In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
import warnings
from sklearn.linear_model import LassoCV
from sklearn.metrics import mean_squared_error
warnings.filterwarnings(action="ignore")
#%matplotlib qt # displays a pop-up of the plot
%matplotlib inline # keeps it within the notebook
```

```
UsageError: unrecognized arguments: # keeps it within the notebook
```

In [2]:
```
%%javascript
IPython.OutputArea.prototype._should_scroll = function(lines) {
    return false;
}
```

In [3]:
```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

In [4]:
```
df=pd.read_csv('C:/application/interview_prep/bank-additional/bank-additional/bank-additional-full.csv', sep=";")
print(df.shape)
df.info()
```

```
(41188, 21)
<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 [51]:
```
df.month.unique()
```

Out[51]:
```
array([6, 4, 3, 1, 8, 7, 2, 5, 0, 9], dtype=int64)
```

In [5]:
```
df.head()
```

Out[5]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
1	57	services	married	high.school	unknown	no	no	telephone	may	mon
2	37	services	married	high.school	no	yes	no	telephone	may	mon
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
4	56	services	married	high.school	no	no	yes	telephone	may	mon

In [6]:
```
df_copy = df
```

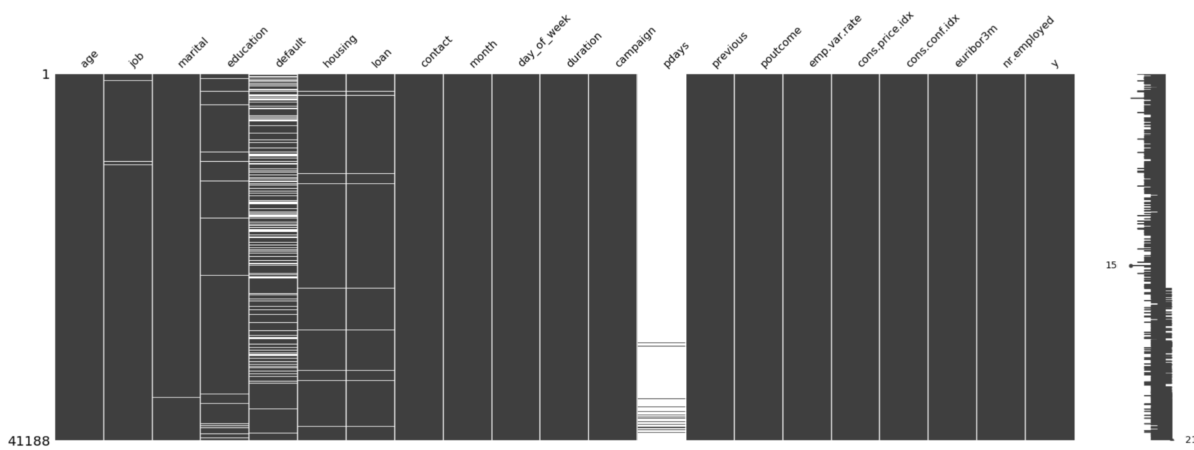
In [7]:
```
df_copy = df_copy.replace('unknown', np.nan)
df_copy = df_copy.replace(999,np.nan)
```

In [8]:
```
df_copy.isna().sum()
```

Out[8]:
```
age                   0
job                 330
marital              80
education          1731
default            8597
housing             990
loan                990
contact               0
month                 0
day_of_week           0
duration              2
campaign              0
pdays             39673
previous              0
poutcome              0
emp.var.rate          0
cons.price.idx        0
cons.conf.idx         0
euribor3m             0
nr.employed           0
y                     0
dtype: int64
```

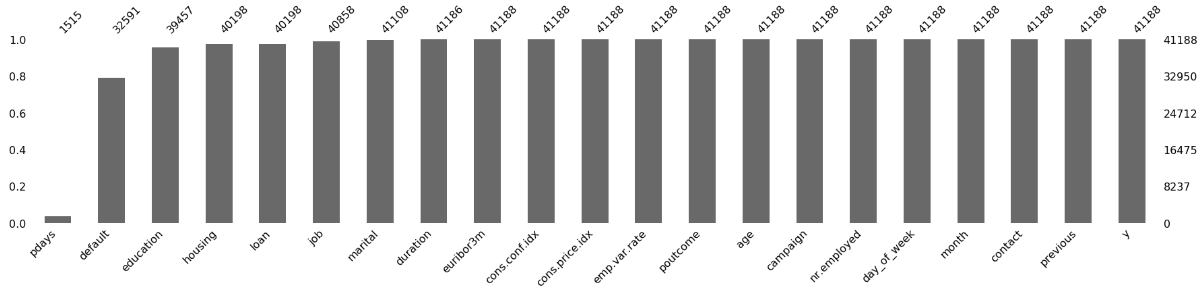
In [9]:
```
# How many missing values are there in our dataset?

missingno.matrix(df_copy, figsize = (30,10))
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x2569b91ff60>



In [10]:
```
missingno.bar(df_copy, sort='ascending', figsize = (30,5))
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x2569be6b5f8>



- The purpose of creating a new dataset that contains all the values that are unknown and replace them with nan values give us the real picture of where data is missing.

- One way to clean dataset is to delete it, but it gives a bad image of the data and it is unrealistic.

- Another way is to find some correlation between the data and fill it in(Imputation).

- From the above analysis we can analyse that variables that has missing value are:-
  - **pdays(39673)**
  - **default(8597)**
  - **education(1731)**
  - **housing(990)**
  - **loan(990)**
  - **job(330)**
  - **marital(80)**
- Out of this 7 columns the values 'marital' missing are very low and missing values in 'default' are actually not missing. It might be a case that customer is not willing to disclose this information to the banking representative . so 'unknown' is a specific value in default and we need to consider it as is.

- So, the missing values in columns **'pdays' , 'education', 'housing' , 'loan' , 'job'** need to be taken care of.

Process of handling missing values - Imputation

- Considering 2 columns 'education' and 'job'
- Initally we will make a cross-tabulation between 'education' and 'job'
- Hypothesis here is that 'job' of a person is infuenced by 'education' of person.
- So inferring 'job' based on education make sense.
- Also, one more hypothesis is that if the age > 60 then the job is retired as most of the take a retirement at the age of 60

In [11]:
```python
def cross_tab(df,f1,f2):
    feature1=list(df[f1].unique())
    feature2=list(df[f2].unique())
    dataframes=[]
    for f in feature2:
        df_f2=df[df[f2]==f]
        df_f1=df_f2.groupby(f1).count()[f2]
        dataframes.append(df_f1)
    df_ct=pd.concat(dataframes,axis=1)
    df_ct.columns=feature2
    df_ct=df_ct.fillna(0)
    return df_ct
```

In [12]:
```python
cross_tab(df,'job','education')
```

Out[12]:

	basic.4y	high.school	basic.6y	basic.9y	professional.course	unknown	university.
admin.	77	3329	151	499	363	249	
blue-collar	2318	878	1426	3623	453	454	
entrepreneur	137	234	71	210	135	57	
housemaid	474	174	77	94	59	42	
management	100	298	85	166	89	123	
retired	597	276	75	145	241	98	
self-employed	93	118	25	220	168	29	
services	132	2682	226	388	218	150	
student	26	357	13	99	43	167	
technician	58	873	87	384	3320	212	
unemployed	112	259	34	186	142	19	
unknown	52	37	22	31	12	131	

In [13]:
```python
df['job'][df['age']>60].value_counts()
```

Out[13]:
```
retired          678
housemaid         54
admin.            47
technician        34
management        30
unknown           21
blue-collar       20
self-employed      9
entrepreneur       8
unemployed         7
services           2
Name: job, dtype: int64
```

- **Inferring education from jobs** :
  - From the cross-tabulation, it can be seen that people with management jobs usually have a university degree.
  - Hence wherever 'job' = management and 'education' = unknown, we can replace 'education' with 'university.degree'.
  - Similarly, 'job' = 'services' then 'education' = 'high.school' and 'job' = 'housemaid' then 'education' = 'basic.4y'.

- **Inferring jobs from education** :
  - If 'education' = 'basic.4y' or 'basic.6y' or 'basic.9y' then the 'job' is usually 'blue-collar'.
  - If 'education' = 'professional.course', then the 'job' = 'technician'.

- **Inferring jobs from age**:
  - As we see, if 'age' > 60, then the 'job' is 'retired,' which makes sense.

In [14]:
```
df.loc[(df['age']>60) & (df['job']=='unknown'), 'job'] = 'retired'
df.loc[(df['education']=='unknown') & (df['job']=='management'), 'education'] = 'university.degree'
df.loc[(df['education']=='unknown') & (df['job']=='services'), 'education'] = 'high.school'
df.loc[(df['education']=='unknown') & (df['job']=='housemaid'), 'education'] = 'basic.4y'
df.loc[(df['job'] == 'unknown') & (df['education']=='basic.4y'), 'job'] = 'blue-collar'
df.loc[(df['job'] == 'unknown') & (df['education']=='basic.6y'), 'job'] = 'blue-collar'
df.loc[(df['job'] == 'unknown') & (df['education']=='basic.9y'), 'job'] = 'blue-collar'
df.loc[(df['job']=='unknown') & (df['education']=='professional.course'), 'job'] = 'technician'
```

In [15]:
```
cross_tab(df,'job','education')
```

Out[15]:

	basic.4y	high.school	basic.6y	basic.9y	professional.course	unknown	university.
admin.	77.0	3329	151.0	499.0	363.0	249.0	
blue-collar	2366.0	878	1448.0	3654.0	453.0	454.0	
entrepreneur	137.0	234	71.0	210.0	135.0	57.0	
housemaid	516.0	174	77.0	94.0	59.0	0.0	
management	100.0	298	85.0	166.0	89.0	0.0	
retired	601.0	276	75.0	145.0	243.0	112.0	
self-employed	93.0	118	25.0	220.0	168.0	29.0	
services	132.0	2832	226.0	388.0	218.0	0.0	
student	26.0	357	13.0	99.0	43.0	167.0	
technician	58.0	873	87.0	384.0	3330.0	212.0	
unemployed	112.0	259	34.0	186.0	142.0	19.0	
unknown	0.0	37	0.0	0.0	0.0	117.0	

- **Imputations for house and loan** : Using cross-tabulation between 'house' and 'job' and between 'loan' and 'job.'
  - Hypothesis is that housing loan status (Yes or No) should be in the proportion of each job category.
  - Hence using the known distribution of the housing loan for each job category, the house loan for unknown people will be predicted such that the prior distribution (% House = Yes's and No's for each job category remains the same).
  - Similarly, we have filled the missing values in the 'loan' variable.

In [16]:
```
jobhousing=cross_tab(df,'job','housing')
cross_tab(df,'job','housing')
```

Out[16]:

job	no	yes	unknown
admin.	4636	5559	227
blue-collar	4362	4752	241
entrepreneur	641	779	36
housemaid	491	540	29
management	1363	1490	71
retired	789	908	44
self-employed	641	740	40
services	1818	2050	101
student	381	471	23
technician	2985	3621	147
unemployed	430	557	27
unknown	85	109	4

In [17]:
```
jobloan=cross_tab(df,'job','loan')
cross_tab(df,'job','loan')
```

Out[17]:

job	no	yes	unknown
admin.	8485	1710	227
blue-collar	7730	1384	241
entrepreneur	1214	206	36
housemaid	877	154	29
management	2414	439	71
retired	1452	245	44
self-employed	1186	195	40
services	3267	601	101
student	710	142	23
technician	5615	991	147
unemployed	838	149	27
unknown	162	32	4

In [18]:
```
def fillhousing(df,jobhousing):
    """Function for imputation via cross-tabulation to fill missing values for
the 'housing' categorical feature"""
    jobs=['housemaid','services','admin.','blue-collar','technician','retired'
,'management','unemployed','self-employed','entrepreneur','student']
    house=["no","yes"]
    for j in jobs:
        ind=df[np.logical_and(np.array(df['housing']=='unknown'),np.array(df[
'job']==j))].index
        mask=np.random.rand(len(ind))<((jobhousing.loc[j]['no'])/(jobhousing.l
oc[j]['no']+jobhousing.loc[j]['yes']))
        ind1=ind[mask]
        ind2=ind[~mask]
        df.loc[ind1,"housing"]='no'
        df.loc[ind2,"housing"]='yes'
    return df


def fillloan(df,jobloan):
    """Function for imputation via cross-tabulation to fill missing values for
the 'loan' categorical feature"""
    jobs=['housemaid','services','admin.','blue-collar','technician','retired'
,'management','unemployed','self-employed','entrepreneur','student']
    loan=["no","yes"]
    for j in jobs:
        ind=df[np.logical_and(np.array(df['loan']=='unknown'),np.array(df['jo
b']==j))].index
        mask=np.random.rand(len(ind))<((jobloan.loc[j]['no'])/(jobloan.loc[j][
'no']+jobloan.loc[j]['yes']))
        ind1=ind[mask]
        ind2=ind[~mask]
        df.loc[ind1,"loan"]='no'
        df.loc[ind2,"loan"]='yes'
    return df
```

In [19]:
```
df=fillhousing(df,jobhousing)
df=fillloan(df,jobloan)
```

In [20]:
```
cross_tab(df,'job','housing')
```

Out[20]:

	no	yes	unknown
admin.	4726	5696	0.0
blue-collar	4485	4870	0.0
entrepreneur	659	797	0.0
housemaid	502	558	0.0
management	1407	1517	0.0
retired	815	926	0.0
self-employed	664	757	0.0
services	1871	2098	0.0
student	392	483	0.0
technician	3060	3693	0.0
unemployed	442	572	0.0
unknown	85	109	4.0

In [21]:
```
cross_tab(df,'job','loan')
```

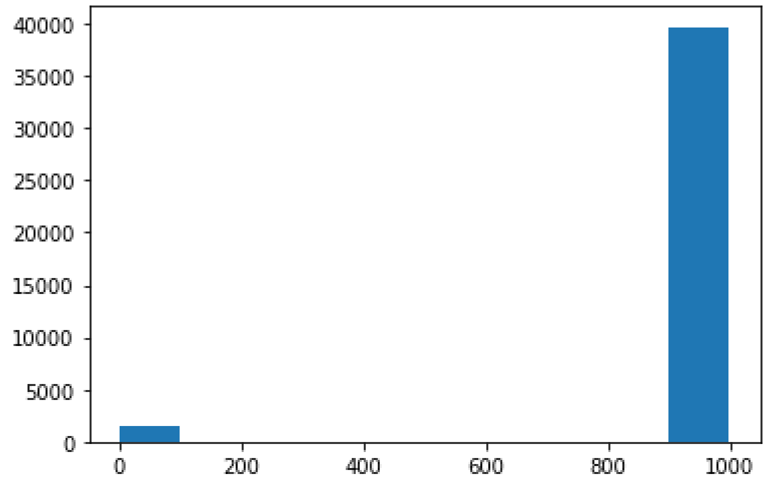
Out[21]:

	no	yes	unknown
admin.	8678	1744	0.0
blue-collar	7939	1416	0.0
entrepreneur	1245	211	0.0
housemaid	900	160	0.0
management	2477	447	0.0
retired	1489	252	0.0
self-employed	1217	204	0.0
services	3350	619	0.0
student	728	147	0.0
technician	5742	1011	0.0
unemployed	860	154	0.0
unknown	162	32	4.0

- **Handing missing values for pdays**

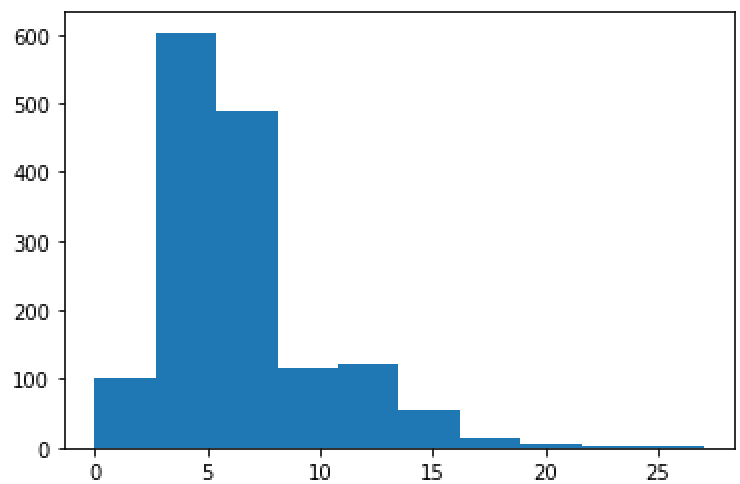
- Below Graph shows distribution of 'pdays'

In [22]:
```
plt.hist(df['pdays'])
plt.show()
```



- Below Distribution shows value of 'pdays' without 999

In [23]:
```
plt.hist(df.loc[df.pdays != 999, 'pdays'])
plt.show()
```



In [24]:
```
pd.crosstab(df['pdays'],df['poutcome'], values=df['age'], aggfunc='count', normalize=True)
```

Out[24]:

poutcome	failure	nonexistent	success
pdays			
0	0.000000	0.000000	0.000364
1	0.000000	0.000000	0.000631
2	0.000000	0.000000	0.001481
3	0.000097	0.000000	0.010561
4	0.000049	0.000000	0.002816
5	0.000097	0.000000	0.001020
6	0.000607	0.000000	0.009396
7	0.000364	0.000000	0.001093
8	0.000146	0.000000	0.000291
9	0.000583	0.000000	0.000971
10	0.000170	0.000000	0.001093
11	0.000073	0.000000	0.000607
12	0.000316	0.000000	0.001093
13	0.000194	0.000000	0.000680
14	0.000121	0.000000	0.000364
15	0.000219	0.000000	0.000364
16	0.000049	0.000000	0.000219
17	0.000121	0.000000	0.000073
18	0.000121	0.000000	0.000049
19	0.000024	0.000000	0.000049
20	0.000024	0.000000	0.000000
21	0.000049	0.000000	0.000000
22	0.000000	0.000000	0.000073
25	0.000024	0.000000	0.000000
26	0.000000	0.000000	0.000024
27	0.000000	0.000000	0.000024
999	0.099786	0.863431	0.000000

- As seen from the above table the majority of pdays missing value occur when the 'poutcome' is 'non-existent'.
- Which means when pdays value is missing because the customer was never contacted.
- To deal with this situation the best possible way is to convert the numeric variable of pdays to categorical with introducting new categories like:-
    - **pdays_missing** : where value is not present
    - **pdays_less_5** : pdays is less than 5
    - **pdays_bet_5_15** : pdays between 5 to 15
    - **pdays_greater_15** : pdays are greater than 15
- Buckets are created according to the distribution plotted above to make sense

In [25]:
```
#Add new categorical variables to our dataframe.
df['pdays_missing'] = 0
df['pdays_less_5'] = 0
df['pdays_greater_15'] = 0
df['pdays_bet_5_15'] = 0
df['pdays_missing'][df['pdays']==999] = 1
df['pdays_less_5'][df['pdays']<5] = 1
df['pdays_greater_15'][(df['pdays']>15) & (df['pdays']<999)] = 1
df['pdays_bet_5_15'][(df['pdays']>=5)&(df['pdays']<=15)]= 1
df = df.drop('pdays', axis=1)
```

In [26]:
```
df.head()
```

Out[26]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon
1	57	services	married	high.school	unknown	no	no	telephone	may	mon
2	37	services	married	high.school	no	yes	no	telephone	may	mon
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon
4	56	services	married	high.school	no	no	yes	telephone	may	mon

Conclusion on Handling missing value

- Used Imputation technique to fill missing value for column 'job', 'education', 'housing', 'loan'
- Imputed values were relation between variable made sense and kept the rest as 'unknow' to handle real world situation were a client/customer might not give all the required values
- Convered 'pdays' to categorical variable making buckets which made sense w.r.t to data distribution

Standardizing the Data

- Standardizing the data is required as all the numerical variables distribution is having different scale and if the model is trained on such data there is a possibility that it will create a Bias

In [27]:
```
numeric_columns = ['age','duration','campaign','previous','emp.var.rate','cons.price.idx','cons.conf.idx','euribor3m','nr.employed','pdays_missing','pdays_less_5','pdays_greater_15','pdays_bet_5_15']
```

In [28]:
```
scaler = MinMaxScaler()
df[numeric_columns] = scaler.fit_transform(df[numeric_columns])
```

In [29]:
```
df.head()
```

Out[29]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_\
0	0.481481	housemaid	married	basic.4y	no	no	no	telephone	may	
1	0.493827	services	married	high.school	unknown	no	no	telephone	may	
2	0.246914	services	married	high.school	no	yes	no	telephone	may	
3	0.283951	admin.	married	basic.6y	no	no	no	telephone	may	
4	0.481481	services	married	high.school	no	no	yes	telephone	may	

In [30]:
```
df_le = df
```

Converting Categorical variables to numeric (using One Hot Encoding)

- Ordinal Variables ('poutcome', 'default', 'housing' and 'loan' are ordinal ordinal variables)
- Nominal Variables ('job', 'maritial', 'education', 'contact', 'month', 'day_of_week' are Nominal Variables)

Handling Ordinal Variables

In [31]:
```
df['poutcome'] = df['poutcome'].map({'failure': -1,'nonexistent': 0,'success': 1})
df['default'] = df['default'].map({'yes': -1,'unknown': 0,'no': 1})
df['housing'] = df['housing'].map({'yes': -1,'unknown': 0,'no': 1})
df['loan'] = df['loan'].map({'yes': -1,'unknown': 0,'no': 1})
df['y'] = df['y'].map({'yes': 1,'no' : 0})
```

In [32]:
```
df.head()
```

Out[32]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_we
0	0.481481	housemaid	married	basic.4y	1	1	1	telephone	may	n
1	0.493827	services	married	high.school	0	1	1	telephone	may	n
2	0.246914	services	married	high.school	1	-1	1	telephone	may	n
3	0.283951	admin.	married	basic.6y	1	1	1	telephone	may	n
4	0.481481	services	married	high.school	1	1	-1	telephone	may	n

Handling Nominal Variables(One Hot Encoding)

In [33]:
```
# One hot encoding of nominal varibles
nominal = ['job','marital','education','contact','month','day_of_week']
df_processed = pd.get_dummies(df,columns=nominal)
```

In [34]:
```
df_processed.head()
```

Out[34]:

	age	default	housing	loan	duration	campaign	previous	poutcome	emp.var.rate	con
0	0.481481	1	1	1	0.053070	0.0	0.0	0	0.9375	
1	0.493827	0	1	1	0.030297	0.0	0.0	0	0.9375	
2	0.246914	1	-1	1	0.045954	0.0	0.0	0	0.9375	
3	0.283951	1	1	1	0.030704	0.0	0.0	0	0.9375	
4	0.481481	1	1	-1	0.062424	0.0	0.0	0	0.9375	

In [35]:
```
len(df_processed.columns)
```

Out[35]: 59

- Dropping 1 features from all the dummy variable as we have n categories only n-1 dummy variables are needed to reperesent that variable

In [36]:

```
drop_feature = ['job_unknown','marital_married','education_unknown','contact_t
elephone', 'month_aug','day_of_week_mon']
df_processed = df_processed.drop(drop_feature,axis=1)
df_processed.head()
```

Out[36]:

	age	default	housing	loan	duration	campaign	previous	poutcome	emp.var.rate	con
0	0.481481	1	1	1	0.053070	0.0	0.0	0	0.9375	
1	0.493827	0	1	1	0.030297	0.0	0.0	0	0.9375	
2	0.246914	1	-1	1	0.045954	0.0	0.0	0	0.9375	
3	0.283951	1	1	1	0.030704	0.0	0.0	0	0.9375	
4	0.481481	1	1	-1	0.062424	0.0	0.0	0	0.9375	

Using Label Encoding

In [37]:

```
le = preprocessing.LabelEncoder()
df_le.job = le.fit_transform(df_le.job)
df_le.marital = le.fit_transform(df_le.marital)
df_le.education = le.fit_transform(df_le.education)
df_le.default = le.fit_transform(df_le.default)
df_le.housing = le.fit_transform(df_le.housing)
df_le.loan = le.fit_transform(df_le.loan)
df_le.contact = le.fit_transform(df_le.contact)
df_le.month = le.fit_transform(df_le.month)
df_le.day_of_week = le.fit_transform(df_le.day_of_week)
df_le.poutcome = le.fit_transform(df_le.poutcome)
df_le.y = le.fit_transform(df_le.y)
df_le.head()
```

Out[37]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	dura
0	0.481481	3	1	0	2	2	2	1	6	1	0.05:
1	0.493827	7	1	3	1	2	2	1	6	1	0.03(
2	0.246914	7	1	3	2	0	2	1	6	1	0.04!
3	0.283951	0	1	1	2	2	2	1	6	1	0.03(
4	0.481481	7	1	3	2	2	0	1	6	1	0.06:

Feature Importance

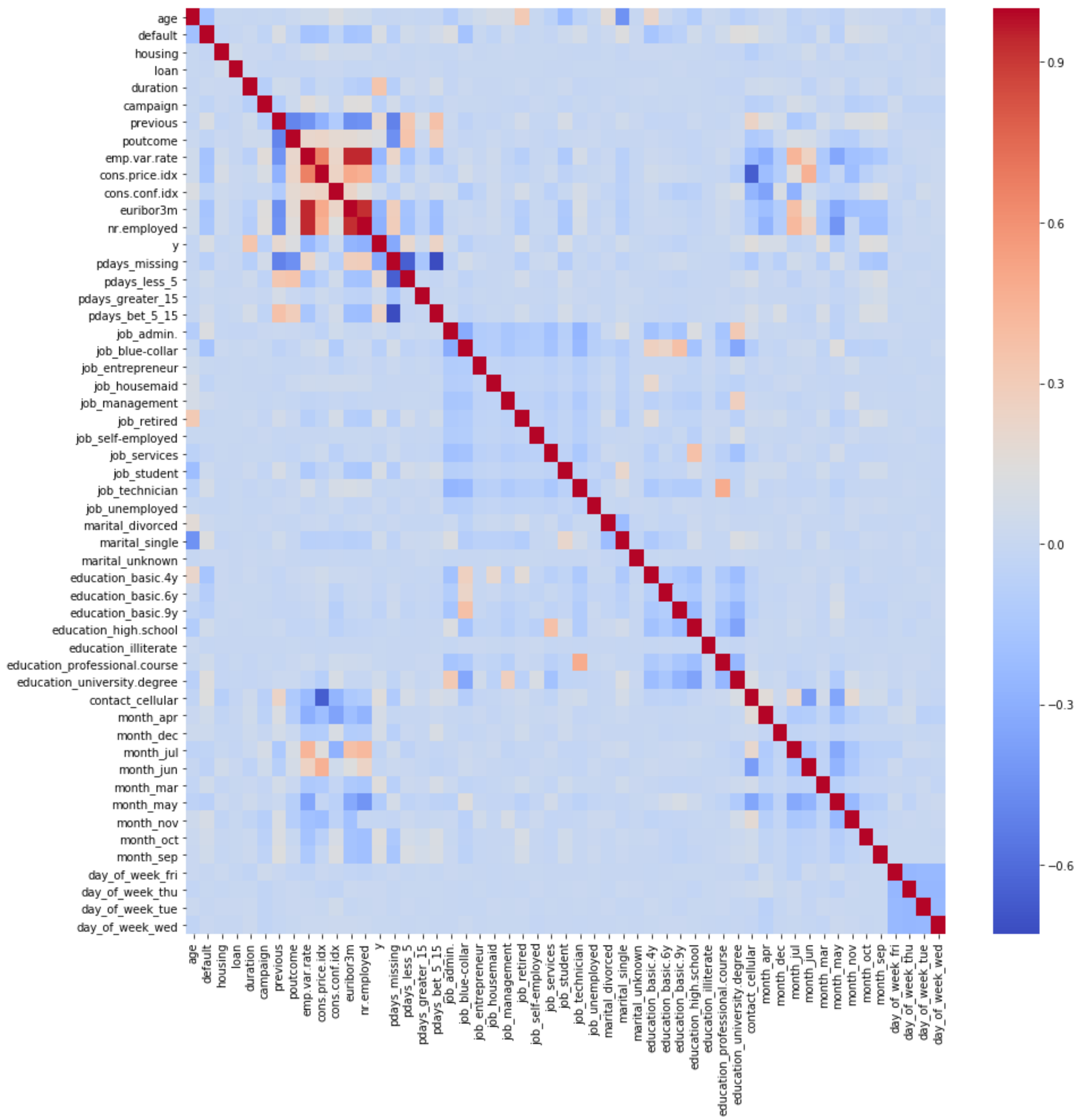
- Will try to find the features which are important to create our base model using Correlation and Lassocv

Feature Importance of One Hot Encoded Data

Using Correlation

In [38]:
```
f, ax = plt.subplots(figsize=(15, 15))
sns.heatmap(df_processed.corr(method='spearman'), annot=False, cmap='coolwarm'
)
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x2569bd42be0>



In [39]:
```
#Correlation with output variable
cor = df_processed.corr()
cor_target = abs(cor["y"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.1]
relevant_features
```

Out[39]:
```
duration           0.405274
previous           0.230181
poutcome           0.129789
emp.var.rate       0.298334
cons.price.idx     0.136211
euribor3m          0.307771
nr.employed        0.354678
y                  1.000000
pdays_missing      0.324877
pdays_less_5       0.209159
pdays_bet_5_15     0.241540
contact_cellular   0.144773
month_mar          0.144014
month_may          0.108271
month_oct          0.137366
month_sep          0.126067
Name: y, dtype: float64
```

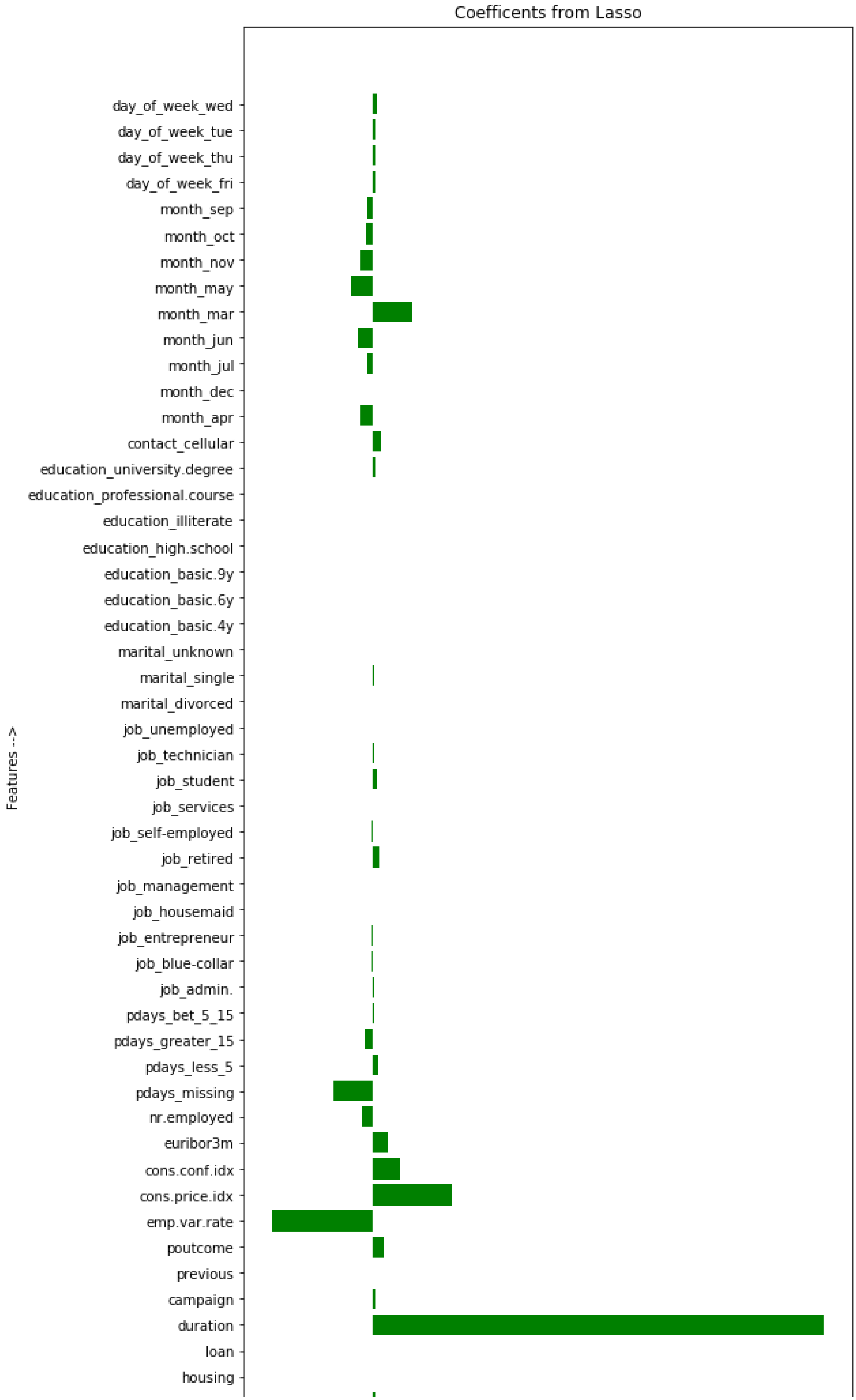
- Important Features according to Correlation w.r.t "y" are :-

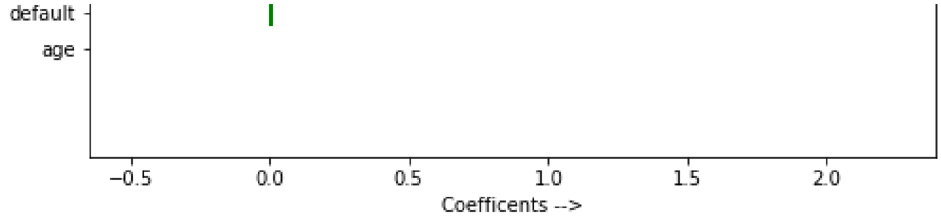
["duration", "previous", "poutcome", "emp.var.rate", "cons.price.idx", "euribor3m", "nr.employed", "pdays_missing","pdays_less_5", "pdays_bet_5_15", "contact_cellular", "month_mar", "month_may", "month_oct", "month_sep"]

Using Lassocv

In [40]:
```
X = df_processed.drop('y', axis=1)
y = df_processed['y']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, strat
ify=y, random_state=1)
#perform lassocv for variable selection
modellasso = LassoCV(alphas = [1, 0.1, 0.001, 0.0001, 10, 1000]).fit(X_train,
y_train)
lassopred = modellasso.predict(X_test)
print("RMSE of Lasso: ", np.sqrt(mean_squared_error(lassopred, y_test)))
coeff = modellasso.coef_
x = list(X_train)
x_pos = [i for i, _ in enumerate(x)]
plt.figure(figsize = (8,20))
plt.barh(x_pos, coeff, color='green')
plt.ylabel("Features -->")
plt.xlabel("Coefficents -->")
plt.title("Coefficents from Lasso")
plt.yticks(x_pos, x)

plt.show()
```

```
RMSE of Lasso:  0.253221081059976
```


Coefficents from Lasso
Features -->
day_of_week_wed
day_of_week_tue
day_of_week_thu
day_of_week_fri
month_sep
month_oct
month_nov
month_may
month_mar
month_jun
month_jul
month_dec
month_apr
contact_cellular
education_university.degree
education_professional.course
education_illiterate
education_high.school
education_basic.9y
education_basic.6y
education_basic.4y
marital_unknown
marital_single
marital_divorced
job_unemployed
job_technician
job_student
job_services
job_self-employed
job_retired
job_management
job_housemaid
job_entrepreneur
job_blue-collar
job_admin.
pdays_bet_5_15
pdays_greater_15
pdays_less_5
pdays_missing
nr.employed
euribor3m
cons.conf.idx
cons.price.idx
emp.var.rate
poutcome
previous
campaign
duration
loan
housing



- Important Features according to lassocv w.r.t "y" are :-

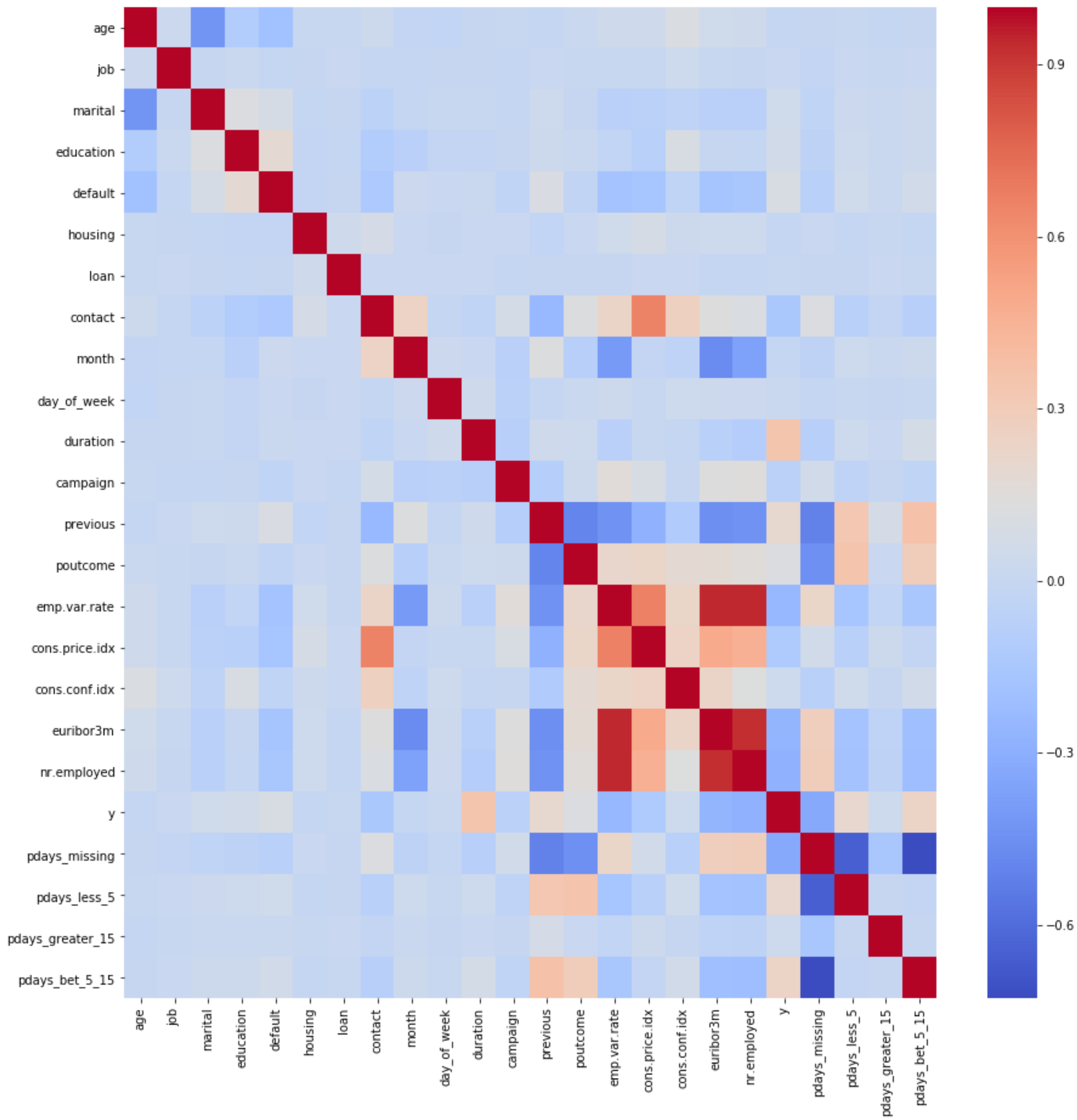
["duration" , "cons.price.idx", "cons.conf.idx", "euribor3m", "poutcome", "month_mar", "pdays_less_5", "job_retired", "job_student", "campaign", "default"]

Feature Importance of Label Encoded Data

Using Correlation

In [41]:
```
f, ax = plt.subplots(figsize=(15, 15))
sns.heatmap(df_le.corr(method='spearman'), annot=False, cmap='coolwarm')
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x2569d1e2e48>



In [42]:
```
#Correlation with output variable
cor = df_le.corr()
cor_target = abs(cor["y"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.1]
relevant_features
```

Out[42]:
```
contact           0.144773
duration          0.405274
previous          0.230181
poutcome          0.129789
emp.var.rate      0.298334
cons.price.idx    0.136211
euribor3m         0.307771
nr.employed       0.354678
y                 1.000000
pdays_missing     0.324877
pdays_less_5      0.209159
pdays_bet_5_15    0.241540
Name: y, dtype: float64
```

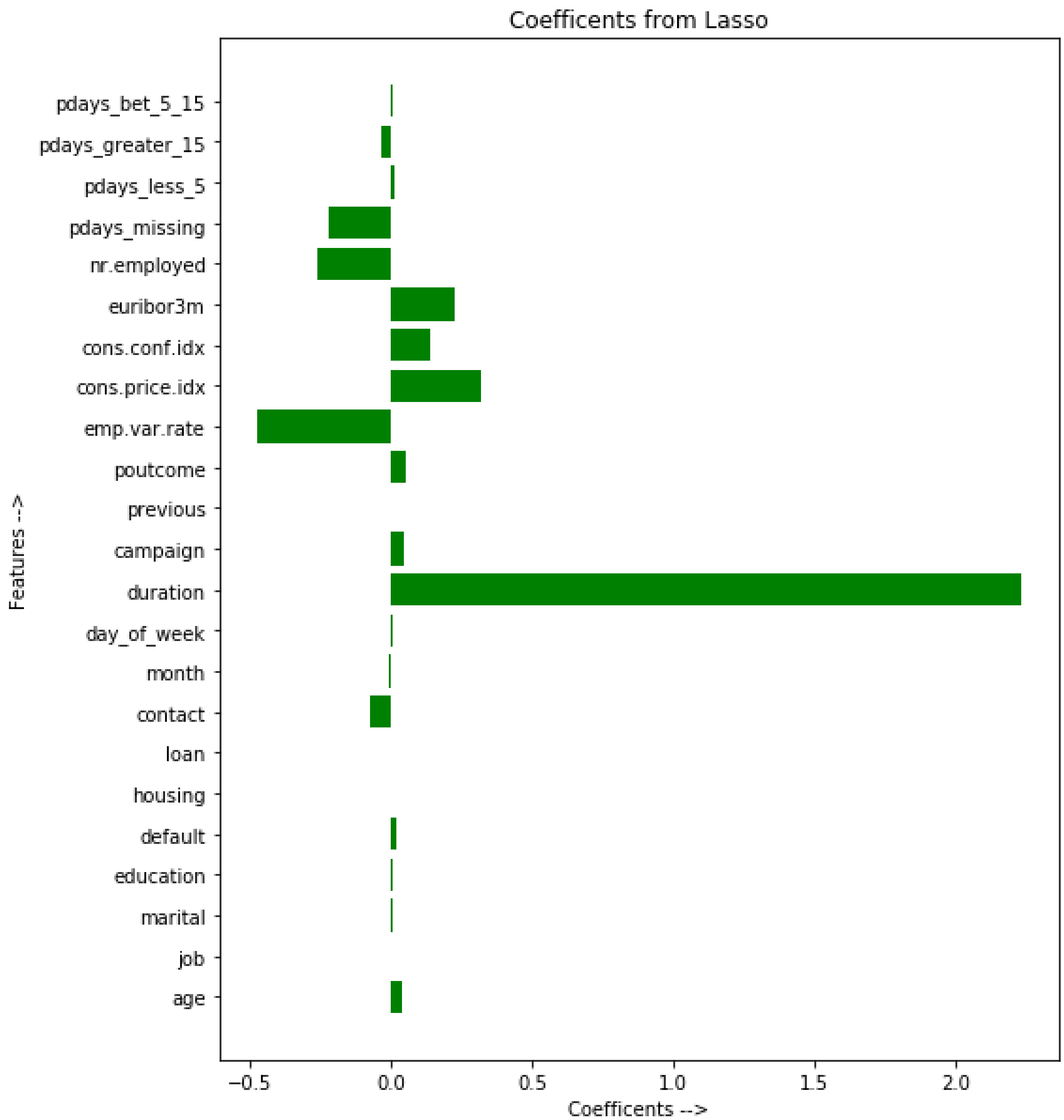
- Important Features according to Correlation w.r.t "y" are :-

["duration","contact", "previous", "poutcome", "emp.var.rate", "cons.price.idx", "euribor3m", "nr.employed", "pdays_missing", "pdays_less_5", "pdays_bet_5_15"]

Using Lassocv

In [43]:
```
X = df_le.drop('y', axis=1)
y = df_le['y']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, strat
ify=y, random_state=1)
#perform lassocv for variable selection
modellasso = LassoCV(alphas = [1, 0.1, 0.001, 0.0001, 10, 1000]).fit(X_train,
y_train)
lassopred = modellasso.predict(X_test)
print("RMSE of Lasso: ", np.sqrt(mean_squared_error(lassopred, y_test)))
coeff = modellasso.coef_
x = list(X_train)
x_pos = [i for i, _ in enumerate(x)]
plt.figure(figsize = (8,10))
plt.barh(x_pos, coeff, color='green')
plt.ylabel("Features -->")
plt.xlabel("Coefficents -->")
plt.title("Coefficents from Lasso")
plt.yticks(x_pos, x)

plt.show()
```

```
RMSE of Lasso:  0.2551378130386552
```



- Important Features according to lassocv w.r.t "y" are :-

["duration", "cons.price.idx", "cons.conf.idx", "euribor3m", "campaign", "poutcome"]

Conclusion on Feature Importance

- The Features which are selected by Correlation and Lassocv for one hot and Label Encoding are :-
  - *Correlation with One hot Encoding*

    ["duration", "previous", "poutcome", "emp.var.rate", "cons.price.idx", "euribor3m", "nr.employed", "pdays_missing","pdays_less_5", "pdays_bet_5_15", "contact_cellular", "month_mar", "month_may", "month_oct", "month_sep"]
  - *Lassocv with one hot Encoding*

    ["duration" , "cons.price.idx", "cons.conf.idx", "euribor3m", "poutcome", "month_mar", "pdays_less_5", "job_retired", "job_student", "campaign", "default"]
  - *Correlation with Label Encoding*

    ["duration","contact", "previous", "poutcome", "emp.var.rate", "cons.price.idx", "euribor3m", "nr.employed", "pdays_missing", "pdays_less_5", "pdays_bet_5_15"]
  - *Lassocv with Label Encoding*

    ["duration", "cons.price.idx", "cons.conf.idx", "euribor3m", "campaign", "poutcome"]

- It is clear from both the feature selection techniques that "duration" is highly related to the output and it will create a Bias if we include "duration" feature in our model building phase, so **dropping "duration"** is the right option

- Additionally duration of call is known after the call is ended which is the case with knowing whether the person will sign up for a "term deposite" or not

Saving the Data for Model building

In [44]:
```
df_processed = df_processed.drop('duration',axis=1)
df_processed.head()
```

Out[44]:

	age	default	housing	loan	campaign	previous	poutcome	emp.var.rate	cons.price.idx
0	0.481481	1	1	1	0.0	0.0	0	0.9375	0.698753
1	0.493827	0	1	1	0.0	0.0	0	0.9375	0.698753
2	0.246914	1	-1	1	0.0	0.0	0	0.9375	0.698753
3	0.283951	1	1	1	0.0	0.0	0	0.9375	0.698753
4	0.481481	1	1	-1	0.0	0.0	0	0.9375	0.698753

In [45]:
```
len(df_processed.columns)
```

Out[45]: 52

In [46]:
```
df_processed.to_csv("C:/application/interview_prep/bank-additional/bank-additi
onal/bank_full_processed.csv", index = False)
```

In [47]:
```
df_le = df_le.drop('duration',axis=1)
df_le.head()
```

Out[47]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	cam
0	0.481481	3	1	0	2	2	2	1	6	1	
1	0.493827	7	1	3	1	2	2	1	6	1	
2	0.246914	7	1	3	2	0	2	1	6	1	
3	0.283951	0	1	1	2	2	2	1	6	1	
4	0.481481	7	1	3	2	2	0	1	6	1	

In [48]:
```
len(df_le.columns)
```

Out[48]: 23

In [49]:
```
df_le.to_csv("C:/application/interview_prep/bank-additional/bank-additional/ba
nk_full_processed_le.csv", index = False)
```

Conclusion

- Found missing values and tried imputating it with cross-functional relations
- Standardized the Data to bring it to the same scale
- Converted Categorical variables to numeric which is required for many ML Modeling algorithms
- Tried finding feature importance using Correlation and Lassocv
- Dropped feature "duration" as it would have created Bias in model building phase

please refer Model Building & Evaluation for next steps