis testing recap

Include the answers in `morning_answers.md`

1. State which test should be used for the following scenarios to calculate p-values. Explain your choice.

   a. You randomly select 50 dogs and 80 cats from a large animal shelter, and want to know if dogs and cats have the same weight.

   ```
     2 sample t-
   test
   ```

   b. A random sample of San Franciscans and Oaklanders were surveyed about their favorite baseball team, and you want to determine if the same proportion of people like the SF Giants.

   ```
     z-test for two
   proportions
   ```

2. A study looked at the incidence of hospitalization for heart failure in Ohio, in 12 groups of patients defined by their astrological sign (based on their birthday). People born under the sign of Pisces have the highest incidence of heart failure. The researchers then performed a z-test compare the incidence of heart failure under Pisces with the incidence of heart failure among all other signs. The p-value is 0.026. What is the problem with concluding people born under the sign of Pisces have higher incidence of heart failure at significance level of 0.05. How would you adjust the p value to reach an alternative conclusion.

   ```
   The level of significance evaluated from the z-test needs to be adjusted for
   multiple testing,
   even though only one explicit test was run. Implicitly 12 tests are run since
   we selected the group with the highest incidence out of 12 and did the z-test
   with that group against the rest of the groups.

   The corrected alpha value is 0.05/12=0.0042. And the test is not
   statistically
   significant since p-value > 0.0042.

   In general, you would define the comparison you are going make before
   collecting
   the data. It is also important that your null hypothesis has a reasonable
   basis.
   Statistical significance should not override reasoning. The size of the
   difference should also be taken into account.
   ```

Part 2: Analyzing Click Through Rate

We will use hypothesis testing to analyze **Click Through Rate (CTR)** on the New York Times website. CTR is defined as the number of clicks the user make per impression that is made upon the user. We are going to determine if there is statistically significant difference between the CTR of the following groups:

```
1. Signed in users v.s. Not signed in users
2. Male v.s. Female
3. Each of 7 age groups against each other (7 choose 2 = 21
tests)
```

```
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as scs
from itertools import combinations
%matplotlib inline
```

1. Calculate the adjustment needed for multiple testing at 0.05 significance level.

```
alpha = 0.05 /
23
```

2. Load `data/nyt1.csv` in a pandas dataframe.

   Use `data.info()` to make sure the datatypes are valid and there are no null values. This data has been cleaned for you, but generally it is good practice to check for those.

```
data = pd.read_csv('data/nyt1.csv')

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 458441 entries, 0 to
458440
Data columns (total 5 columns):
Age             458441 non-null int64
Gender          458441 non-null int64
Impressions     458441 non-null int64
Clicks          458441 non-null int64
Signed_In       458441 non-null int64
dtypes: int64(5)
```

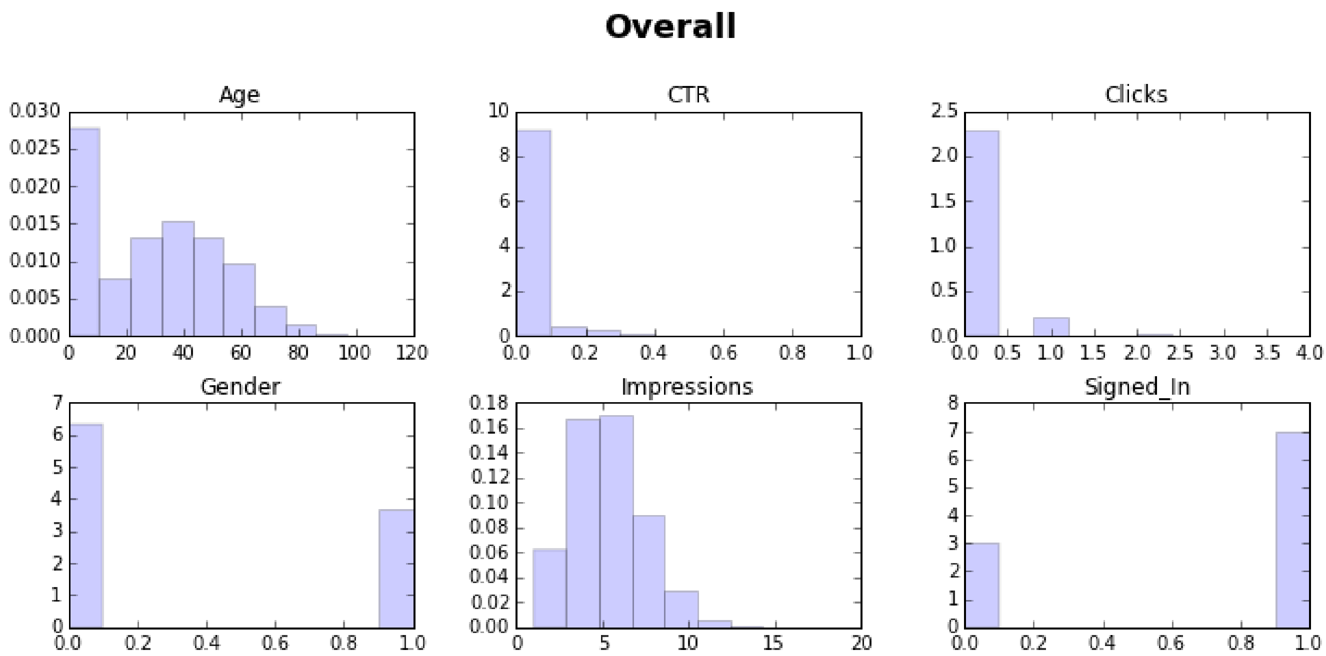
3. Make a new column `CTR` using the `Impressions` and the `Clicks` columns. Remember to remove the rows with `0` impressions.

```
data = data[data['Impressions'] != 0]

data['CTR'] = data['Clicks'] /
data['Impressions'].astype(float)
```

4. Plot the distribution of each column in the dataframe. Do that using `data.hist()`. Check out the

argments you can use with the function here . Set the `figsize=(12,5)` to make sure the graph is readable.

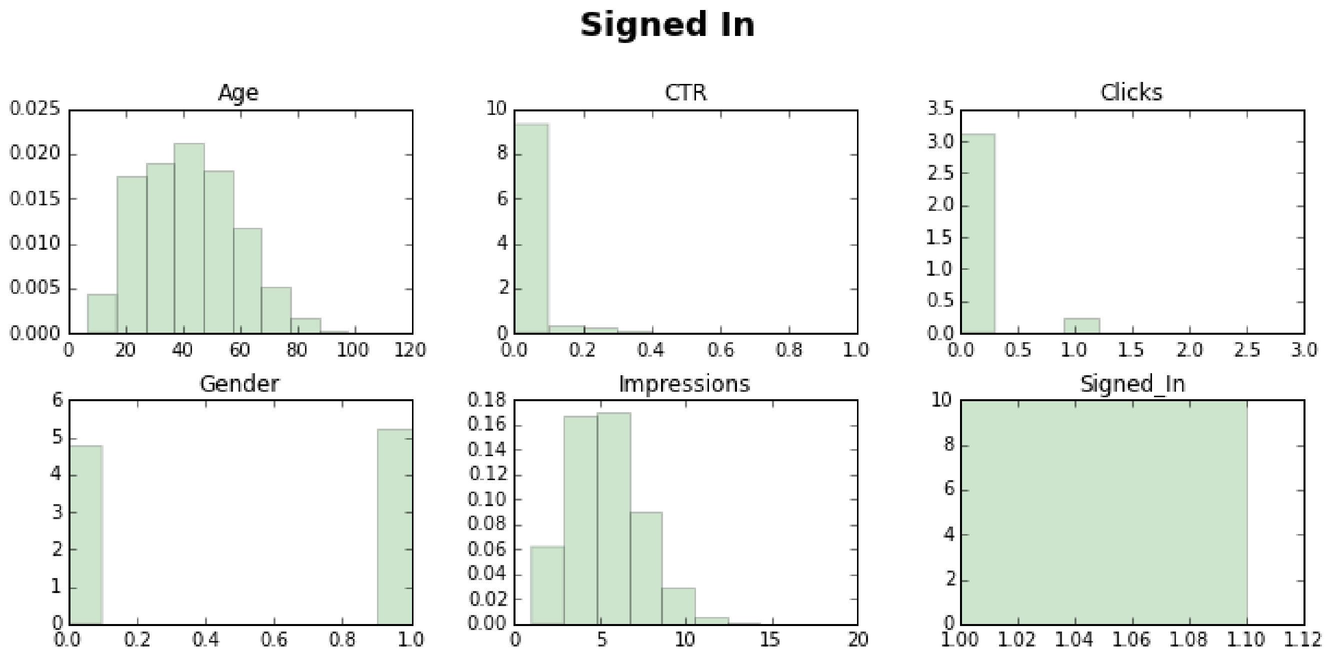
```
def plot_hist(df, title, color):
    df.hist(figsize=(12, 5), grid=False, normed=True, color=color,
alpha=.2)


    plt.suptitle(title, size=18, weight='bold', y=1.05)

plot_hist(data, 'Overall', 'b')
```

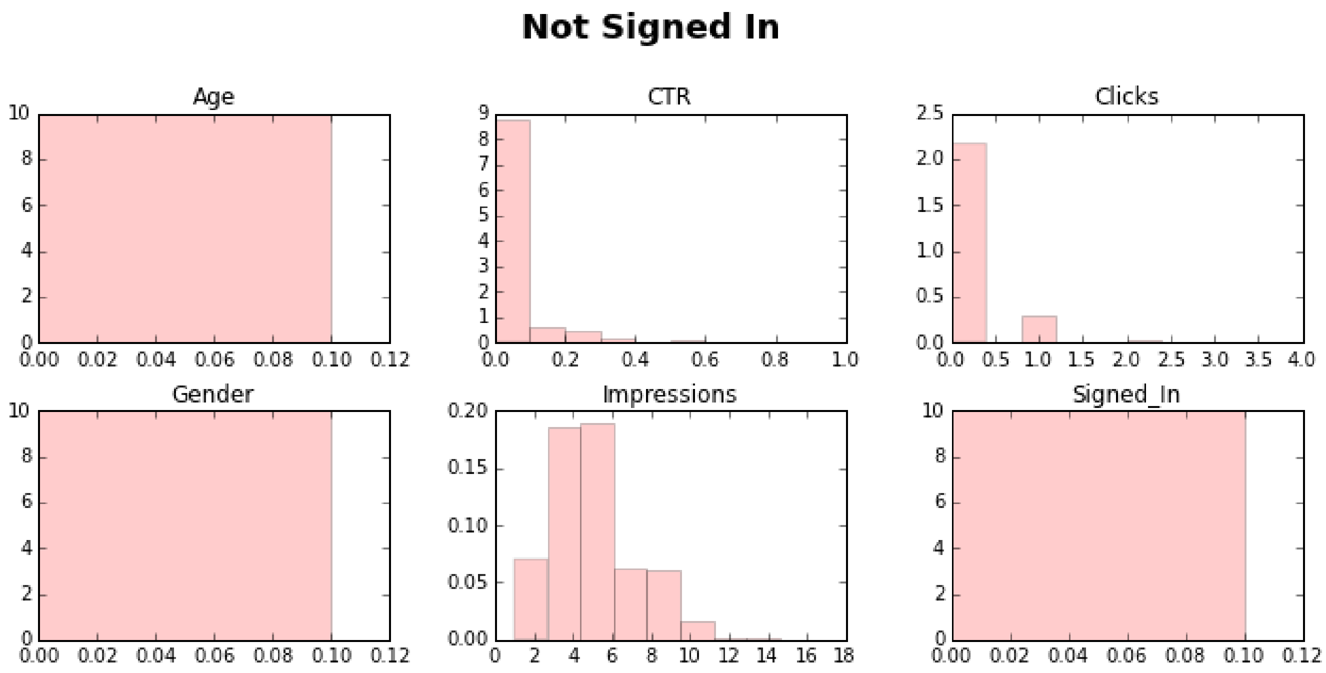


5. Make 2 dataframes - one a dataframe of 'users who are signed in' and a second of 'users who are not signed in'. Plot the distributions of the columns in each of the dataframes. By visually inspecting the two sets of distributions, describe the differences between users who are signed in and not signed in?

```
signin_data = data[data['Signed_In'] == 1]
notsignin_data = data[data['Signed_In'] == 0]

plot_hist(signin_data, 'Signed In', 'g')
plot_hist(notsignin_data, 'Not Signed In',
'r')
```

```
Users who are not signed in are all females aged 0, suggesting that
the
gender and age are not registered unless the user is signed in.
```





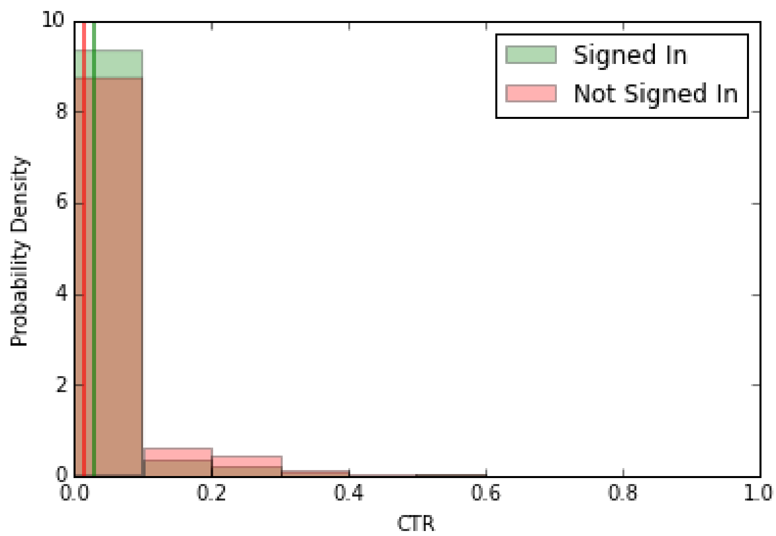
6. Use a Welch t-test to determine if the mean CTR between the signed-in users and the non-signed-in users is statistically different. Explain how you arrive at your conclusion.

   The Welch t-test assumes the two populations in which the samples are drawn from have different variances.

   ```
   scipy.stats.ttest_ind(a, b,
   equal_var=False)
   ```

```
def t_test(gp1_df, gp2_df, gp1_name, gp2_name):
    fig = plt.figure()
    gp1_mean = gp1_df['CTR'].mean()
    gp2_mean = gp2_df['CTR'].mean()

    print '%s Mean CTR: %s' % (gp1_name, gp1_mean)
    print '%s Mean CTR: %s' % (gp2_name, gp2_mean)
    print 'diff in mean:' , abs(gp2_mean - gp1_mean)
    p_val = scs.ttest_ind(gp1_df['CTR'], gp2_df['CTR'], equal_var=False)
[1]
    print 'p value is:', p_val

    gp1_df['CTR'].hist(normed=True, label=gp1_name, color='g', alpha=0.3)
    gp2_df['CTR'].hist(normed=True, label=gp2_name, color='r', alpha=0.3)
    plt.axvline(gp1_mean, color='r', alpha=0.6, lw=2)
    plt.axvline(gp2_mean, color='g', alpha=0.6, lw=2)

    plt.ylabel('Probability Density')
    plt.xlabel('CTR')
    plt.legend()
    plt.grid('off')


t_test(signin_data, notsignin_data, 'Signed In', 'Not Signed In')
```

```
Signed In Mean CTR: 0.0142536352321
Not Signed In Mean CTR:
0.0283549070617
diff in mean: 0.0141012718295
p value is: 0.0
```



7. Determine if the mean CTR between male users and female users is statistically different. Is the difference in mean CTR between signed-in users and non-signed-in users more worthy of further investigation than that between male and female? Explain your answer. `Male: 1, Female: 0`

```
male = signin_data[signin_data['Gender'] == 1]
female = signin_data[signin_data['Gender'] ==
0]
t_test(male, female, 'M', 'F')
```

```
M Mean CTR: 0.0139185242976
F Mean CTR: 0.0146220121839
diff in mean: 0.000703487886268
p value is: 0.00100285273131
```

```
The difference in CTR between signed in and non-signed users is more
worthy of further investigation since the difference in CTR is greater.
The female/male CTR difference is only marginally significant (0.0010 <
0.00217).
The signed-in/non_signed CTR difference is more significant than that of
male/female (0.0 < 0.00217).
```

8. Calculate a new column called AgeGroup, which bins Age into the following buckets
   `'(18, 24]', '(24, 34]', '(34, 44]', '(44, 54]', '(54, 64]', '(64, 1000]', '(7, 18]'`

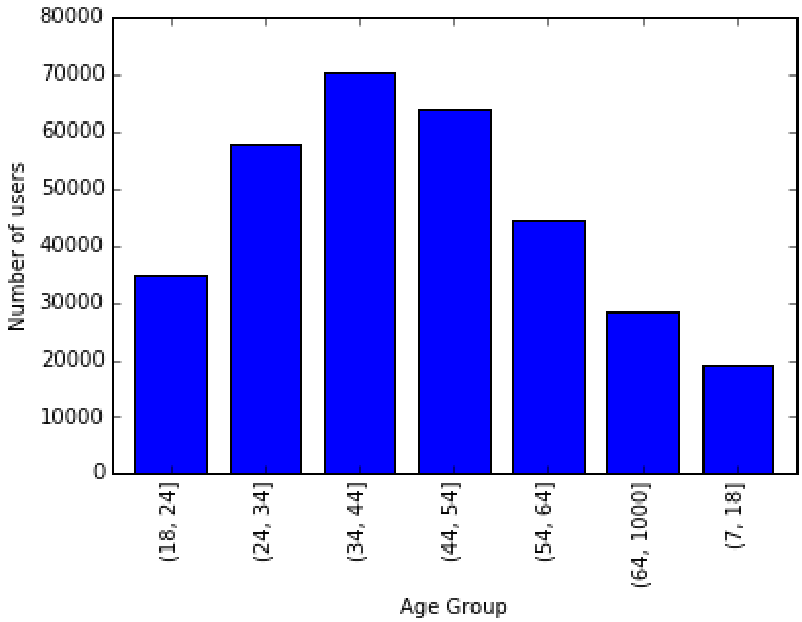
   Use only the rows where the users are signed in. The non-signed in users all have age 0, which indicates the data is not available.

   Use pandas' cut function.
   `pandas.cut(signin_data['Age'], [7, 18, 24, 34, 44, 54, 64, 1000])`

   (**Estimated Time: 5 mins**)

```
signin_data['age_groups'] = pd.cut(signin_data['Age'], [7, 18, 24, 34, 44,
54, 64, 1000])
```

```
signin_data['age_groups'].value_counts().sort_index().plot(kind='bar',
grid=False)
plt.xlabel('Age Group')
plt.ylabel('Number of users')
```



9. Determine the pairs of age groups where the difference in mean CTR is statistically significant. Collect the p values and the difference of the means in each pair in a `DataFrame`.

   Rank (in descending order) the difference in mean CTR for the pairs that are statistically significant.

   Comment on the trend you observe for groups `(64, 1000]`, `(54, 64]` and `(7, 18]`. Feel free to include additional trends you observe.

   Rank (in ascending order) the difference in mean CTR for the pairs that are *statistically insignificant*. State the 3 groups that are the least different in mean CTR and provide an explanation for why that is.

```
results = pd.DataFrame()

combos = combinations(pd.unique(signin_data['age_groups']), 2)


for age1, age2 in combos:
  ctr1 = signin_data[signin_data['age_groups'] == age1]['CTR']
  ctr2 = signin_data[signin_data['age_groups'] == age2]['CTR']
  p_val = scs.ttest_ind(ctr1, ctr2, equal_var=False)[1]
  ctr1_mean = ctr1.mean()
  ctr2_mean = ctr2.mean()
  diff = abs(ctr1_mean - ctr2_mean)
  results = results.append(dict(one=age1, two=age2,
                              mean1=ctr1_mean, mean2=ctr2_mean,
                              diff=diff, p=p_val),
ignore_index=True)
results = results[['one', 'two', 'mean1', 'mean2', 'diff', 'p']]


results[results['p'] < alpha].sort('diff', ascending=False)
```

```
Each of '(64, 1000]', '(7, 18]' and '(54, 64]' age group has CTR
significantly
greater than than the other 4 age groups, i.e.
'(18, 24]', '(24, 34]', '(34, 44]', '(44, 54]'.
This indicates the oldest 2 groups and the youngest group are the mostly
likely to click through. Perhaps the oldest groups would generally click in
to read an article and do less browsing. The youngest group might just be
clicking a lot more because they are eaily distracted.

Whilst '(64, 1000]' has a higher CTR than '(7, 18]' which in turn has a
higher
CTR than '(54, 64]', and the differences are all statistically significant.
These
differences are less significant than that between these 3 groups and the
rest of
the groups.
```

	one	two	mean1	mean2	diff	p
10	(64, 1000]	(18, 24]	0.029803	0.009720	0.020082	2.458627e-272
8	(64, 1000]	(44, 54]	0.029803	0.009958	0.019845	1.430923e-295
7	(64, 1000]	(24, 34]	0.029803	0.010146	0.019656	7.860398e-285
0	(34, 44]	(64, 1000]	0.010286	0.029803	0.019516	5.245541e-288
22	(7, 18]	(18, 24]	0.026585	0.009720	0.016865	6.900980e-144
18	(44, 54]	(7, 18]	0.009958	0.026585	0.016628	4.014382e-151
14	(24, 34]	(7, 18]	0.010146	0.026585	0.016439	7.449266e-146
3	(34, 44]	(7, 18]	0.010286	0.026585	0.016299	4.575147e-146
25	(18, 24]	(54, 64]	0.009720	0.020307	0.010586	1.007813e-130
20	(44, 54]	(54, 64]	0.009958	0.020307	0.010349	2.525271e-151
16	(24, 34]	(54, 64]	0.010146	0.020307	0.010160	5.668132e-141
5	(34, 44]	(54, 64]	0.010286	0.020307	0.010020	7.523228e-144
11	(64, 1000]	(54, 64]	0.029803	0.020307	0.009496	9.214903e-56
23	(7, 18]	(54, 64]	0.026585	0.020307	0.006278	8.273993e-20
9	(64, 1000]	(7, 18]	0.029803	0.026585	0.003218	3.563408e-05

15 rows × 6 columns

```
results[results['p'] > alpha].sort('diff',
ascending=True)
```

```
The differences in CTR amongst '(18, 24]', '(24, 34]', '(34, 44]' and '(44,
54]'
are not significant. This indicates the users aged from 18 - 54 are clicking
through at similar ratios. This may be due to similar browsing behavior, ie
a lot of scanning of articles, but not a lot of clicking into the articles
and reading them.
```

	one	two	mean1	mean2	diff	p
1	(34, 44]	(24, 34]	0.010286	0.010146	0.000140	0.624662
13	(24, 34]	(44, 54]	0.010146	0.009958	0.000189	0.514689
19	(44, 54]	(18, 24]	0.009958	0.009720	0.000237	0.477902
2	(34, 44]	(44, 54]	0.010286	0.009958	0.000329	0.233928
15	(24, 34]	(18, 24]	0.010146	0.009720	0.000426	0.213658
4	(34, 44]	(18, 24]	0.010286	0.009720	0.000566	0.087470

6 rows × 6 columns