Problem Statement

The Portuguese Bank had run a telemarketing campaign in the past, making sales calls for a term-deposit product. Whether a prospect had bought the product or not is mentioned in the column named 'response'.

The marketing team wants to launch another campaign, and they want to learn from the past one. You, as an analyst, decide to build a supervised model in R and achieve the following goals: Reduce the marketing cost by X% and acquire Y% of the prospects (compared to random calling), where X and Y are to be maximized Present the financial benefit of this project to the marketing team

bank client data:

1 - age (numeric)

2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')

3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed) 4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

5 - default: has credit in default? (categorical: 'no','yes','unknown')

6 - housing: has housing loan? (categorical: 'no','yes','unknown')

7 - loan: has personal loan? (categorical: 'no','yes','unknown')

Related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: 'cellular','telephone')

9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')

10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

Other attributes:

12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)

13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

14 - previous: number of contacts performed before this campaign and for this client (numeric)

15 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

Social and economic context attributes

16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)

17 - cons.price.idx: consumer price index - monthly indicator (numeric)

18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)

19 - euribor3m: euribor 3 month rate - daily indicator (numeric)

20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):

21 - y - has the client subscribed a term deposit? (binary: 'yes','no')

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import pyplot
import collections
```

In [9]:
```
df = pd.read_csv("C:/Users/jemis/Desktop/bank-additional/bank-additional/bank-additional-full.csv",sep=";")
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
age               41188 non-null int64
job               41188 non-null object
marital           41188 non-null object
education         41188 non-null object
default           41188 non-null object
housing           41188 non-null object
loan              41188 non-null object
contact           41188 non-null object
month             41188 non-null object
day_of_week       41188 non-null object
duration          41188 non-null int64
campaign          41188 non-null int64
pdays             41188 non-null int64
previous          41188 non-null int64
poutcome          41188 non-null object
emp.var.rate      41188 non-null float64
cons.price.idx    41188 non-null float64
cons.conf.idx     41188 non-null float64
euribor3m         41188 non-null float64
nr.employed       41188 non-null float64
y                 41188 non-null object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [12]:
```
df.describe()
```

Out[12]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	4118
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	9
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	9
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	9
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	9
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	9
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	9

In [15]:
```
df.head(50)
```

Out[15]:

	age	job	marital	education	default	housing	loan	contact	mont
0	56	housemaid	married	basic.4y	no	no	no	telephone	ma
1	57	services	married	high.school	unknown	no	no	telephone	ma
2	37	services	married	high.school	no	yes	no	telephone	ma
3	40	admin.	married	basic.6y	no	no	no	telephone	ma
4	56	services	married	high.school	no	no	yes	telephone	ma
5	45	services	married	basic.9y	unknown	no	no	telephone	ma
6	59	admin.	married	professional.course	no	no	no	telephone	ma
7	41	blue-collar	married	unknown	unknown	no	no	telephone	ma
8	24	technician	single	professional.course	no	yes	no	telephone	ma
9	25	services	single	high.school	no	yes	no	telephone	ma
10	41	blue-collar	married	unknown	unknown	no	no	telephone	ma
11	25	services	single	high.school	no	yes	no	telephone	ma
12	29	blue-collar	single	high.school	no	no	yes	telephone	ma
13	57	housemaid	divorced	basic.4y	no	yes	no	telephone	ma
14	35	blue-collar	married	basic.6y	no	yes	no	telephone	ma
15	54	retired	married	basic.9y	unknown	yes	yes	telephone	ma
16	35	blue-collar	married	basic.6y	no	yes	no	telephone	ma
17	46	blue-collar	married	basic.6y	unknown	yes	yes	telephone	ma
18	50	blue-collar	married	basic.9y	no	yes	yes	telephone	ma
19	39	management	single	basic.9y	unknown	no	no	telephone	ma
20	30	unemployed	married	high.school	no	no	no	telephone	ma
21	55	blue-collar	married	basic.4y	unknown	yes	no	telephone	ma
22	55	retired	single	high.school	no	yes	no	telephone	ma
23	41	technician	single	high.school	no	yes	no	telephone	ma
24	37	admin.	married	high.school	no	yes	no	telephone	ma
25	35	technician	married	university.degree	no	no	yes	telephone	ma
26	59	technician	married	unknown	no	yes	no	telephone	ma
27	39	self-employed	married	basic.9y	unknown	no	no	telephone	ma
28	54	technician	single	university.degree	unknown	no	no	telephone	ma
29	55	unknown	married	university.degree	unknown	unknown	unknown	telephone	ma
30	46	admin.	married	unknown	no	no	no	telephone	ma
31	59	technician	married	unknown	no	yes	no	telephone	ma
32	49	blue-collar	married	unknown	no	no	no	telephone	ma
33	54	management	married	basic.4y	unknown	yes	no	telephone	ma
34	54	blue-collar	divorced	basic.4y	no	no	no	telephone	ma

	age	job	marital	education	default	housing	loan	contact	mont
35	55	unknown	married	basic.4y	unknown	yes	no	telephone	ma
36	34	services	married	high.school	no	no	no	telephone	ma
37	52	technician	married	basic.9y	no	yes	no	telephone	ma
38	41	admin.	married	university.degree	no	yes	no	telephone	ma
39	56	technician	married	basic.4y	no	yes	no	telephone	ma
40	58	management	unknown	university.degree	no	yes	no	telephone	ma
41	32	entrepreneur	married	high.school	no	yes	no	telephone	ma
42	38	admin.	single	professional.course	no	no	no	telephone	ma
43	57	admin.	married	university.degree	no	no	yes	telephone	ma
44	44	admin.	married	university.degree	unknown	yes	no	telephone	ma
45	42	technician	single	professional.course	unknown	no	no	telephone	ma
46	57	admin.	married	university.degree	no	yes	yes	telephone	ma
47	40	blue-collar	married	basic.9y	no	no	yes	telephone	ma
48	35	admin.	married	university.degree	no	yes	no	telephone	ma
49	45	blue-collar	married	basic.9y	no	yes	no	telephone	ma

50 rows × 21 columns

In [19]:
```
data_dict = df.T.to_dict().values()
```

In [22]:
```
from sklearn.feature_extraction import DictVectorizer
vec = DictVectorizer()
signal_array = vec.fit_transform(data_dict).toarray()
feature_names = vec.get_feature_names()
# signal_array = data.as_matrix() #spits out a numpy matrix
# feature_names = list(data)
df = pd.DataFrame(signal_array,columns=feature_names)
df.head()
```

Out[22]:

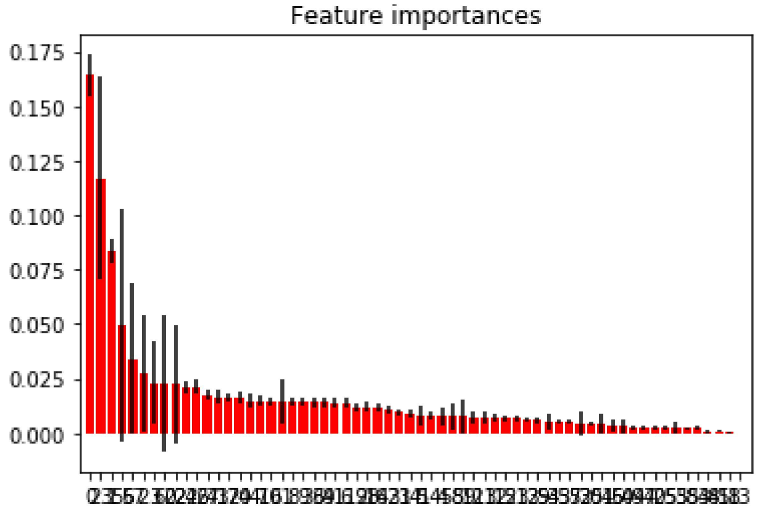
	age	campaign	cons.conf.idx	cons.price.idx	contact=cellular	contact=telephone	day_of_wee
0	56.0	1.0	-36.4	93.994	0.0	1.0	
1	57.0	1.0	-36.4	93.994	0.0	1.0	
2	37.0	1.0	-36.4	93.994	0.0	1.0	
3	40.0	1.0	-36.4	93.994	0.0	1.0	
4	56.0	1.0	-36.4	93.994	0.0	1.0	

5 rows × 65 columns

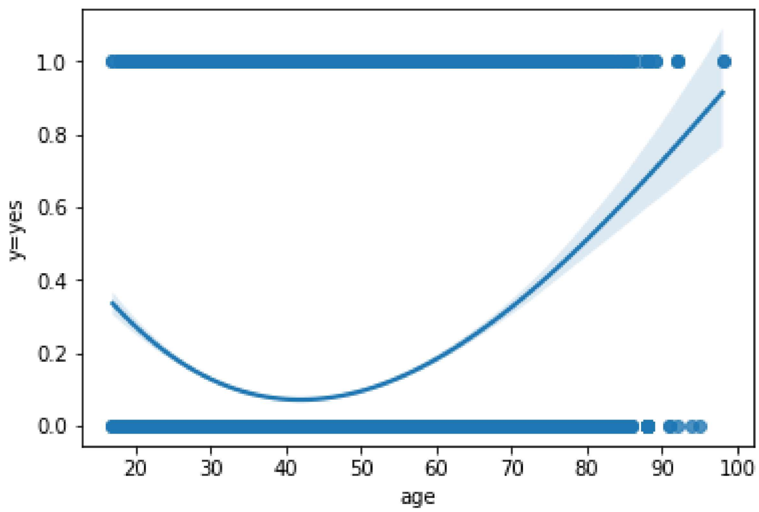
In [24]:
```
import numpy as np
import matplotlib.pyplot as plt

from sklearn.datasets import make_classification
from sklearn.ensemble import RandomForestClassifier

X = signal_array[:,:-2]
X = np.hstack((X[:,:14],X[:,15:]))
y = signal_array[:,-1]
# Build a forest and compute the feature importances
forest = RandomForestClassifier(n_estimators=250,
                              random_state=0)

forest.fit(X, y)
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(X.shape[1]):
    print("%d. feature %s (%f)" % (f + 1, feature_names[indices[f]], importanc
es[indices[f]]))

# Plot the feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(X.shape[1]), importances[indices],
       color="r", yerr=std[indices], align="center")
plt.xticks(range(X.shape[1]), indices)
plt.xlim([-1, X.shape[1]])
plt.show()
```

```
Feature ranking:
1. feature age (0.164047)
2. feature emp.var.rate (0.117021)
3. feature campaign (0.083560)
4. feature month=sep (0.049478)
5. feature nr.employed (0.034052)
6. feature cons.conf.idx (0.027570)
7. feature cons.price.idx (0.023012)
8. feature poutcome=nonexistent (0.022943)
9. feature education=unknown (0.022474)
10. feature euribor3m (0.021194)
11. feature housing=unknown (0.021185)
12. feature housing=yes (0.017653)
13. feature marital=divorced (0.016720)
14. feature education=basic.9y (0.016283)
15. feature education=professional.course (0.016191)
16. feature marital=married (0.014782)
17. feature day_of_week=mon (0.014618)
18. feature day_of_week=wed (0.014473)
19. feature poutcome=success (0.014427)
20. feature day_of_week=thu (0.014243)
21. feature day_of_week=tue (0.014166)
22. feature job=student (0.014008)
23. feature job=unknown (0.014003)
24. feature loan=unknown (0.013831)
25. feature day_of_week=fri (0.013753)
26. feature education=illiterate (0.011851)
27. feature job=admin. (0.011798)
28. feature education=basic.6y (0.011275)
29. feature loan=yes (0.010415)
30. feature job=housemaid (0.009447)
31. feature job=self-employed (0.009024)
32. feature contact=telephone (0.008300)
33. feature duration (0.008157)
34. feature contact=cellular (0.007694)
35. feature pdays (0.007676)
36. feature poutcome=failure (0.007590)
37. feature default=unknown (0.007252)
38. feature default=no (0.007184)
39. feature job=management (0.007027)
40. feature education=basic.4y (0.006778)
41. feature education=university.degree (0.006760)
42. feature job=retired (0.006212)
43. feature job=blue-collar (0.005778)
44. feature month=nov (0.005462)
45. feature job=services (0.005384)
46. feature job=technician (0.004991)
47. feature month=mar (0.004532)
48. feature job=entrepreneur (0.004431)
49. feature month=jun (0.004220)
50. feature marital=unknown (0.003309)
51. feature month=jul (0.003013)
52. feature month=dec (0.002521)
53. feature month=apr (0.002500)
54. feature loan=no (0.002475)
55. feature housing=no (0.002460)
56. feature month=oct (0.002417)
```

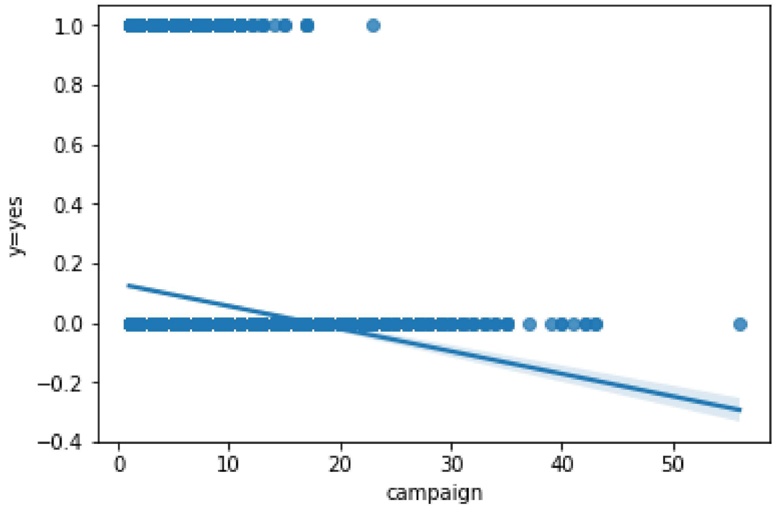
```
57. feature job=unemployed (0.002256)
58. feature month=may (0.002140)
59. feature month=aug (0.000844)
60. feature marital=single (0.000843)
61. feature education=high.school (0.000297)
62. feature default=yes (0.000001)
```



In [27]:
```
x = sns.regplot(x="age", y="y=yes", order=3, data=df, truncate=True)
```

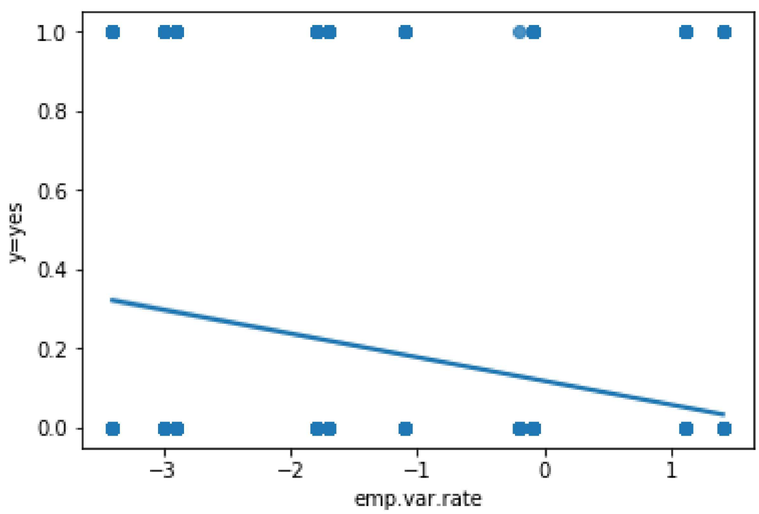


In [33]:
```
y = sns.regplot(x="campaign", y="y=yes", order=1, data=df, truncate=True)
```

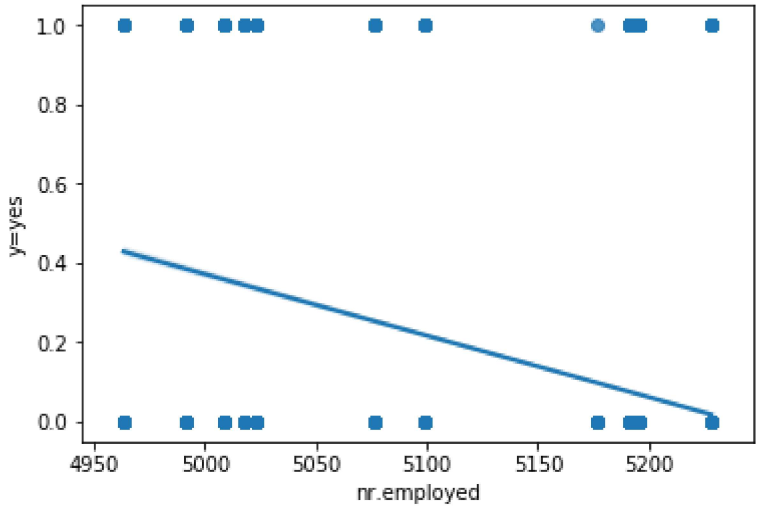


It that any campaign after 20 is useless. Hence no customer must be approached more than 20 times

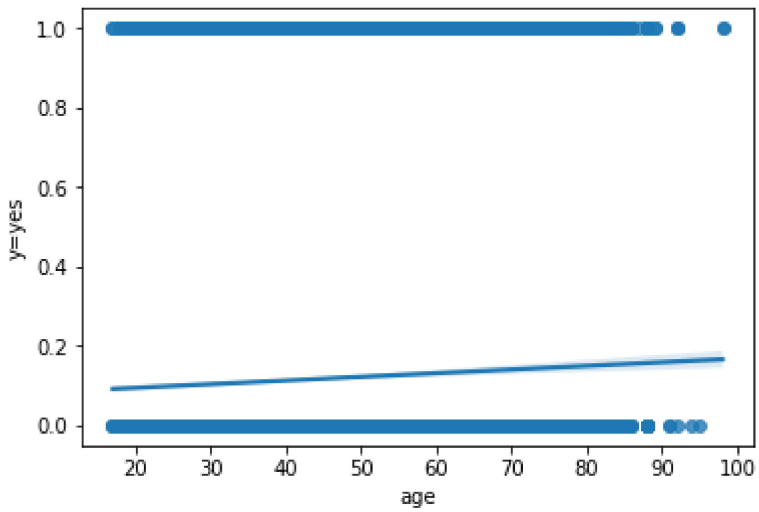
In [36]:
```
y = sns.regplot(x="emp.var.rate", y="y=yes", order=1, data=df, truncate=True)
```



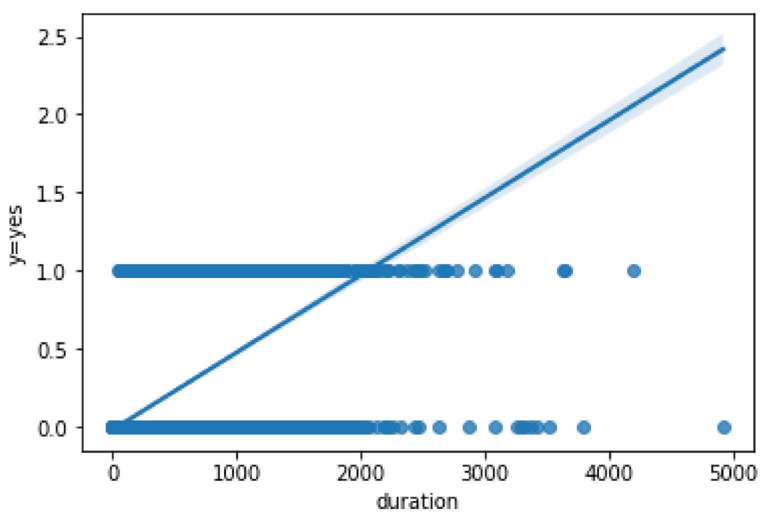
In [37]:
```
y= sns.regplot(x="nr.employed", y="y=yes", order=1, data=df, truncate=True)
```



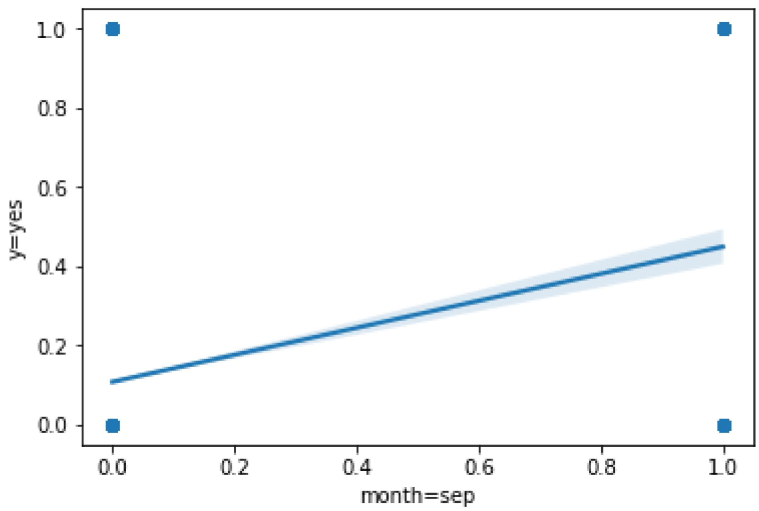
In [38]:
```
y= sns.regplot(x="age", y="y=yes", order=1, data=df, truncate=True)
```



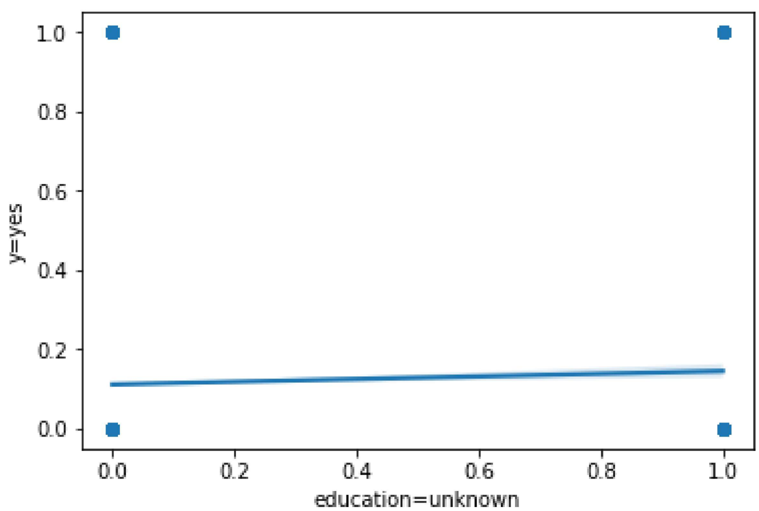
In [39]:
```
y= sns.regplot(x="duration", y="y=yes", order=1, data=df, truncate=True)
```



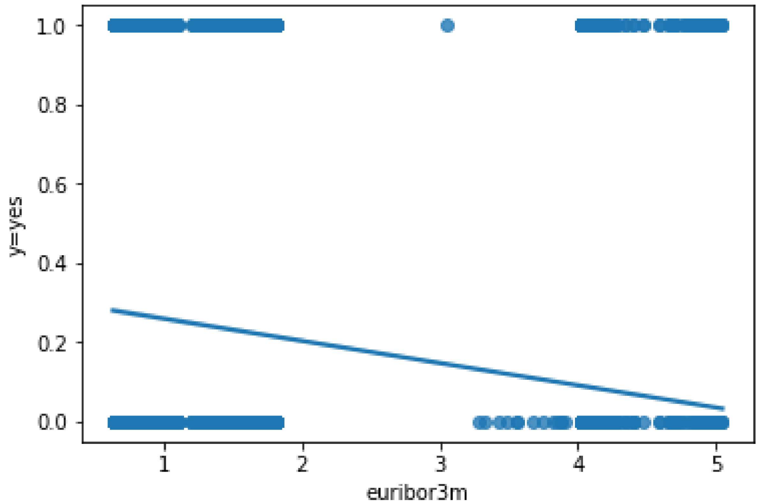
In [40]:
```
y = sns.regplot(x="month=sep", y="y=yes", order=1, data=df, truncate=True)
```



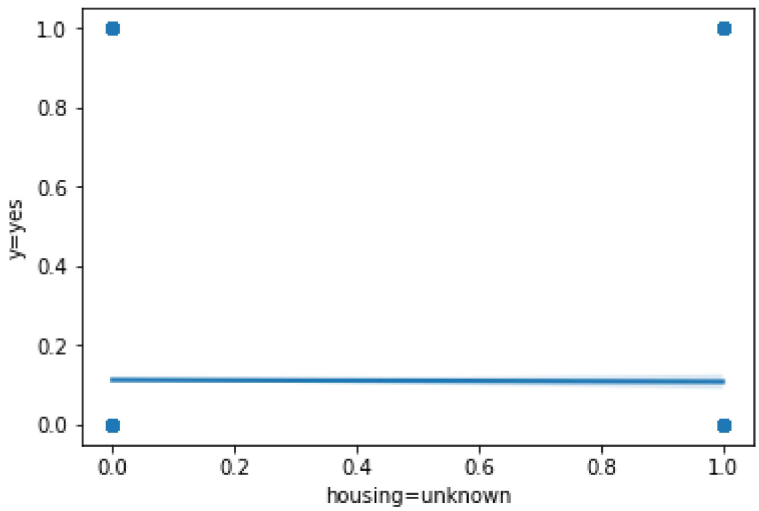
In [41]:
```
y = sns.regplot(x="education=unknown", y="y=yes", order=1, data=df, truncate=True)
```



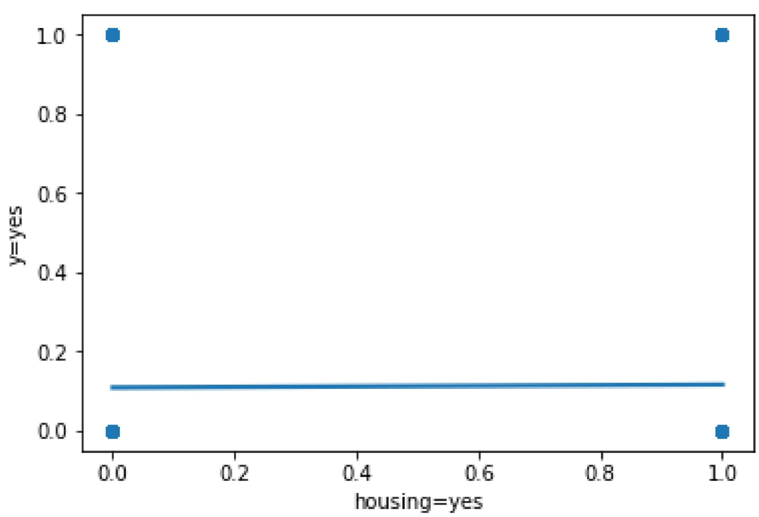
In [42]:
```
y = sns.regplot(x="euribor3m", y="y=yes", order=1, data=df, truncate=True)
```



In [43]:
```
y = sns.regplot(x="housing=unknown", y="y=yes", order=1, data=df, truncate=Tru
e)
```



In [47]:
```
y = sns.regplot(x="housing=yes", y="y=yes", order=1, data=df, truncate=True)
```



Optimizing Cost Using Campaign:

In [48]:
```
sum(df['y=yes'])/sum(df['campaign'])
```

Out[48]:
```
0.043875408967982296
```

In [46]:
```
print( "Nth Call \t Efficiency")
for i in range(1,30):
    ef = sum(df.loc[df['campaign']==i]['y=yes']) / float(df.loc[df['campaign']
>= i].shape[0])
    print (str((i))+" \t\t "+str(ef))
```

```
Nth Call         Efficiency
1                0.05584150723511702
2                0.05143124097511254
3                0.04423551171393342
4                0.03261296660117878
5                0.024077046548956663
6                0.022156573116691284
7                0.015793848711554447
8                0.009566685424873381
9                0.012345679012345678
10               0.010968921389396709
11               0.01380897583429229
12               0.004335260115606936
13               0.007054673721340388
14               0.002105263157894737
15               0.0049261083743842365
16               0.0
17               0.013157894736842105
18               0.0
19               0.0
20               0.0
21               0.0
22               0.0
23               0.008620689655172414
24               0.0
25               0.0
26               0.0
27               0.0
28               0.0
29               0.0
```

Observation: After the 6th call is not acceptable since it has a conversion ratio of less than 1.6%.since market good conversion ratio 2.5-10% we will igrone campaign after 6th campaign .please refer below link for further explation.

[https://www.wordstream.com/blog/ws/2014/03/17/what-is-a-good-conversion-rate (https://www.wordstream.com/blog/ws/2014/03/17/what-is-a-good-conversion-rate)](https://www.wordstream.com/blog/ws/2014/03/17/what-is-a-good-conversion-rate)

In [49]:
```
# Calculate how many calls were made in total
total_calls = sum(df['campaign'])
print(total_calls)
```

```
105754.0
```

In [50]:
```
# Calculate how many calls were made after the 6th call
extra_calls = sum(df[df['campaign']>6]['campaign']) - 6*df[df['campaign']>6].s
hape[0]
print(extra_calls)
```

```
12040.0
```

In [54]:
```
# Calculate reduction in marketing cost
reduction=100*extra_calls/total_calls
print("REDUCTION IN COST:",reduction,"%")
```

```
REDUCTION IN COST: 11.384912154622993 %
```

In [55]:
```
total_sales=float(df[df['y=yes']==1].shape[0])
print(total_sales)
```

```
4640.0
```

In [56]:
```
less_costly_sales=float(df[(df['campaign'] <= 6) & (df['y=yes']==1)].shape[0])
print(less_costly_sales)
```

```
4529.0
```

In [57]:
```
sales_percent=100*less_costly_sales/total_sales
print(sales_percent)
```

```
97.60775862068965
```

conclusion:

A reduction of about 11.4% in marketing cost can be achieved while maintaining 97.6% sales if any person is called less than 6 times.