# Assn05-bowen

May 17, 2020

## 1 Assignment 5: Data Preparation

- Section: 01
- Name: Bryce Owen
- Due date: March 25 2020
- Purpose: Preparing data using standardization, categorization, binning, and outliers

### 1.1 Working with the Data (Chapter 3)

**11. Derive an index field and add it to the dataset**

[7]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

bank_train = pd.read_csv("bank_marketing_training")
print(bank_train.shape)
bank_train['index'] = pd.Series(range(0,26874))
bank_train.head()
```

```
(26874, 21)
```

[7]:

| | age | job | marital | education | default | housing | loan | contact | month | day_of_week | ... | days_since_previous | previous | previous_outcome |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 56 | housemaid | married | basic.4y | no | no | no | telephone | may | mon | ... | 999 | 0 | nonexistent |
| 1 | 57 | services | married | high.school | unknown | no | no | telephone | may | mon | ... | 999 | 0 | nonexistent |
| 2 | 41 | blue-collar | married | unknown | unknown | no | no | telephone | may | mon | ... | 999 | 0 | nonexistent |
| 3 | 25 | services | single | high.school | no | yes | no | telephone | may | mon | ... | 999 | 0 | nonexistent |
| 4 | 29 | blue-collar | single | high.school | no | no | yes | telephone | may | mon | ... | 999 | 0 | nonexistent |

```
   emp.var.rate cons.price.idx  cons.conf.idx  euribor3m  nr.employed  \
0           1.1         93.994          -36.4      4.857         5191
1           1.1         93.994          -36.4      4.857         5191
2           1.1         93.994          -36.4      4.857         5191
3           1.1         93.994          -36.4      4.857         5191
4           1.1         93.994          -36.4      4.857         5191

   response  index
0        no      0
1        no      1
2        no      2
3        no      3
4        no      4

[5 rows x 22 columns]
```

**12. For the *days_since_previous* field, change the field value 999 to the appropriate code for missing values**

[19]:
```
import numpy as np
bank_train['days_since_previous'] = bank_train['days_since_previous'].
 ↪replace({999:np.NaN})
bank_train.head()
```

[19]:
```
   age          job  marital    education  default housing loan    contact  \
0   56    housemaid  married     basic.4y       no      no   no  telephone
1   57     services  married  high.school  unknown      no   no  telephone
2   41  blue-collar  married      unknown  unknown      no   no  telephone
3   25     services   single  high.school       no     yes   no  telephone
4   29  blue-collar   single  high.school       no      no  yes  telephone

  month day_of_week  ...  days_since_previous  previous  previous_outcome  \
0   may         mon  ...                  NaN         0       nonexistent
1   may         mon  ...                  NaN         0       nonexistent
2   may         mon  ...                  NaN         0       nonexistent
3   may         mon  ...                  NaN         0       nonexistent
4   may         mon  ...                  NaN         0       nonexistent

   emp.var.rate cons.price.idx  cons.conf.idx  euribor3m  nr.employed  \
0           1.1         93.994          -36.4      4.857         5191
1           1.1         93.994          -36.4      4.857         5191
2           1.1         93.994          -36.4      4.857         5191
3           1.1         93.994          -36.4      4.857         5191
4           1.1         93.994          -36.4      4.857         5191

   response  index
```

```
0        no      0
1        no      1
2        no      2
3        no      3
4        no      4

[5 rows x 22 columns]
```

**13. For the *education* field, reexpress the field values as the numeric values shown in table 3.1**

[21]:
```
bank_train['education_numeric'] = bank_train['education']
dict_edu = {'education_numeric': {'illiterate': 0, 'basic.4y': 4, 'basic.6y':␣
↪6, 'basic.9y': 9, 'high.school': 12, 'professional.course': 12, 'university.
↪degree': 16, 'unknown': np.NaN}}
bank_train.replace(dict_edu, inplace = True)
bank_train.head()
```

[21]:
```
   age          job  marital    education  default housing loan    contact  \
0   56    housemaid  married     basic.4y       no      no   no  telephone
1   57     services  married  high.school  unknown      no   no  telephone
2   41  blue-collar  married      unknown  unknown      no   no  telephone
3   25     services   single  high.school       no     yes   no  telephone
4   29  blue-collar   single  high.school       no      no  yes  telephone

  month day_of_week  ...  previous  previous_outcome  emp.var.rate  \
0   may         mon  ...         0       nonexistent           1.1
1   may         mon  ...         0       nonexistent           1.1
2   may         mon  ...         0       nonexistent           1.1
3   may         mon  ...         0       nonexistent           1.1
4   may         mon  ...         0       nonexistent           1.1

   cons.price.idx cons.conf.idx  euribor3m  nr.employed  response  index  \
0          93.994         -36.4      4.857         5191        no      0
1          93.994         -36.4      4.857         5191        no      1
2          93.994         -36.4      4.857         5191        no      2
3          93.994         -36.4      4.857         5191        no      3
4          93.994         -36.4      4.857         5191        no      4

   education_numeric
0                4.0
1               12.0
2                NaN
3               12.0
4               12.0

[5 rows x 23 columns]
```

**14. Standardize the field *age*. Print out a list of the first 10 records, including the variables *age* and *age_z***

[23]:
```
from scipy import stats

bank_train['age_z'] = stats.zscore(bank_train['age'])
bank_train.head(10)[['age','age_z']]
```

[23]:
```
   age     age_z
0   56  1.539625
1   57  1.635778
2   41  0.097330
3   25 -1.441118
4   29 -1.056506
5   57  1.635778
6   35 -0.479588
7   39 -0.094976
8   30 -0.960353
9   55  1.443472
```

**15. Obtain a listing of all records that are outliers according to the field *age_z*. Print out a listing of the 10 largest *age_z* values**

[33]:
```
bank_train.query('age_z > 3 | age_z < -3')
bank_train_outliers = bank_train.query('age_z > 3 | age_z < -3')
bank_train_sort = bank_train_outliers.sort_values(['age_z'], ascending = False)
bank_train_sort.head(10)[['age_z']]
```

[33]:
```
          age_z
24840  4.904980
24833  4.904980
26520  4.712674
26015  4.712674
23628  4.616521
25098  4.616521
26516  4.616521
26509  4.616521
18179  4.616521
18191  4.616521
```

**16. For the *job* field, combine the jobs with less than 5% of the records into a field called *other***

[26]:
```
# UNSURE HOW TO COMPLETE

job_count = (bank_train.groupby('job').count()['index']/bank_train.shape[0]) *␣
 ↪100
job_count = job_count.to_frame()
job_count[job_count['index'] < 5]
```

```
dict_job = {"job": {"entrepreneur": "other", "housemaid": "other", "retired":␣
 ↪"other", "self-employed": "other", "student": "other", "unemployed":␣
 ↪"other", "unknown": "other"}}
bank_train.replace(dict_job, inplace = True)
bank_train.head()
```

[26]:
```
   age          job  marital    education  default housing loan    contact  \
0   56        other  married     basic.4y       no      no   no  telephone
1   57     services  married  high.school  unknown      no   no  telephone
2   41  blue-collar  married      unknown  unknown      no   no  telephone
3   25     services   single  high.school       no     yes   no  telephone
4   29  blue-collar   single  high.school       no      no  yes  telephone

  month day_of_week  ...  previous  previous_outcome  emp.var.rate  \
0   may         mon  ...         0       nonexistent           1.1
1   may         mon  ...         0       nonexistent           1.1
2   may         mon  ...         0       nonexistent           1.1
3   may         mon  ...         0       nonexistent           1.1
4   may         mon  ...         0       nonexistent           1.1

   cons.price.idx cons.conf.idx  euribor3m  nr.employed  response  index  \
0          93.994         -36.4      4.857         5191        no      0
1          93.994         -36.4      4.857         5191        no      1
2          93.994         -36.4      4.857         5191        no      2
3          93.994         -36.4      4.857         5191        no      3
4          93.994         -36.4      4.857         5191        no      4

      age_z
0  1.539625
1  1.635778
2  0.097330
3 -1.441118
4 -1.056506

[5 rows x 23 columns]
```

**17. Rename the *default* predictor to *credit_default***

[98]:
```
bank_train = bank_train.rename(columns={'default': 'credit_default'})
bank_train.head()
```

[98]:
```
   age          job  marital    education credit_default housing loan  \
0   56    housemaid  married     basic.4y             no      no   no
1   57     services  married  high.school        unknown      no   no
2   41  blue-collar  married      unknown        unknown      no   no
3   25     services   single  high.school             no     yes   no
4   29  blue-collar   single  high.school             no      no  yes
```

```
     contact month day_of_week  ...  previous_outcome  emp.var.rate  \
0  telephone   may         mon  ...       nonexistent           1.1
1  telephone   may         mon  ...       nonexistent           1.1
2  telephone   may         mon  ...       nonexistent           1.1
3  telephone   may         mon  ...       nonexistent           1.1
4  telephone   may         mon  ...       nonexistent           1.1

   cons.price.idx  cons.conf.idx euribor3m  nr.employed  response  index  \
0          93.994          -36.4     4.857         5191        no      0
1          93.994          -36.4     4.857         5191        no      1
2          93.994          -36.4     4.857         5191        no      2
3          93.994          -36.4     4.857         5191        no      3
4          93.994          -36.4     4.857         5191        no      4

   education_numeric     age_z
0                4.0  1.539625
1               12.0  1.635778
2                NaN  0.097330
3               12.0 -1.441118
4               12.0 -1.056506

[5 rows x 24 columns]
```

**18. For the variable *month*, change the field values to 1-12, but keep the variable as categorical**

[106]:
```
bank_train['month'] = bank_train['month'].replace({'jan':'1', 'feb':'2','mar':
↪'3','apr':'4','may':'5','jun':'6','jul':'7','aug':'8','sep':'9','oct':
↪'10','nov':'11','dec':'12',})
bank_train.head()
```

[106]:
```
   age          job  marital    education credit_default housing loan  \
0   56    housemaid  married     basic.4y             no      no   no
1   57     services  married  high.school        unknown      no   no
2   41  blue-collar  married      unknown        unknown      no   no
3   25     services   single  high.school             no     yes   no
4   29  blue-collar   single  high.school             no      no  yes

     contact month day_of_week  ...  previous_outcome  emp.var.rate  \
0  telephone     5         mon  ...       nonexistent           1.1
1  telephone     5         mon  ...       nonexistent           1.1
2  telephone     5         mon  ...       nonexistent           1.1
3  telephone     5         mon  ...       nonexistent           1.1
4  telephone     5         mon  ...       nonexistent           1.1

   cons.price.idx  cons.conf.idx euribor3m  nr.employed  response  index  \
0          93.994          -36.4     4.857         5191        no      0
1          93.994          -36.4     4.857         5191        no      1
```

```
2          93.994          -36.4     4.857          5191        no      2
3          93.994          -36.4     4.857          5191        no      3
4          93.994          -36.4     4.857          5191        no      4

   education_numeric     age_z
0                4.0  1.539625
1               12.0  1.635778
2                NaN  0.097330
3               12.0 -1.441118
4               12.0 -1.056506

[5 rows x 24 columns]
```

**19. Do the following for the *duration* field** ##### a). Standardize the variable ##### b). Identify how many outliers there are and identify the most extreme outlier

[123]:
```
bank_train['duration_z'] = stats.zscore(bank_train['duration'])

bank_train.query('duration_z > 3 | duration_z < -3')
bank_train_duration_outliers = bank_train.query('duration_z > 3 | duration_z <␣
 ↪-3')
bank_train_duration_sort = bank_train_duration_outliers.
 ↪sort_values(['duration_z'], ascending = False)
print('Number of outliers:', bank_train_duration_outliers.shape[0])
print('Most extreme outlier: ')
bank_train_duration_sort.head(1)[['duration_z']]
```

```
Number of outliers: 549
Most extreme outlier:
```

[123]:
```
       duration_z
15764   17.995198
```

**20. Do the following for the *campaign* field** ##### a). Standardize the variable ##### b). Identify how many outliers there are and identify the most extreme outlier

[122]:
```
bank_train['campaign_z'] = stats.zscore(bank_train['campaign'])

bank_train.query('campaign_z > 3 | campaign_z < -3')
bank_train_campaign_outliers = bank_train.query('campaign_z > 3 | campaign_z <␣
 ↪-3')
bank_train_campaign_sort = bank_train_campaign_outliers.
 ↪sort_values(['campaign_z'], ascending = False)
print('Number of outliers:', bank_train_campaign_outliers.shape[0])
print('Most extreme outlier: ')
bank_train_campaign_sort.head(1)[['campaign_z']]
```

```
Number of outliers: 548
Most extreme outlier:
```

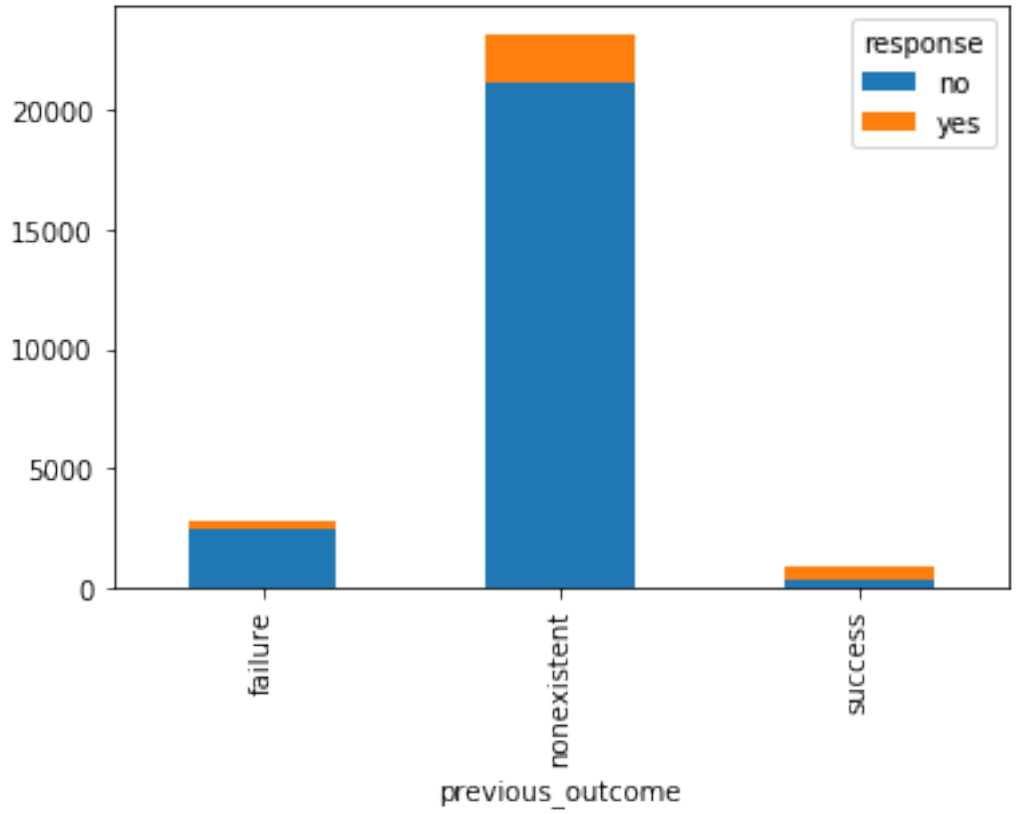
[122]:
```
       campaign_z
12257   14.711334
```

## 1.2 Working with the Data (Chapter 4)

**15. Create a bar graph of the *previous_outcome* variable, with *response* overlay**

[126]:
```
crosstab_01 = pd.crosstab(bank_train['previous_outcome'],␣
 ↪bank_train['response'])
crosstab_01.plot(kind = 'bar', stacked = True)
```

[126]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1b0e6860>
```

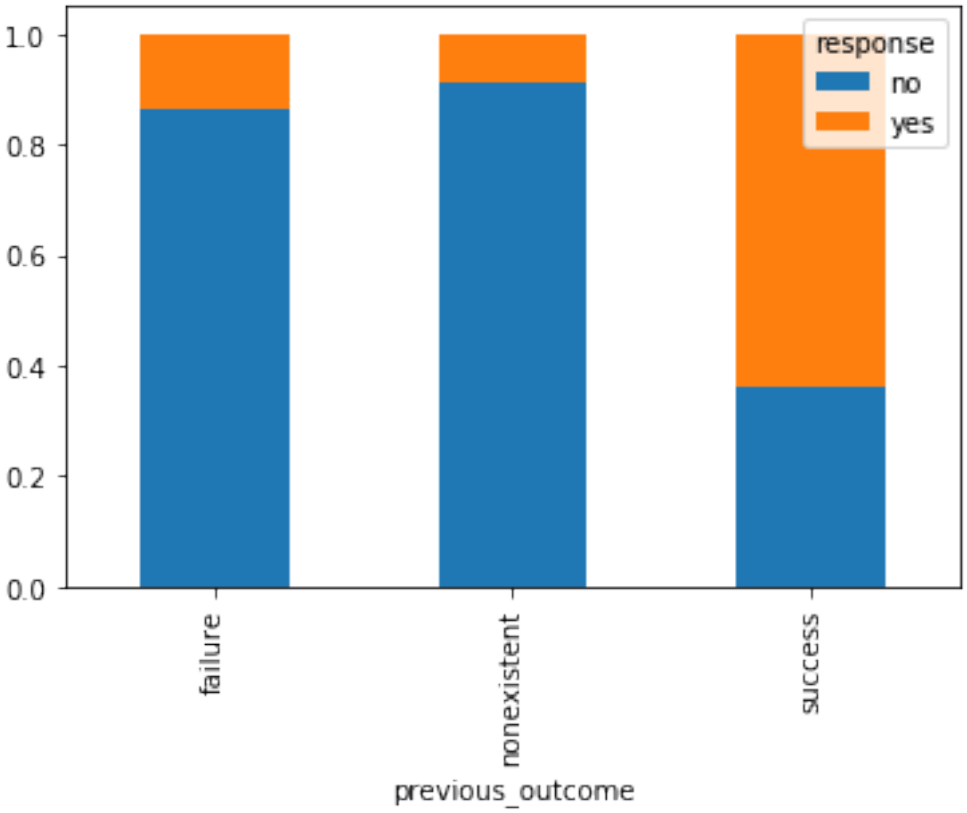



**16. Create a normalized bar graph of *previous_outcome* variable with *response* overlay. Describe the relationship between *previous_outcome* and *response***

[127]:
```
crosstab_normal = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_normal.plot(kind = 'bar', stacked = True)
```

```
# If the previous outcome was a success, then the respondant was more likely to␣
 ↪respond. The inverse is also true.
```

[127]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1b17fd68>
```




**17. Create a contingency table of *previous_outcome* and *response*. Compare the contingency table with the nonnormalized bar graph and the normalized bar graph**

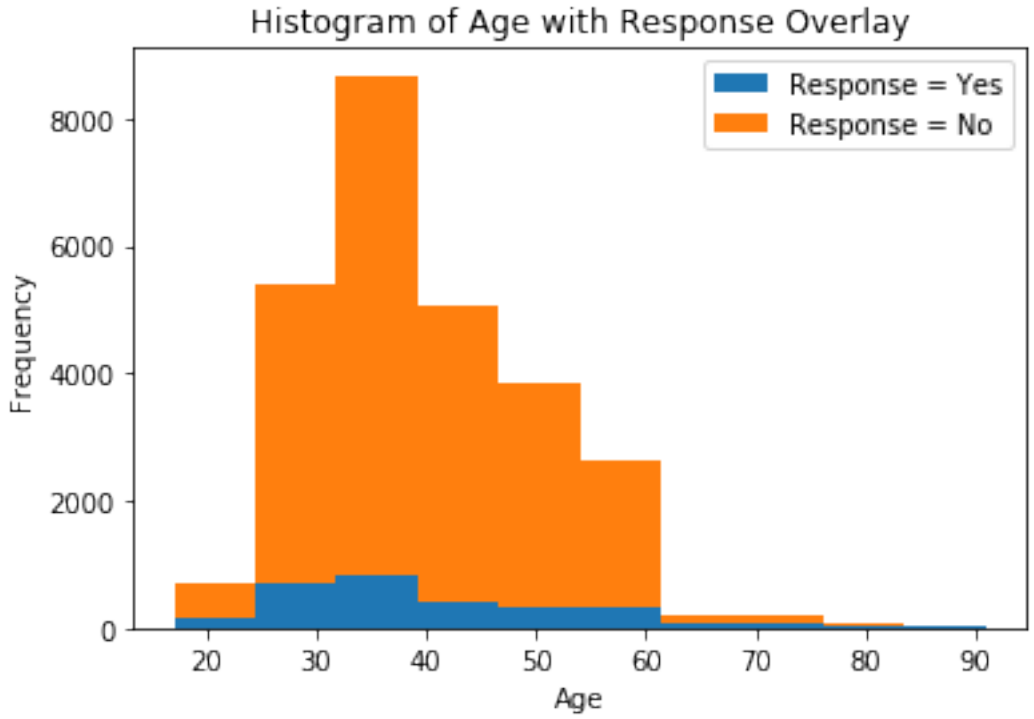
[128]:
```
crosstab_02 = pd.crosstab(bank_train['response'],␣
 ↪bank_train['previous_outcome'])
round(crosstab_02.div(crosstab_02.sum(0), axis = 1)*100, 1)
#The contingency tabe and the normalized bar graph both look at response rates␣
 ↪for each previous outcome and are the same values
```

[128]:

| previous_outcome | failure | nonexistent | success |
|---|---|---|---|
| response | | | |
| no | 86.1 | 91.2 | 36.0 |
| yes | 13.9 | 8.8 | 64.0 |

**18. Create a histogram of *age* with *response* overlay**

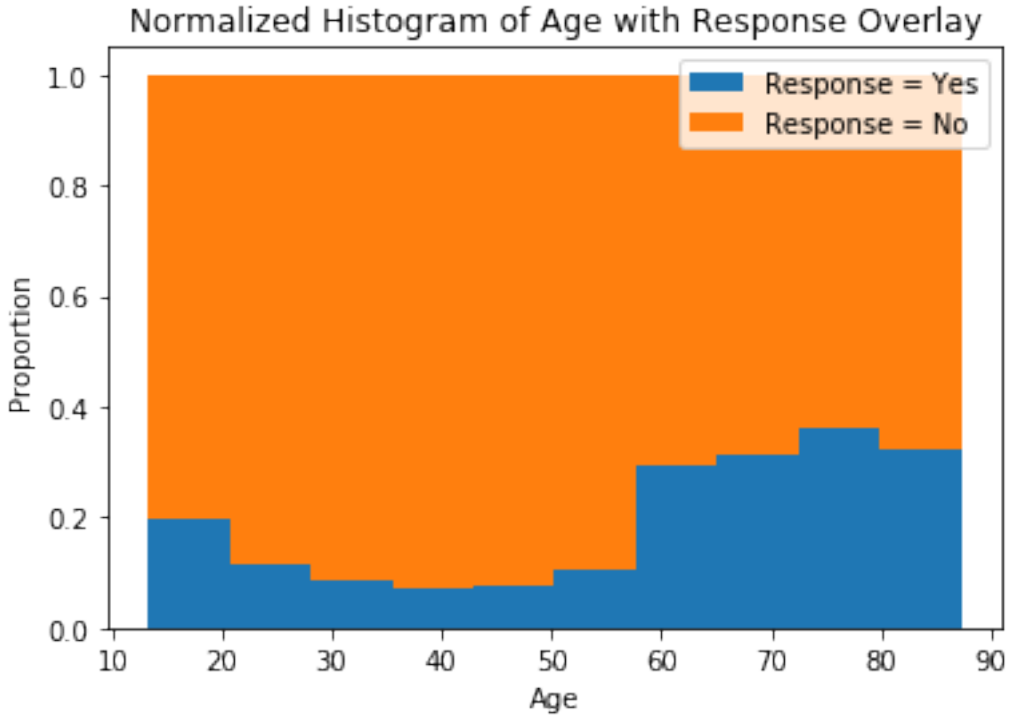
[131]:
```
bank_train_age_yes = bank_train[bank_train.response == "yes"]['age']
bank_train_age_no = bank_train[bank_train.response == "no"]['age']
plt.hist([bank_train_age_yes, bank_train_age_no], bins = 10, stacked = True)
plt.legend(['Response = Yes', 'Response = No'])
plt.title('Histogram of Age with Response Overlay')
plt.xlabel('Age');
plt.ylabel('Frequency');
plt.show()
```




**19. Create a normalized histogram of *age* with *response* overlay. Describe the relationship between *age* and *response***

[146]:
```
n_table = np.column_stack((n[0], n[1]))
n_norm = n_table / n_table.sum(axis=1)[:, None]
ourbins = np.column_stack((bins[0:10], bins[1:11]))
p1 = plt.bar(x = ourbins[:,0], height = n_norm[:,0], width = ourbins[:, 1] -␣
 ↪ourbins[:, 0])
p2 = plt.bar(x = ourbins[:,0], height = n_norm[:,1], width = ourbins[:, 1] -␣
 ↪ourbins[:, 0], bottom = n_norm[:,0])
plt.legend(['Response = Yes', 'Response = No'])
plt.title('Normalized Histogram of Age with Response Overlay')
plt.xlabel('Age'); plt.ylabel('Proportion'); plt.show()
```

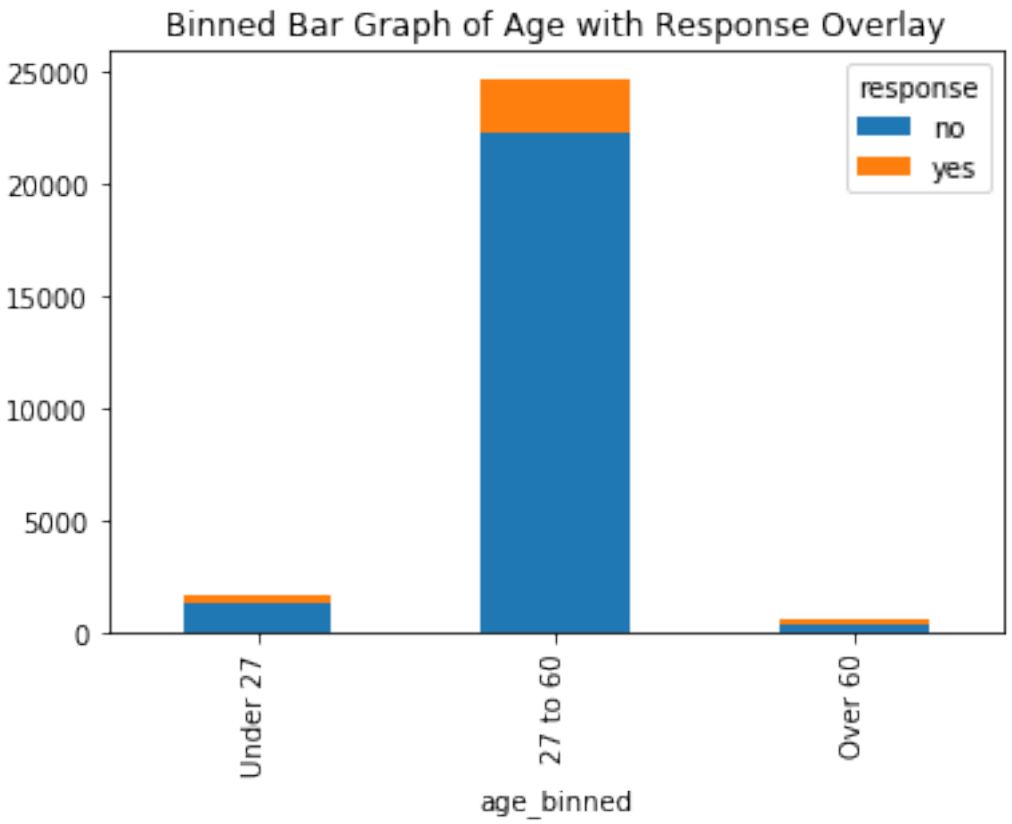
```
# The overall number of responses was highest among the 30-60 age range, but␣
 ↪the highest percentage of responses came form the 60-80 age group
```




**20. Bin the *age* variable using the bins specified in this chapter and create a bar chart of the binned *age* variable with *response* overlay**

[148]:
```
bank_train['age_binned'] = pd.cut(x = bank_train['age'], bins = [0, 27, 60.01,␣
 ↪100], labels=["Under 27", "27 to 60", "Over 60"], right = False)
crosstab_02 = pd.crosstab(bank_train['age_binned'], bank_train['response'])
crosstab_02.plot(kind='bar', stacked = True, title = 'Binned Bar Graph of Age␣
 ↪with Response Overlay')
```

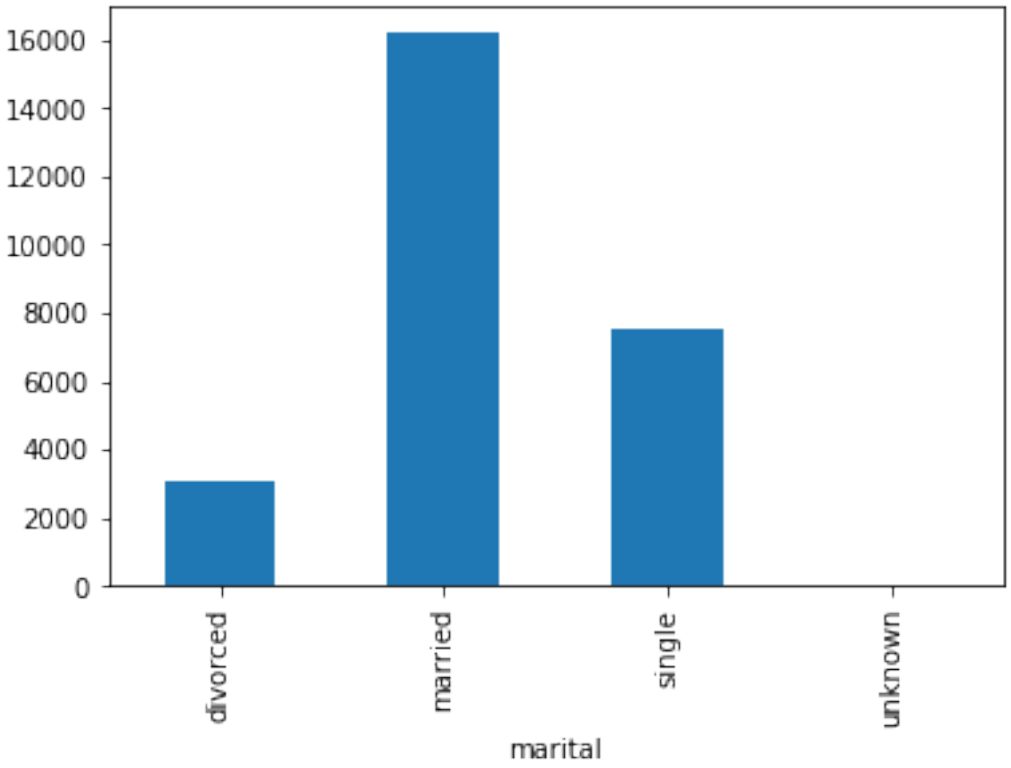
[148]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1cd31f98>
```

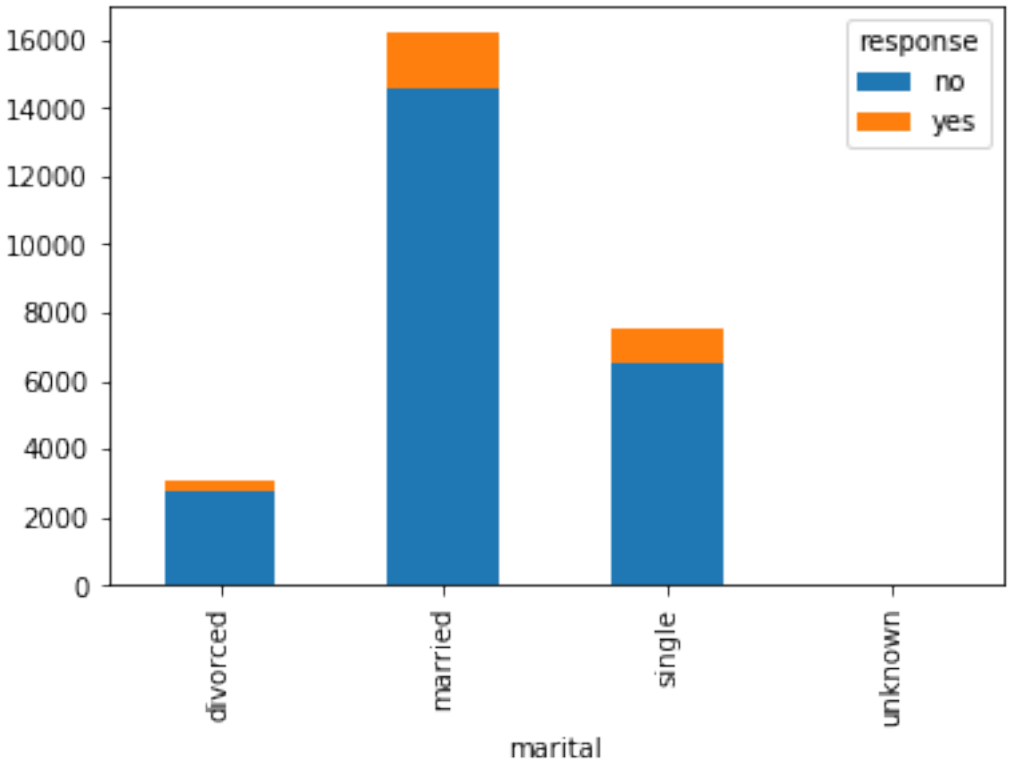


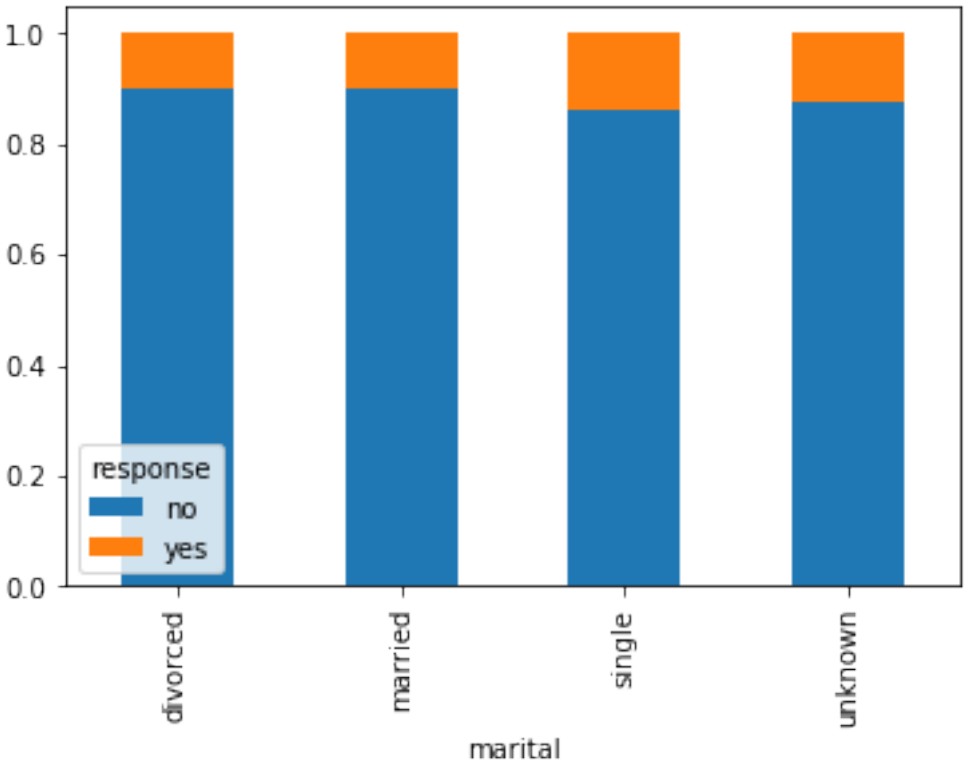

**21. "Produce the following graphs. What is the strength of each graph? Weakness?** ##### a. Bar graph of marital ##### b. Bar graph of marital, with overlay of response ##### c. Normalized bar graph of marital, with overlay of response

[12]:
```
# A. Strength: shows the total number of people in each marital category.␣
 ↪Weakness: Has no response data.
bank_train.groupby('marital')['index'].nunique().plot(kind='bar')
# B. Strength: shows the total number of people in each marital category plus␣
 ↪responses vs non responses. Weakness: Does not show the response rate as a␣
 ↪percentage of the group.
crosstab_01 = pd.crosstab(bank_train['marital'], bank_train['response'])
crosstab_01.plot(kind = 'bar', stacked = True)
# C. Strength: shows the percentage of each group that responded. Weakness:␣
 ↪Does not show total amounts of responses in each group.
crosstab_normal = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_normal.plot(kind = 'bar', stacked = True)
```

[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1d241908>
```


16000
14000
12000
10000
8000
6000
4000
2000
0
divorced
married
single
unknown
marital


response
no
yes
16000
14000
12000
10000
8000
6000
4000
2000
0
divorced
married
single
unknown
marital




**22. Use the graph from exercise 21c, describe the relationship between *marital* and *response***

[ ]:
```
# There really is not any statistical difference between the response rates␣
↪from different marital groups (~ 10% each)
```

**23. Do the following with the variables *marital* and *response*** ##### a. Build a contingency table, being careful to have the correct variables representing the rows and columns. Report the counts and the column percentages ##### b. Describe what the contingency table is telling you

[19]:
```
crosstab_03 = pd.crosstab(bank_train['response'], bank_train['marital'])
print('Crosstab counts:')
print(crosstab_03)
print('Crosstab percentages: ')
print(round(crosstab_03.div(crosstab_03.sum(0), axis = 1)*100, 1))
# B. The contingency tables are giving us the counted responses and counted␣
↪response rate respectively for each marital status
```

```
Crosstab counts:
marital   divorced  married  single  unknown
```

```
response
no            2743    14579    6514       50
yes            312     1608    1061        7
Crosstab percentages:
marital   divorced  married  single  unknown
response
no            89.8     90.1    86.0     87.7
yes           10.2      9.9    14.0     12.3
```