Homework 1

Clarissa Tai - rt2822

Due: Friday Oct 7th 11:59pm ET

In this homework we'll do some data exploration and perform a hypothesis test.

Instructions

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

When completed,

1. Replace Name and UNI in the first cell and filename
2. Kernel -> Restart & Run All to run all cells in order
3. Print Preview -> Print (Landscape Layout) -> Save to pdf
4. Post pdf to GradeScope

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:

- **purpose**: The purpose of the loan, such as: credit_card, debt_consolidation, etc.
- **annual_inc**: Annual income of the borrower
- **home_ownership**: The borrower's relationship with their primary residence
- **loan_amnt**: The amount of money applied for
- **outcome**: The result of the loan: paid off or default

In [2]:
```
# 1. (1pt) Load the data from ../data/loan_data_subset.csv into the variable df
#    using the column 'id' as the index with index_col='id'
#    note: use the default separator ','

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

In [3]:
```
# 2. (1pt) Using .shape, how many rows and columns does the dataset have?

print(f'dataframe has {df.shape[0]} rows and {df.shape[1]} columns.')
```

```
dataframe has 1000 rows and 5 columns.
```

In [4]:
```
# 3. (1pt) Display the first 3 rows of the dataset using .head()

df.head(3)
```

Out[4]:

	purpose	annual_inc	home_ownership	loan_amnt	outcome
id					
id0	credit_card	40000	MORTGAGE	7875	paid off
id1	debt_consolidation	47000	MORTGAGE	9325	paid off
id2	debt_consolidation	28264	RENT	10600	paid off

In [5]:
```
# 4. (1pt) Print out the first 3 rows of the numeric feature columns included in the dataset
#    (3 rows x 2 columns)

df.select_dtypes(include=np.number).head(3)
```

Out[5]:

	annual_inc	loan_amnt
id		
id0	40000	7875
id1	47000	9325
id2	28264	10600

In [6]:

```
# 5. (1pt) Print out the first 3 rows of the the categorical feature columns in the dataset
#    (3 rows x 3 columns)

df.select_dtypes(include='object').head(3)
```

Out[6]:

	purpose	home_ownership	outcome
id			
id0	credit_card	MORTGAGE	paid off
id1	debt_consolidation	MORTGAGE	paid off
id2	debt_consolidation	RENT	paid off

In [7]:

```
# 6. (1pt) Display all columns for rows with id from id100 to id102 inclusive
#    We should see 3 rows, 5 columns

df.loc['id100':'id102']
```

Out[7]:

	purpose	annual_inc	home_ownership	loan_amnt	outcome
id					
id100	credit_card	75000	RENT	10000	paid off
id101	other	72000	RENT	3000	paid off
id102	debt_consolidation	79000	RENT	16000	paid off

In [8]:

```
# 7. (3pt) Display annual_inc and home_ownership columns for the 3 rows with highest annual_inc
#    We should see 3 rows, 2 columns

df.sort_values(by='annual_inc',ascending=False)[['annual_inc','home_ownership']].iloc[:3]
```

Out[8]:

id	annual_inc	home_ownership
id768	367000	MORTGAGE
id201	334000	OWN
id419	310000	MORTGAGE

In [9]:

```
# 8. (3pt) What is the mean annual_inc for rows with:
#        (loan_amnt greater than the median loan_amnt) and
#        (outcome of 'paid off') and
#        (home_ownership of 'MORTGAGE' or 'OWN')

mean_annual_inc = df.loc[(df.loan_amnt>df.loan_amnt.median())&
                         (df.outcome=='paid off')&
                         (df.home_ownership.isin(['MORTGAGE','OWN']))].annual_inc.mean()

# Print the mean annual income found with precision of 2

print(f'{mean_annual_inc = :0.2f}')
```

```
mean_annual_inc = 98223.29
```

In [10]:

```
# 9. (1pt) Calculate frequencies of the different values seen in column 'purpose' using .value_counts()
#    Store in purpose_counts.

purpose_counts = df.purpose.value_counts()

print(purpose_counts)
```

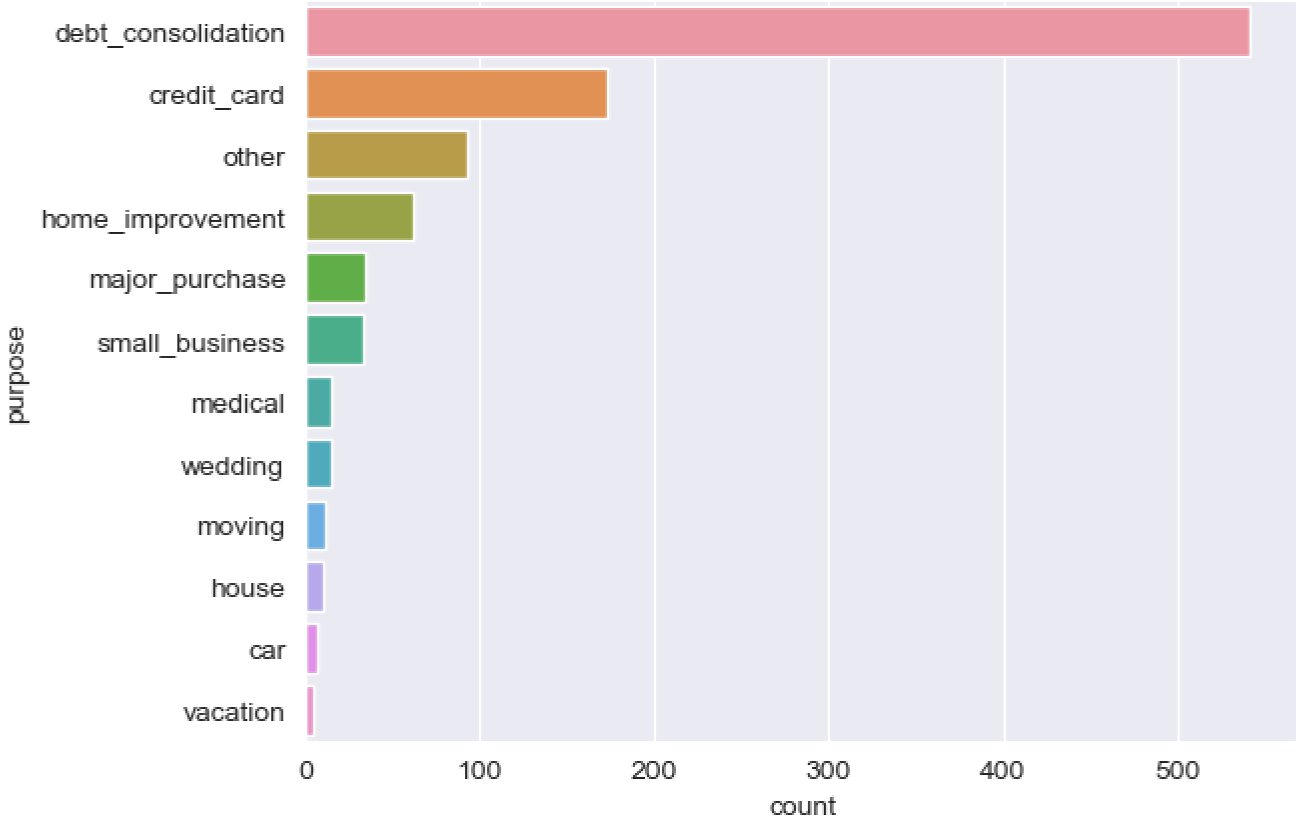
```
debt_consolidation    542
credit_card           173
other                  93
home_improvement       62
major_purchase         34
small_business         33
medical                15
wedding                15
moving                 12
house                  10
car                     7
vacation                4
Name: purpose, dtype: int64
```

In [11]:

```
# 10. (3pt) Plot the frequency of each of the categories seen in the 'purpose' column using sns.countplot()
#   Order the bars using the purpose_counts.index, generated in the cell above,
#      which is sorted by frequency by default. (use the order= argument in sns.countplot())
#   Because there are many values, and some of the labels are long,
#      place 'purpose' on the y-axis instead of the x-axis (use y= instead of x=).

sns.countplot(y='purpose',data=df,order=purpose_counts.index)
```

Out[11]:

```
<AxesSubplot: xlabel='count', ylabel='purpose'>
```



In [12]:

```
# 11. (2pt) What is the mean loan_amnt for each category in purpose?
#     Use groupby()
#     Sort the resulting series by value ascending (default)

df.groupby('purpose').loan_amnt.mean().sort_values()
```

Out[12]:
```
purpose
moving                 4933.333333
car                    5542.857143
medical                6666.666667
vacation               7700.000000
wedding                9153.333333
other                  9758.064516
major_purchase        11732.352941
home_improvement      12114.516129
credit_card           12776.589595
debt_consolidation    14440.221402
house                 14717.500000
small_business        15344.696970
Name: loan_amnt, dtype: float64
```

In [13]:
```
# 12. (1pt) Display the summary statistics of annual_inc using .describe()
#     Round all values to the hundredths place (precision of 2) using .round()

df.annual_inc.describe().round(2)
```

Out[13]:
```
count      1000.00
mean      68158.89
std       40271.75
min       10000.00
25%       42000.00
50%       60000.00
75%       83000.00
max      367000.00
Name: annual_inc, dtype: float64
```

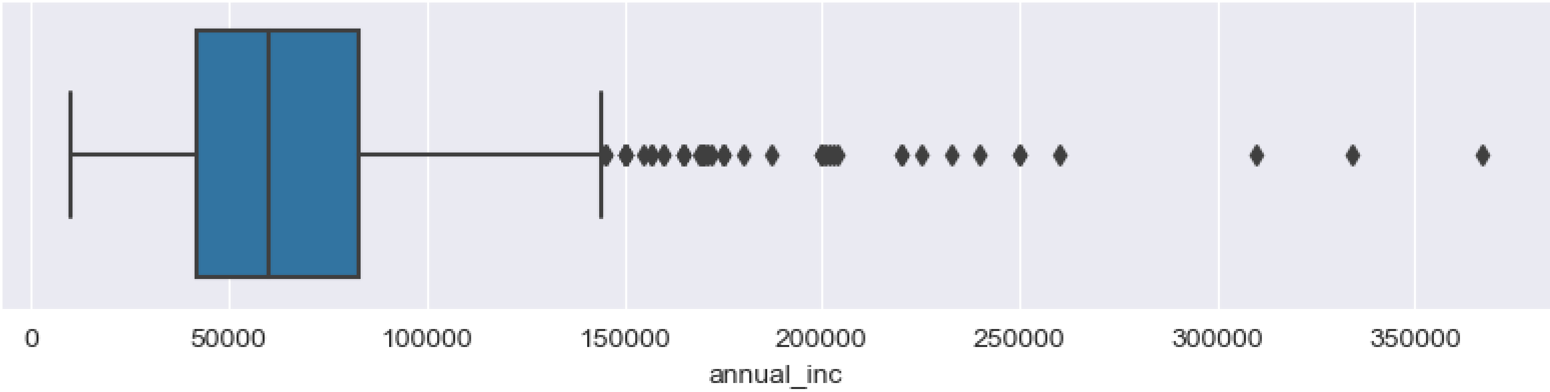
In [14]:
```
# 13. (2pt) There appears to be a fairly large difference between mean and median in annual_inc.
#   Print out the absolute difference in mean annual_inc and median annual_inc to a precision of 2
#   To calculate the absolute value, use np.abs()

annual_inc_mean = df.annual_inc.mean()

annual_inc_median = df.annual_inc.median()

print(f'absolute difference = {np.abs(annual_inc_mean-annual_inc_median):0.2f}')
```

```
absolute difference = 8158.89
```

In [15]:
```
# 14. (2pt) Display a boxplot of annual_inc using sns.boxplot.
```

```
#  To make a wide plot, use plt.subplots with 1 row, 1 column of axes and a figsize of (10,2)
fig,ax = plt.subplots(1,1,figsize=(10,2))

#  Plot a boxplot of annual_inc using sns.boxplot() and ax with annual_inc on the x-axis
sns.boxplot(x='annual_inc',data=df)
```

Out[15]: <AxesSubplot: xlabel='annual_inc'>

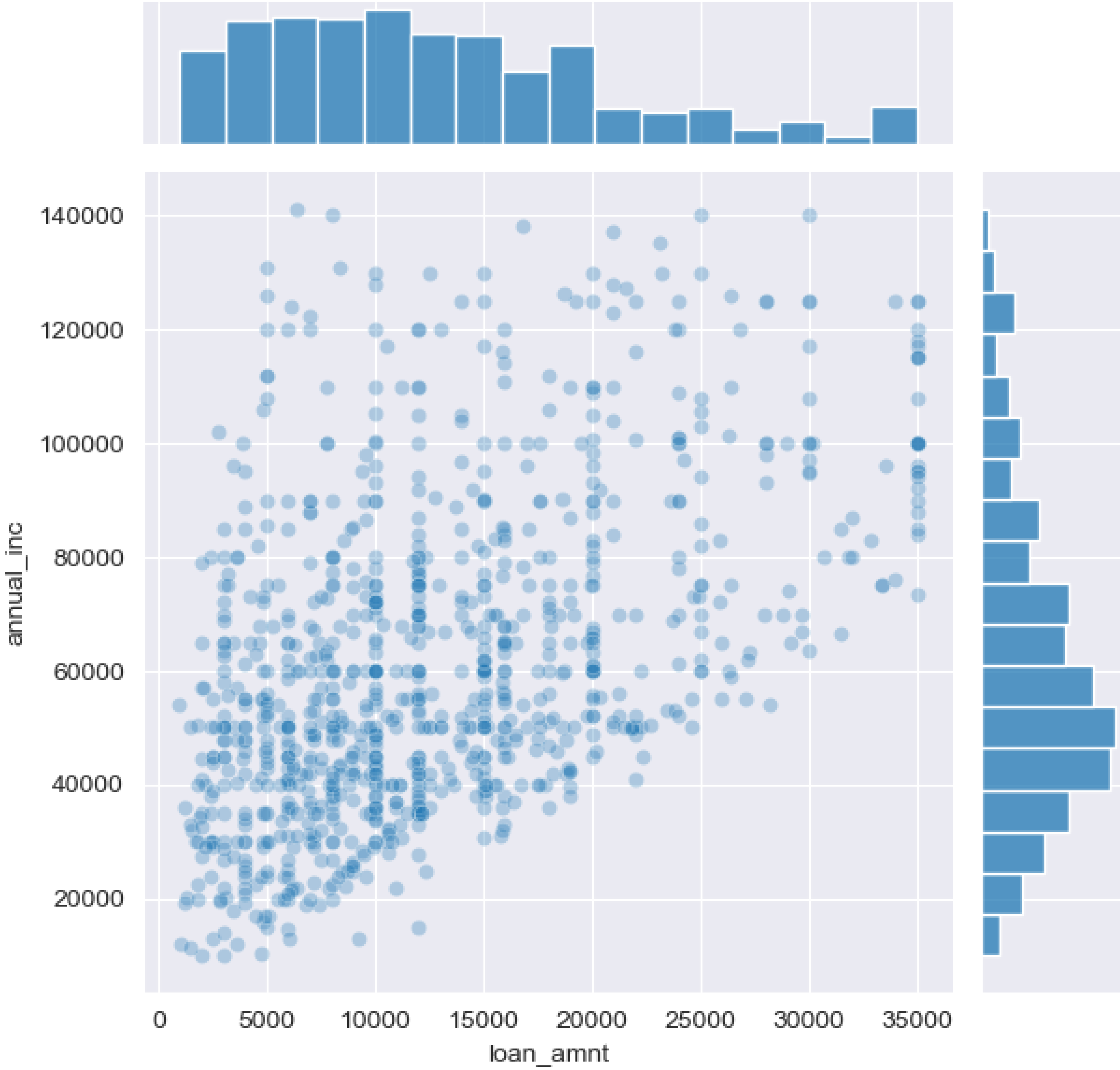


In [16]:
```
# 15. (1pt) We'll remove some of records with the highest annual_inc, treating them as outliers.
#    What is the 95th percentile of annual_inc? (use .percentile() from numpy or .quantile() from pandas)
#    Eg. Where is the cutoff where we remove extremely high values but keep 95% of the data?

annual_inc_95 = df['annual_inc'].quantile(0.95)

print(f'95th percentile of annual_inc: {annual_inc_95:0.2f}')
```

95th percentile of annual_inc: 141195.95

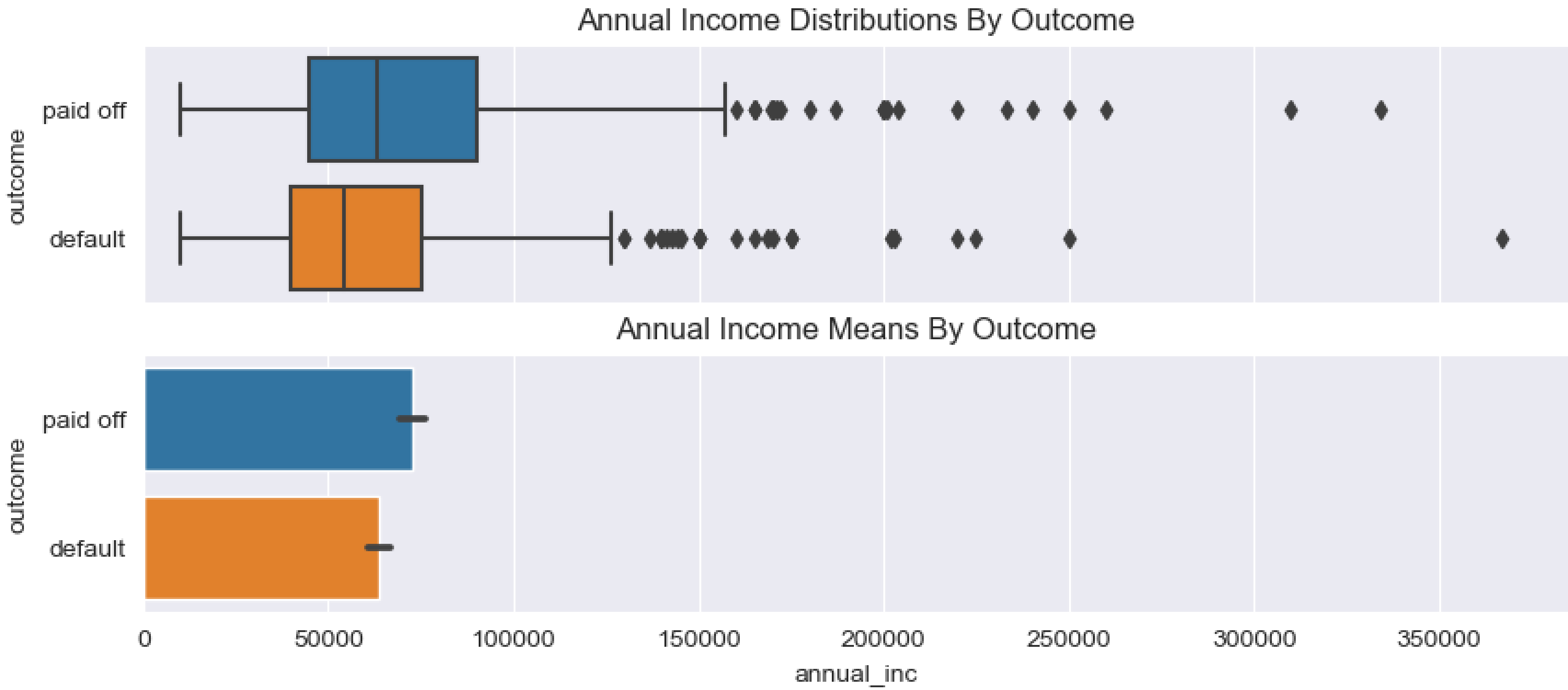
In [17]:
```
# 16. (3pt) Plot loan_amnt (x-axis) against annual_inc (y-axis) using sns.jointplot(), excluding outliers
#     Only include rows where annual_inc < annual_inc_95
#     Set alpha=0.3 to add transparency to markers

sns.jointplot(x='loan_amnt',y='annual_inc',data=df.loc[(df.annual_inc<annual_inc_95)],alpha=0.3)
```

Out[17]: <seaborn.axisgrid.JointGrid at 0x12086c9d0>



In [18]:
```
# 17. (5pt) Visualize annual income (annual_inc) by outcome.
#     Outcome takes two values: 'paid off' and 'default'

# NOTE: In all of the below use all rows of df, no longer limiting to df.annual_inc < annual_inc_95

# Here we'll create 2 plots, one that compares the distributions of annual_inc by outcome,
```

```
# the other comparing the mean of annual_inc by outcome

# Create a subplot with 2 rows and 1 column with figsize of (10,4)
# Use sharex=True to share the x-axis across the two plots
# Capture the return values of plt.subplots() as fig,ax
fig,ax = plt.subplots(2, 1, figsize=(10,4), sharex=True)

# On the first axis (ax[0]) use sns.boxplot() to compare the distribution of annual_inc by outcome
#   Place 'annual_inc' on the x-axis and 'outcome' on the y-axis.
sns.boxplot(x='annual_inc', y='outcome', data=df, ax=ax[0])

# Set the title on the first axis ax[0] to be 'Annual Income Distributions By Outcome'
ax[0].set_title('Annual Income Distributions By Outcome')

# On the second axis (ax[1]) use sns.barplot() to compare the means of annual_inc by outcome
#   Place 'annual_inc' on the x-axis and 'outcome' on the y-axis.
sns.barplot(x='annual_inc', y='outcome', data=df, ax=ax[1])

# Set the title on the second plot to be 'Annual Income Means By Outcome'
ax[1].set_title('Annual Income Means By Outcome')

# Remove the label on the x-axis of ax[0] using set_xlabel() (as it overlaps with the ax[1] title)
ax[0].set_xlabel(None);
```



Part 2: Hypothesis Testing

The plots in the question above indicate a difference in annual_inc by outcome.

Let's test the hypothesis that there is a difference in mean annual_inc for loans with an outcome of 'paid off' vs loans with an outcome of 'default'.

In [19]:
```
# 18. (3pt) Calculate the difference in mean annual_inc between 'paid off' and 'default'
#     Use: mean_annual_inc_paid_off - mean_annual_inc_default

# Calculate the mean value for each group
mean_annual_inc_paid_off = df.loc[df.outcome=='paid off'].annual_inc.mean()
mean_annual_inc_default = df.loc[df.outcome=='default'].annual_inc.mean()
observed_mean_diff = mean_annual_inc_paid_off - mean_annual_inc_default
```

```
# Print the the value of observed_mean_diff with a precision of 2
print(f'{observed_mean_diff = :0.2f}')
```

```
observed_mean_diff = 9062.74
```

In [20]:
```
# 19. (5pt) We'll perform a permutation test to see how significant this difference is
#    by generating 1,000 random permutation samples of mean difference

rand_mean_diffs = []
n_samples = 1000
n_paid_off = df[df.outcome == 'paid off'].shape[0] # the number of observations (rows) with outcome of 'paid off'
print(f'{n_paid_off = :d}')

for i in range(n_samples):

    # Get a random permutation of df.annual_inc
    # Use the pandas .sample() function with
    #    sample size the same size as original dataset
    #    sampling without replacement
    #    random_state == i (the index of the loop) for consistency in grading
    rand_perm = df.annual_inc.sample(n=len(df),replace=False,random_state = i)

    # Take the mean of the first n_paid_off random values
    rand_mean_paid_off = rand_perm[:n_paid_off].mean()

    # Take the mean of the remaining random values
    rand_mean_default = rand_perm[n_paid_off:].mean()

    # Append the difference (rand_mean_paid_off - rand_mean_default) to the list rand_mean_diffs
    rand_mean_diffs.append(rand_mean_paid_off - rand_mean_default)

# Convert rand_mean_diffs into a numpy array so we can use numpy functions
rand_mean_diffs = np.array(rand_mean_diffs)

# check that we have the correct amount of data by asserting that the length of rand_mean_diffs == n_samples
assert rand_mean_diffs.shape[0] == n_samples

# check that we only have one array of differences
assert rand_mean_diffs.ndim == 1

# Display the first three values in rand_mean_diffs so we know when it's done.
rand_mean_diffs[:3]
```

```
n_paid_off = 500
```

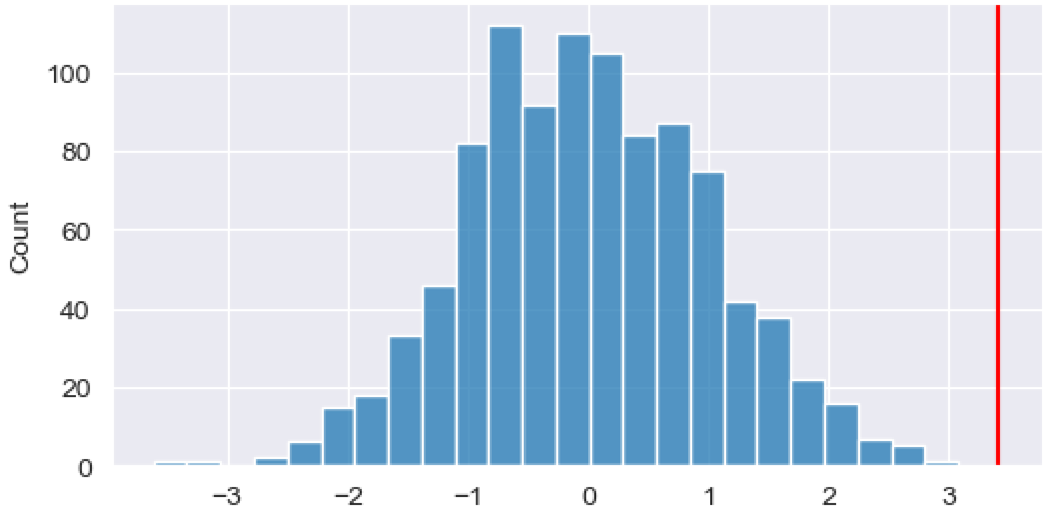
Out[20]:
```
array([ 2323.292,  3927.652, -4313.772])
```

In [21]:
```
# 20. (5pt) Before we plot the data, let's transform all values to their z-score

# Calculate the sample mean of our rand_mean_diffs using .mean()
mean_rand_mean_diffs = rand_mean_diffs.mean()

# Calculate the sample standard deviation using .std()
std_rand_mean_diffs = rand_mean_diffs.std()

# Transform rand_mean_diffs to rand_mean_diffs_zscore by
#    first subtracting the mean and
#    then dividing by the std dev
rand_mean_diffs_zscore = (rand_mean_diffs-mean_rand_mean_diffs)/std_rand_mean_diffs

# Transform the observed_mean_diff as well by subtracting the mean and dividing by the std dev
observed_mean_diff_zscore = (observed_mean_diff-mean_rand_mean_diffs)/ std_rand_mean_diffs

# To check our transformation, check that the zscore mean is near 0 and std dev is near 1
print(f'{rand_mean_diffs_zscore.mean() = :0.3f}')
print(f'{rand_mean_diffs_zscore.std()  = :0.3f}')
print(f'{observed_mean_diff_zscore     = :0.3f}')

assert np.abs(rand_mean_diffs_zscore.mean() - 0) < .0001, 'rand_mean_diffs_zscore.mean() should be close to zero'
assert np.abs(rand_mean_diffs_zscore.std()  - 1) < .0001, 'rand_mean_diffs_zscore.std() should be close to 1'
```

```
rand_mean_diffs_zscore.mean() = 0.000
rand_mean_diffs_zscore.std()  = 1.000
observed_mean_diff_zscore     = 3.415
```

In [22]:
```
# 21. (2pt) Plot our observed metric against our samples.

# Use subplots to create a figure with 1 row, 1 columna and figsize of (6,3)
fig, ax = plt.subplots(1, 1, figsize=(6,3))

# Use seaborn histplot to plot the distribution of rand_mean_diffs_zscore on ax
sns.histplot(rand_mean_diffs_zscore, ax = ax)

# Use ax.axvline() to plot a line at our observed_mean_diff_zscore
# Make the line red using color='r'
ax.axvline(observed_mean_diff_zscore, color = 'r')
```

Out[22]:
```
<matplotlib.lines.Line2D at 0x120b861d0>
```



In [23]:
```
# 22. (3pt) The plot seems to indicate a real difference in values. What is the p-value?
#    Calculate a two-tailed p_value using np.abs()
#    Recall that we want the proportion of random samples (rand_mean_diffs_zscore) with an absolute value
#      greater than or equal to the absolute value of the observed difference (observed_mean_diff_zscore).
p_value = sum(np.abs(np.array(rand_mean_diffs))>=np.abs(observed_mean_diff))/len(rand_mean_diffs)

# print the p-value found
p_value
```

Out[23]:
```
0.001
```

In [ ]: