Homework 1

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Due: Sat Oct. 12 @ 11:59pm

In this homework we'll do some data exploration and perform an A/B test.

Instructions

Follow the comments below and fill in the blanks (____) to complete.

Where a text response is asked for, please enter as a comment, starting each line with #.

Environment Setup

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pylab as plt

sns.set_style('darkgrid')

%matplotlib inline
```

Part 1: Data Exploration

One data science task, and a common one used for data science interviews, is to predict defaults on loans.
We're going to load a subset of a common loan dataset and explore some of the features.

Here is a brief description of the features included:

- **loan_amnt**: The amount of money applied for
- **term**: The period over which the load should be repaid
- **annual_inc**: Annual income of the borrower
- **purpose**: The purpose of the loan, such as: credit_card, debt_consolidation, etc.
- **home_ownership**: The borrower's relationship with their primary residence
- **outcome**: The result of the loan

In [3]:
```
# 1.  (1pt) Load the data from ../data/loan_data_subset.csv into the variable df

df = pd.read_csv('../data/loan_data_subset.csv')
```

In [4]:
```
# 2. (1pt) Print out information about the dataframe using .info()

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 6 columns):
loan_amnt         20000 non-null int64
term              20000 non-null object
annual_inc        20000 non-null int64
purpose           20000 non-null object
home_ownership    20000 non-null object
outcome           20000 non-null object
dtypes: int64(2), object(4)
memory usage: 937.6+ KB
```

In [ ]:
```
# 3. (1pt) Looking at the info print out, how many values are missing (null)?

# 0
```

In [5]:
```
# 4. (1pt) Using .shape, how many rows does the dataset have?

print(f'dataframe has {2000} rows')
```

```
dataframe has 2000 rows
```

In [6]:
```
# 5. (1pt) Print the first 5 rows of the dataset using .head

df.head()
```

Out[6]:

	loan_amnt	term	annual_inc	purpose	home_ownership	outcome
0	11000	60 months	59004	home_improvement	MORTGAGE	paid off
1	14000	36 months	120000	credit_card	RENT	default
2	10000	36 months	110000	small_business	MORTGAGE	default
3	23350	60 months	65000	debt_consolidation	MORTGAGE	default
4	12000	60 months	49000	major_purchase	MORTGAGE	paid off

In [8]:

```
# 6. (1pt) Print out rows with labels 100 to 104 inclusive, with all columns, using .
#   Note that we're using row labels and not positional index, so use .loc instead of

df.loc[100:104]
```

Out[8]:

	loan_amnt	term	annual_inc	purpose	home_ownership	outcome
100	4200	60 months	44500	home_improvement	OWN	default
101	18000	60 months	117000	debt_consolidation	MORTGAGE	paid off
102	4375	36 months	35000	house	RENT	default
103	15000	60 months	52884	debt_consolidation	MORTGAGE	paid off
104	24000	36 months	56758	debt_consolidation	MORTGAGE	paid off

In [ ]:

```
# 7. (1pt) What appears to be one numeric feature included in the dataset (column lab

# loan_amnt & annual_inc
```

In [ ]:

```
# 8. (1pt) What appears to be one categorical feature in the dataset?

# purpose & home_ownership & outcome
```

In [ ]:

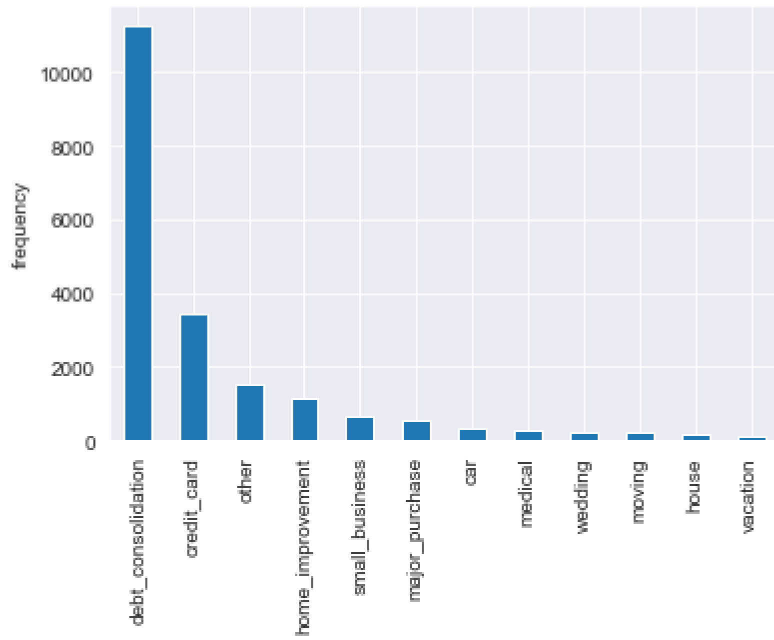
```
# 9. (1pt) What appears to be one ordinal feature in the dataset?

# term
```

In [24]:

```
# 10. (1pt) Plot the frequencies of the values in 'purpose' using .value_counts() and

df['purpose'].value_counts().plot.bar();

# 11. (1pt) label the y axis as 'frequency'
plt.ylabel('frequency')
```

Out[24]:

```
Text(0, 0.5, 'frequency')
```



In [40]:

```
# 12. (1pt) Print out the summary statistics of the annual_inc column using .describe

df['annual_inc'].describe()
```

Out[40]:

```
count    2.000000e+04
mean     6.824335e+04
std      4.420020e+04
min      2.000000e+03
25%      4.200000e+04
50%      6.000000e+04
75%      8.200000e+04
max      1.200000e+06
Name: annual_inc, dtype: float64
```

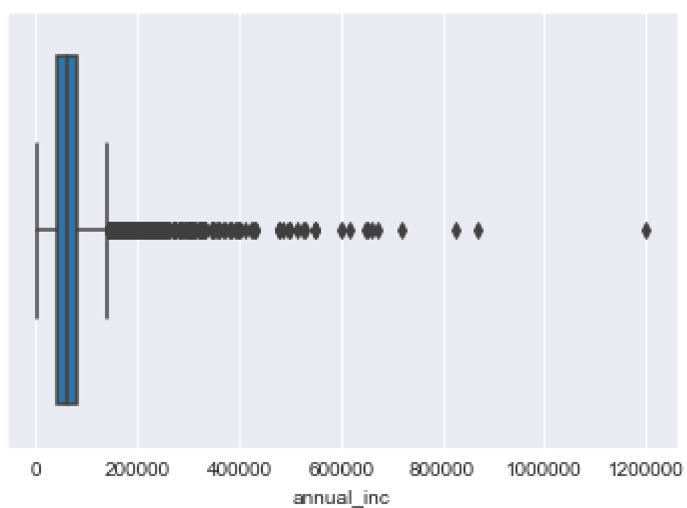
In [42]:
```
# There appears to be a fairly large difference between mean and median

# 13. (1pt) calculate the mean of annual_inc using .mean()
annual_inc_mean = df['annual_inc'].mean()

# 14. (1pt) calculate the median of annual_inc using .median()
annual_inc_median = df['annual_inc'].median()

# 15. (1pt) what is the difference (to 2 significant digits) between the mean and med
diff = annual_inc_mean - annual_inc_median
print(f'mean - median = {diff:0.2f}')
```

```
mean - median = 8243.35
```

In [ ]:
```
# 16. (1pt) Why might there be such a large difference between mean and median?

# Because means take outliers into account, medians don't.
```

In [43]:
```
# 17. (1pt) Generate a boxplot of annual_inc using sns.boxplot
sns.boxplot(df['annual_inc'])
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x294460fae80>

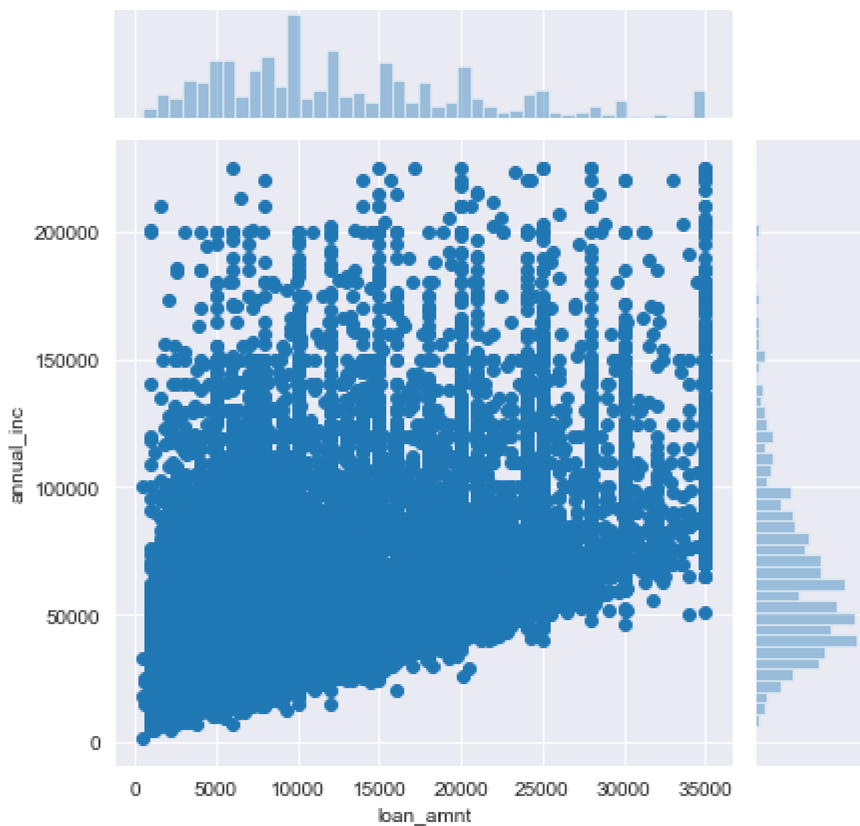


In [60]:

```
# It certainly looks like annual_inc is skewed to the right.

# 18. (1pt) What is the 99th percentile of annual_inc? (use np.percentile)
#    Eg. Where is the cutoff where we remove extremely high values but keep 99% of th
annual_inc_99 = np.percentile(df['annual_inc'],99)
print(f'99th percentile of annual_inc: {annual_inc_99:0.2f}')

# 19. (3pt) Plot loan_amnt (x-axis) against annual_inc (y-axis) using jointplot
#     only including rows where annual_inc < annual_inc_99
df1 = df[df['annual_inc']< annual_inc_99]
sns.jointplot(x = df1['loan_amnt'], y = df1['annual_inc'])
```

```
99th percentile of annual_inc: 225010.00
```

Out[60]: `<seaborn.axisgrid.JointGrid at 0x29446334630>`



In [66]:

```
# As we saw above, 'debt_consolidation' is the most common purpose for a loan.
#
# 20. (2pt) What is the mean loan_amnt where:
#    df.purpose == 'debt_consolidation' and df.annual_inc < annual_inc_99?

amnt = df1[df1['purpose'] == 'debt_consolidation']['loan_amnt'].mean()
print(f'mean loan amount for debt consolidation for most annual incomes: {amnt:0.2f}')
```

```
mean loan amount for debt consolidation for most annual incomes: 14166.53
```

In [86]:

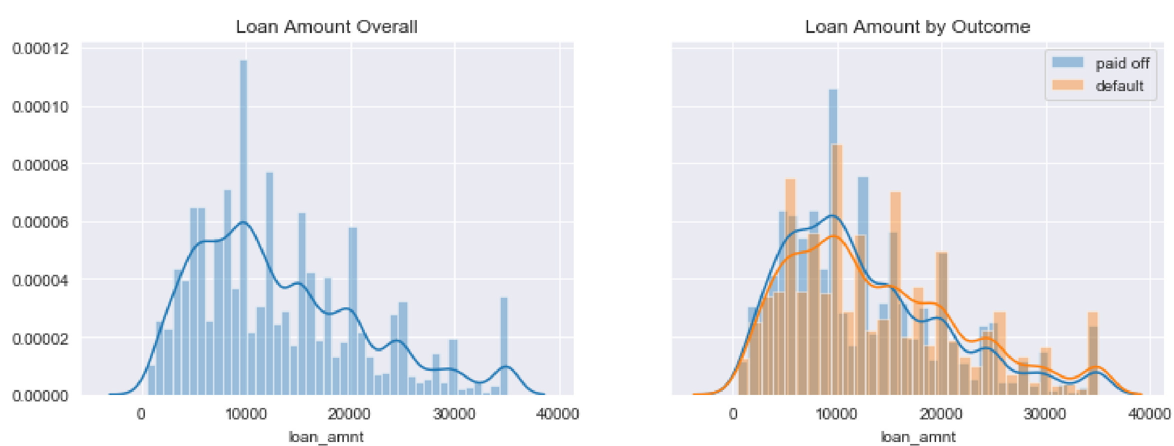
```
df[df.outcome == 'paid off']['loan_amnt']
```

Out[86]:

```
0        11000
4        12000
5        20000
7        13650
8         6675
         ...  
19986    15000
19988     8000
19996     3250
19997     9000
19998    35000
Name: loan_amnt, Length: 10000, dtype: int64
```

In [90]:
```
# One purpose of this dataset is to attempt to predict loan outcome.
# Here, we'll create 2 plots, one of loan_amnt overall and another with loan_amnt by

# 21. (2pt) create a subplot with 1 row and 2 columns with figsize of (12,4)
fig,ax = plt.subplots(1,2,figsize = (12,4), sharex = True, sharey = True)

# 22. (1pt) on the first set of axes (ax[0]) use distplot to plot the distribution of
sns.distplot(df['loan_amnt'],ax = ax[0])

# 23. (1pt) set the title on the first plot to be 'Loan Amount Overall'
ax[0].set_title('Loan Amount Overall')

# 24. (2pt) on the second set of axes (ax[1])
#    use loc and distplot to plot loan_amnt where df.outcome == 'paid off' and set la
sns.distplot(df[df.outcome == 'paid off'].loc[:,'loan_amnt'], ax = ax[1],label = 'pai

# 25. (2pt) again on the second set of axes (ax[1])
#    use loc and distplot to plot loan_amnt where df.outcome == 'default' and set lab
sns.distplot(df[df.outcome == 'default'].loc[:,'loan_amnt'],ax = ax[1],label='default

# 26. (1pt) set the title on the second plot to be 'Loan Amount by Outcome'
ax[1].set_title('Loan Amount by Outcome')

# 27. (1pt) finally, add a legend to ax[1]
ax[1].legend()
```

Out[90]: <matplotlib.legend.Legend at 0x29447d21dd8>



Part 2: Hypothesis Testing with an A/B test

Suppose we work at a large company that is developing online data science tools.

Currently the tool has interface type A but we'd like to know if using interface tool B might be more efficient. To measure this, we'll look at length of active work on a project (aka project length).

We'll perform an A/B test where half of the projects will use interface A and half will use interface B.

In [92]:
```
# 28. (2pt) Read in project lengths from '../data/project_lengths' into df_project an
df_project = pd.read_csv('../data/project_lengths.csv')
df_project.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
lengths_A    1000 non-null float64
lengths_B    1000 non-null float64
dtypes: float64(2)
memory usage: 15.8 KB
```

In [94]:
```
# 29. (3pt) calculate the difference in mean project length between interface A and B
#     print the result with 2 significant digits
observed_mean_diff = df_project['lengths_B'].mean()-df_project['lengths_A'].mean()
print(f'observed difference: {observed_mean_diff}')
```

```
observed difference: -1.5819526645396227
```

In [98]:
```
combined_times = np.concatenate([df_project.lengths_A.values, df_project.lengths_B.va
combined_times
permuted = np.random.permutation(combined_times)
permuted
```

Out[98]:
```
array([ 3.85877591, 33.88434356, 13.2096332 , ...,  5.99535834,
        2.73414445,  2.27195089])
```

In [99]:
```
# We'll perform a permutation test to see how significant this result is
# generate 10000 random permutation samples of mean difference

rand_mean_diffs = []
n_samples = 10000
combined_times = np.concatenate([df_project.lengths_A.values, df_project.lengths_B.va
n_A = sum(df_project.lengths_A.notnull()) # number of observations for page A

for i in range(n_samples):

    # 30. (1pt) get a random permutation of combined_times
    rand_perm = np.random.permutation(combined_times)

    # 31. (1pt) take the mean of the first n_A random values
    rand_mean_A = rand_perm[:n_A].mean()

    # 32. (1pt) take the mean of the remaining random values
    rand_mean_B = rand_perm[n_A:].mean()

    # 33. (1pt) append the difference (rand_mean_B - rand_mean_A) to rand_mean_diffs
    rand_mean_diffs.append(rand_mean_B - rand_mean_A)

# check that we have the correct amount of data by printing out the length of rand_me
# this should equal n_samples
print(len(rand_mean_diffs))
```

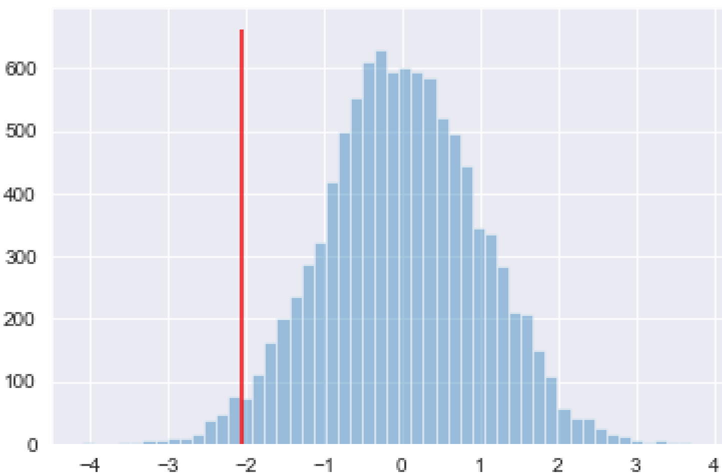
```
10000
```

In [101]:
```
# Before we plot the data, let's transform all values to their z-score

# 34. (1pt) calculate the sample mean of our rand_mean_diffs using np.mean
mean_rand_mean_diffs = np.mean(rand_mean_diffs)

# 35. (1pt) calculate the sample standard deviation using np.std
std_rand_mean_diffs = np.std(rand_mean_diffs)

# 36. (2pt) transform rand_mean_diffs to rand_mean_diffs_zscore by subtracting the me
rand_mean_diffs_zscore = (rand_mean_diffs - mean_rand_mean_diffs)/std_rand_mean_diffs

# 37. (2pt) transform the observed_mean_diff to observed_mean_diff_zscore by subtract
observed_mean_diff_zscore = (observed_mean_diff - mean_rand_mean_diffs)/std_rand_mean
observed_mean_diff_zscore
```

Out[101]:
```
-2.039573324716882
```

In [103]:

```
# 38. (2pt) Use seaborn distplot to plot the distribution of rand_mean_diffs_zscore,
ax = sns.distplot(rand_mean_diffs_zscore, norm_hist=False, kde=False)

# 39. (2pt) use ax.vlines with *ax.get_ylim() to plot a line at our observed_mean_dif
ax.vlines(observed_mean_diff_zscore, *ax.get_ylim(), color='r');
```



In [105]:

```
# the plot seems to indicate a likely difference in scores
#
# 40. (3pt) calculate a two-tailed p_value (to three significant digits)
#    using np.abs, len rand_mean_diffs and observed_mean_diff
p_value = sum(np.abs(np.array(rand_mean_diffs)) >= np.abs(observed_mean_diff))/len(ra
print(f'p_value: {p_value:0.3f}')
```

```
p_value: 0.041
```