

```
In [141]:
```

```
import pandas as pd
```

```
In [142]:
```

```
data = pd.read_csv("D:\KSR\Python\ExcelFile\investment_banking.csv")
```

```
In [143]:
```

```
data.shape
```

```
Out[143]:
```

```
(753089, 9)
```

```
In [144]:
```

```
data.head(5)
```

```
Out[144]:
```

	broker_id	city
0	BRXX-1	PLANTATION, FL
1	BRXX-1	BRANFORD, CT
2	BRXX-1	JONESBORO, GA
3	BRXX-2	VIENNA, VA
4	BRXX-3	CHAGRIN FALLS, OH

```
In [145]:
```

```
data[['broker_id']].nunique() #1178brokers (objective --> how many brokers are loyal)
```

```
Out[145]:
```

```
broker_id    1178  
dtype: int64
```

```
In [146]:
```

```
data.isna().sum() #missing values
```

```
Out[146]:
```

```
broker_id      0  
city          0  
broker_type    0  
fund_category  0  
email_opened   434545  
webex_meet     667429  
sales_call     573091
```

```
firm_sales          0  
global_sales        0  
dtype: int64
```

In [147]:

```
(data.isna().sum() / data.shape[0]) *100
```

Out[147]:

```
broker_id      0.000000  
city          0.000000  
broker_type    0.000000  
fund_category  0.000000  
email_opened   57.701679  
webex_meet     88.625514  
sales_call     76.098708  
firm_sales     0.000000  
global_sales    0.000000  
dtype: float64
```

In [148]:

```
#missing value treatment  
data['webex_meet'] = data['webex_meet'].fillna("N")  
data['email_opened'] = data['email_opened'].fillna("N")  
data['sales_call'] = data['sales_call'].fillna("N")
```

In [149]:

```
(data.isna().sum() / data.shape[0]) *100
```

Out[149]:

```
broker_id      0.0  
city          0.0  
broker_type    0.0  
fund_category  0.0  
email_opened   0.0  
webex_meet     0.0  
sales_call     0.0  
firm_sales     0.0  
global_sales    0.0  
dtype: float64
```

In [150]:

```
data.head(5)
```

Out[150]:

	broker_id	city
0	BRXX-1	PLANTATION, FL
1	BRXX-1	BRANFORD, CT
2	BRXX-1	JONESBORO, GA
3	BRXX-2	VIENNA, VA
4	BRXX-3	CHAGRIN FALLS, OH

In [151]:

```
data.groupby('broker_type')['broker_id'].nunique()
```

Out[151]:

```
broker_type
Inter-dealer broker    1173
full-service broker      5
Name: broker_id, dtype: int64
```

In [152]:

```
data[['city','state']] = data['city'].str.split(", ",n=1,expand =True)
```

In [153]:

```
data.head(5)
```

Out[153]:

	broker_id	city
0	BRXX-1	PLANTATION
1	BRXX-1	BRANFORD
2	BRXX-1	JONESBORO
3	BRXX-2	VIENNA
4	BRXX-3	CHAGRIN FALLS

In [154]:

```
data[['state']].head(5)
```

Out[154]:

	state
0	FL
1	CT
2	GA
3	VA
4	OH

In [155]:

```
data['state'].nunique()
```

Out[155]:

In [156]:

```
data[data['state'].str.len()>=7].sort_values("state", ascending = False).head(10)
```

Out[156]:

		broker_id	city
64117	BRXX-80		KNOXVILLE
105020	BRXX-80		KNOXVILLE
161873	BRXX-80		KNOXVILLE
168087	BRXX-80		KNOXVILLE
168090	BRXX-80		KNOXVILLE
188332	BRXX-80		KNOXVILLE
215953	BRXX-80		KNOXVILLE
215964	BRXX-80		KNOXVILLE
257010	BRXX-80		KNOXVILLE
466084	BRXX-80		KNOXVILLE

In [157]:

```
data['state'].unique()
```

Out[157]:

```
array(['FL', 'CT', 'GA', 'VA', 'OH', 'CA', 'WA', 'MD', 'NJ',
       'SC', 'OR', 'NY', 'TX', 'NC', 'KS', 'UT', 'PA', 'AZ',
       'TN', 'HI', 'AL', 'OK', 'MA', 'WV', 'NH', 'IN', 'MI',
       'ME', 'MN', 'DC', 'MS', 'IL', 'LA', 'CO', 'MO', 'IA',
       'ND', 'WI', 'KY', 'ID', 'DE', 'NM', 'RI', 'AR', 'PR',
       'WY', 'SD', 'AK', 'MT', 'VT', 'NE', 'NV', 'MD', 'CT',
       'WI', 'TN', 'TN', 'VT', 'CA', 'GU', 'DC', 'DC'], dtype=object)
```

In [158]:

```
#corrections to state columns
data['state']=data['state'].str.replace(' ','')
data['state'] = data['state'].str.replace(',','')
```

In [159]:

```
data['state'].unique()
```

Out[159]:

```
array(['FL', 'CT', 'GA', 'VA', 'OH', 'CA', 'WA', 'MD', 'NJ', 'SC', 'OR',
       'NY', 'TX', 'NC', 'KS', 'UT', 'PA', 'AZ', 'TN', 'HI', 'AL', 'OK',
       'MA', 'WV', 'NH', 'IN', 'MI', 'ME', 'MN', 'DC', 'MS', 'IL', 'LA',
       'CO', 'MO', 'IA', 'ND', 'WI', 'KY', 'ID', 'DE', 'NM', 'RI', 'AR',
```

```
'PR', 'WY', 'SD', 'AK', 'MT', 'VT', 'NE', 'NV', 'TNTN', 'GU',
'DCDC' ], dtype=object)
```

In [160]:

```
data[data['state'].str.len()>=4].sort_values("state", ascending = False).head(10)
```

Out[160]:

	broker_id	city
64117	BRXX-80	KNOXVILLE
105020	BRXX-80	KNOXVILLE
161873	BRXX-80	KNOXVILLE
168087	BRXX-80	KNOXVILLE
168090	BRXX-80	KNOXVILLE
188332	BRXX-80	KNOXVILLE
215953	BRXX-80	KNOXVILLE
215964	BRXX-80	KNOXVILLE
257010	BRXX-80	KNOXVILLE
466084	BRXX-80	KNOXVILLE

In [161]:

```
data['state'] = data['state'].str.replace('TNTN', 'TN')
data['state'] = data['state'].str.replace('DCDC', 'DC')
```

In [162]:

```
data[data['state'].str.len()==2].sort_values("state", ascending = False).head(10)
#make sure at any cost this should not yeild any results
```

Out[162]:

	broker_id	city
689078	BRXX-298	ROCK SPRINGS
448643	BRXX-327	CHEYENNE
393351	BRXX-253	CODY
672717	BRXX-298	AFTON
654993	BRXX-262	ROCK SPRINGS
372991	BRXX-78	GILLETTE
529140	BRXX-374	CHEYENNE
182298	BRXX-172	CHEYENNE
198107	BRXX-456	CODY
417882	BRXX-172	CASPER

In [163]:

```
data['state'].str.isnumeric().sum()
```

Out[163]:

```
np.int64(0)
```

In [164]:

```
data['city'].str.isnumeric().sum()
```

Out[164]:

```
np.int64(37)
```

In [165]:

```
data[data['city'].str.isnumeric()].head(40)
```

Out[165]:

	broker_id	city
12956	BRXX-188	64150
31538	BRXX-77	15801
45478	BRXX-188	64150
95111	BRXX-77	15801
107878	BRXX-188	64150
122236	BRXX-70	95678
143794	BRXX-77	15801
151921	BRXX-77	15801
158007	BRXX-77	15801
170498	BRXX-188	64150
174723	BRXX-188	64150
178474	BRXX-77	15801
231891	BRXX-188	64150
233080	BRXX-188	64150
236546	BRXX-70	95678
239104	BRXX-70	95678
242904	BRXX-70	95678
258485	BRXX-77	15801
266507	BRXX-188	64150
286301	BRXX-70	95678
343116	BRXX-70	95678
361358	BRXX-77	15801
384772	BRXX-70	95678
434361	BRXX-77	15801
452242	BRXX-70	95678
485769	BRXX-77	15801
527815	BRXX-70	95678
531297	BRXX-77	15801
536996	BRXX-77	15801
549610	BRXX-77	15801
553111	BRXX-188	64150
566408	BRXX-188	64150
570387	BRXX-77	15801
578599	BRXX-77	15801
599098	BRXX-77	15801

609244	BRXX-77	15801
633459	BRXX-77	15801

In [166]:

```
#37 records have some numbers in city columns (mistake)
```

In [167]:

```
(37 /data.shape[0]) *100 # = ~0.005% there is mistake
```

Out[167]:

```
0.004913098
```

In [168]:

```
data[data['city'].str.isnumeric()]['city'].unique()
```

Out[168]:

```
array(['64150', '15801', '95678'], dtype=object)
```

In [169]:

```
data['city']= data['city'].str.replace('64150','Riverside')
data['city']= data['city'].str.replace('15801','DuBois')
data['city']= data['city'].str.replace('95678','Roseville')
#external source ---> change pin to city name
```

In [170]:

```
data['city'].str.isnumeric().sum()
```

Out[170]:

```
np.int64(0)
```

In [171]:

```
data['email_opened'].unique()
```

Out[171]:

```
array(['N', 'Y'], dtype=object)
```

In [172]:

```
data[data['email_opened'].str.len()>1].head(5)
```

```
Out[172]:
```

	broker_id	city
--	-----------	------

```
In [173]:
```

```
data['email_opened'].str.isnumeric().sum()
```

```
Out[173]:
```

```
np.int64(0)
```

```
In [174]:
```

```
#Assignment  
#check if there is no character in firm sales/ global sales
```

```
In [175]:
```

```
data.dtypes
```

```
Out[175]:
```

```
broker_id      object  
city          object  
broker_type    object  
fund_category  object  
email_opened   object  
webex_meet     object  
sales_call     object  
firm_sales     float64  
global_sales   float64  
state          object  
dtype: object
```

```
In [176]:
```

```
data['firm_sales'].astype(str).str.isnumeric().sum()
```

```
Out[176]:
```

```
np.int64(0)
```

```
In [177]:
```

```
data['global_sales'].astype(str).str.isnumeric().sum()
```

```
Out[177]:
```

```
np.int64(0)
```

In [178]:

```
data[data['broker_id'] == 'BRXX-1'].head(5)
```

Out[178]:

	broker_id	city
0	BRXX-1	PLANTATION
1	BRXX-1	BRANFORD
2	BRXX-1	JONESBORO
7	BRXX-1	OWINGS MILLS
13	BRXX-1	AUSTIN

In [179]:

```
data.groupby('broker_id')[['firm_sales', 'global_sales']].sum()
```

Out[179]:

broker_id	firm_sales	global_sales
BRXX-1	11157673.73	1.07E+08
BRXX-10	0	7.48E+05
BRXX-100	267918.14	8.15E+06
BRXX-1000	0	0.00E+00
BRXX-1001	0	1.09E+06
...
BRXX-995	0	1.81E+04
BRXX-996	0	3.20E+04
BRXX-997	0	1.66E+05
BRXX-998	0	0.00E+00
BRXX-999	0	1.29E+04

1178 rows × 2 columns

In [180]:

```
data[data['broker_id'] == 'BRXX-1'][['firm_sales']].sum()
```

Out[180]:

```
firm_sales    11157673.73
dtype: float64
```

In [181]:

```
data[data['broker_id'] == 'BRXX-1'][['global_sales']].sum().astype(int)
```

Out[181]:

```
global_sales    106631687
dtype: int64
```

In [182]:

```
#how much he has purchased in our bank  
(11157673.73/106631687) * 100
```

Out[182]:

```
10.46375055
```

In [183]:

```
#BRXX-1 ---> 10% from our bank and 90% from others
```

In [201]:

```
df = data.groupby('broker_id')[['firm_sales', 'global_sales']].sum().reset_index()
```

In [202]:

```
df.head(10)
```

Out[202]:

	broker_id	firm_sales
0	BRXX-1	11157673.73
1	BRXX-10	0
2	BRXX-100	267918.14
3	BRXX-1000	0
4	BRXX-1001	0
5	BRXX-1002	29387.17
6	BRXX-1003	0
7	BRXX-1004	0
8	BRXX-1005	77.23
9	BRXX-1006	0

In [203]:

```
df['loyalty_Per'] = (df['firm_sales']/df['global_sales']) * 100
```

In [204]:

```
df.head(10)
```

Out[204]:

	broker_id	firm_sales
0	BRXX-1	11157673.73
1	BRXX-10	0
2	BRXX-100	267918.14
3	BRXX-1000	0
4	BRXX-1001	0

5	BRXX-1002	29387.17
6	BRXX-1003	0
7	BRXX-1004	0
8	BRXX-1005	77.23
9	BRXX-1006	0

In [205]:

```
df.sort_values("loyalty_Per", ascending = False).head(10)
```

Out[205]:

		broker_id	firm_sales
8	BRXX-1005	77.23	
23	BRXX-1019	5571.97	
42	BRXX-1036	245.76	
621	BRXX-498	13042.03	
858	BRXX-710	27438.3	
895	BRXX-744	4352339.58	
137	BRXX-1121	754618.93	
335	BRXX-24	15800032.61	
1118	BRXX-945	25429.96	
287	BRXX-197	1000213.01	

In [206]:

```
#expected output
#broker_id / firm_sales / global_sales / loyalty_per / loyalty_category
```

In [207]:

```
def loyalty_check(loy_percent):
    if loy_percent == 100:
        return "Loyal Broker"
    elif loy_percent > 85 and loy_percent < 100:
        return "Steadyfast Broker"
    elif loy_percent >= 50 and loy_percent < 85:
        return "Reasonably Devoted Brokers (Moderate)"
    elif loy_percent < 50 and loy_percent > 0:
        return "Less Inclined Brokers"
    elif loy_percent == 0:
        return "Non-Committed Brokers"
    else:
        return "Stagnant Brokers"
```

In [208]:

```
df['loyalty_Category'] = df['loyalty_Per'].apply(loyalty_check)
```

In [192]:

```
df.head(10)
```

```
Out[192]:
```

		broker_id	firm_sales
0	BRXX-1		11157673.73
1	BRXX-10		0
2	BRXX-100		267918.14
3	BRXX-1000		0
4	BRXX-1001		0
5	BRXX-1002		29387.17
6	BRXX-1003		0
7	BRXX-1004		0
8	BRXX-1005		77.23
9	BRXX-1006		0

```
In [193]:
```

```
df.shape
```

```
Out[193]:
```

```
(1178, 5)
```

```
In [213]:
```

```
df2 = df.groupby('loyalty_Category')[['broker_id']].count().sort_values('broker_id', ascending=False)
```

```
In [214]:
```

```
df.dtypes
```

```
Out[214]:
```

```
broker_id          object
firm_sales        float64
global_sales      float64
loyalty_Per       float64
loyalty_Category  object
dtype: object
```

```
In [215]:
```

```
#Assignment
# total brokers = 1178
```

```
In [217]:
```

```
df2['Loyalty_Broker_Percentage'] = (df2['No_of_brokers'] / 1178) * 100
```

```
In [198]:
```

df.head(10)

Out[198]:

	loyalty_Category	No_of_brokers
0	Non-Committed Brokers	686
1	Less Inclined Brokers	310
2	Stagnant Brokers	166
3	Reasonably Devoted Brokers (Moderate)	7
4	Steadyfast Broker	5
5	Loyal Broker	4

In [218]:

df.head(10)

Out[218]:

	broker_id	firm_sales
0	BRXX-1	11157673.73
1	BRXX-10	0
2	BRXX-100	267918.14
3	BRXX-1000	0
4	BRXX-1001	0
5	BRXX-1002	29387.17
6	BRXX-1003	0
7	BRXX-1004	0
8	BRXX-1005	77.23
9	BRXX-1006	0

In [122]:

data.head(2)

Out[122]:

	broker_id	city
0	BRXX-1	PLANTATION
1	BRXX-1	BRANFORD

In [238]:

```
df3 = pd.merge(data, df, on = "broker_id", how = "inner") \
[[ "broker_id", "city", "state", "broker_type", "fund_category", "email_opened", "webex_meet", "sales
```

In [239]:

df3.head(5)

Out[239]:

	broker_id	city
0	BRXX-1	PLANTATION
1	BRXX-1	BRANFORD
2	BRXX-1	JONESBORO

3	BRXX-2	VIENNA
4	BRXX-3	CHAGRIN FALLS

In [227]:

```
df3.groupby(['webex_meet', 'loyalty_Category'])[['broker_id']].nunique()
```

Out[227]:

		broker_id
webex_meet	loyalty_Category	
N	Less Inclined Brokers	310
	Loyal Broker	4
	Non-Committed Brokers	658
	Reasonably Devoted Brokers (Moderate)	7
	Stagnant Brokers	156
	Steadyfast Broker	5
Y	Less Inclined Brokers	191
	Non-Committed Brokers	56
	Reasonably Devoted Brokers (Moderate)	1
	Stagnant Brokers	11
	Steadyfast Broker	2

In [247]:

```
df4 = df3.groupby(['broker_type', 'loyalty_Category'])[['broker_id']].nunique().sort_values('
```

In [248]:

```
df4.head(10)
```

Out[248]:

		broker_id
broker_type	loyalty_Category	
Inter-dealer broker	Non-Committed Brokers	685
	Less Inclined Brokers	306
	Stagnant Brokers	166
	Reasonably Devoted Brokers (Moderate)	7
	Steadyfast Broker	5
	Loyal Broker	4
full-service broker	Less Inclined Brokers	4
	Non-Committed Brokers	1

In []:

broker_type	fund_category
Inter-dealer broker	Emerging-Markets Local-Currency Bond
Inter-dealer broker	Utilities
Inter-dealer broker	Intermediate Government
Inter-dealer broker	Intermediate Government
full-service broker	Target-Date 2050

broker_type	fund_category
Inter-dealer broker	Emerging-Markets Local-Currency Bond
Inter-dealer broker	Utilities
Inter-dealer broker	Intermediate Government
Inter-dealer broker	Intermediate Government
full-service broker	Target-Date 2050

broker_type	fund_category
Inter-dealer broker	Emerging-Markets Local-Currency Bond
Inter-dealer broker	Utilities
Inter-dealer broker	Intermediate Government
Inter-dealer broker	Intermediate Government
full-service broker	Target-Date 2050

broker_type	fund_category
Inter-dealer broker	Mid-Cap Growth
Inter-dealer broker	Bank Loan
Inter-dealer broker	World Small/Mid Stock
Inter-dealer broker	Allocation--70% to 85% Equity
Inter-dealer broker	High Yield Muni
Inter-dealer broker	Long-Short Credit
Inter-dealer broker	Large Growth
Inter-dealer broker	Short-Term Bond
Inter-dealer broker	Allocation--30% to 50% Equity
Inter-dealer broker	Allocation--50% to 70% Equity

broker_type	fund_category
Inter-dealer broker	Mid-Cap Growth
Inter-dealer broker	Bank Loan
Inter-dealer broker	World Small/Mid Stock
Inter-dealer broker	Allocation--70% to 85% Equity
Inter-dealer broker	High Yield Muni
Inter-dealer broker	Long-Short Credit
Inter-dealer broker	Large Growth
Inter-dealer broker	Short-Term Bond
Inter-dealer broker	Allocation--30% to 50% Equity
Inter-dealer broker	Allocation--50% to 70% Equity

broker_type	fund_category
Inter-dealer broker	Ultrashort Bond
Inter-dealer broker	Preferred Stock
Inter-dealer broker	Intermediate Government
Inter-dealer broker	Small Value
Inter-dealer broker	Intermediate-Term Bond
Inter-dealer broker	Allocation--50% to 70% Equity
Inter-dealer broker	Diversified Emerging Mkts
Inter-dealer broker	Intermediate-Term Bond
Inter-dealer broker	World Large Stock
Inter-dealer broker	Allocation--70% to 85% Equity

broker_type	fund_category
Inter-dealer broker	Equity Energy
Inter-dealer broker	World Small/Mid Stock
Inter-dealer broker	Emerging Markets Bond
Inter-dealer broker	World Bond
Inter-dealer broker	Short-Term Bond
Inter-dealer broker	Allocation--70% to 85% Equity
Inter-dealer broker	Foreign Large Blend
Inter-dealer broker	Corporate Bond
Inter-dealer broker	World Large Stock
Inter-dealer broker	Nontraditional Bond
Inter-dealer broker	Foreign Large Value
Inter-dealer broker	Nontraditional Bond
Inter-dealer broker	High Yield Bond
Inter-dealer broker	World Allocation
Inter-dealer broker	Short-Term Bond
Inter-dealer broker	World Allocation
Inter-dealer broker	Bank Loan
Inter-dealer broker	Large Value
Inter-dealer broker	Large Growth
Inter-dealer broker	Multisector Bond
Inter-dealer broker	High Yield Bond
Inter-dealer broker	Convertibles
Inter-dealer broker	Large Blend
Inter-dealer broker	Small Blend
Inter-dealer broker	Large Value
Inter-dealer broker	Allocation--50% to 70% Equity
Inter-dealer broker	Intermediate-Term Bond
Inter-dealer broker	Diversified Emerging Mkts
Inter-dealer broker	Multialternative
Inter-dealer broker	Mid-Cap Growth
Inter-dealer broker	Intermediate-Term Bond
Inter-dealer broker	Bank Loan
Inter-dealer broker	World Allocation
Inter-dealer broker	Target-Date 2040
Inter-dealer broker	Short-Term Bond

Inter-dealer broker	Emerging-Markets Local-Currency Bond
Inter-dealer broker	Mid-Cap Value

broker_type	fund_category
-------------	---------------

broker_type	fund_category
Inter-dealer broker	Emerging-Markets Local-Currency Bond
Inter-dealer broker	Utilities
Inter-dealer broker	Intermediate Government
Inter-dealer broker	World Large Stock
Inter-dealer broker	Intermediate-Term Bond

global_sales
1. 07E+08
7. 48E+05
8. 15E+06
0. 00E+00
1. 09E+06
9. 65E+04
4. 35E+04
4. 81E+04
7. 72E+01
3. 00E+04

global_sales	loyality_Per
1. 07E+08	10. 46375
7. 48E+05	0
8. 15E+06	3. 287194
0. 00E+00	NaN
1. 09E+06	0

9. 65E+04	30. 444123
4. 35E+04	0
4. 81E+04	0
7. 72E+01	100
3. 00E+04	0

global_sales	loyality_Per
77. 23	100
5571. 97	100
245. 76	100
13042. 03	100
27627. 97	99. 313486
4389608. 62	99. 150971
775703. 36	97. 281895
16787455. 29	94. 118092
27142. 96	93. 688971
1203312. 21	83. 121654

global_sales	loyality_Per
1. 07E+08	10. 46375
7. 48E+05	0
8. 15E+06	3. 287194
0. 00E+00	NaN
1. 09E+06	0
9. 65E+04	30. 444123
4. 35E+04	0
4. 81E+04	0
7. 72E+01	100
3. 00E+04	0

```
ng = False).reset_index().rename(columns = {'broker_id': 'No_of_brokers'})
```

Loyalty_Broker_Percentage
58.234295
26.315789
14.091681
0.594228
0.424448
0.339559

global_sales	loyality_Per
1.07E+08	10.46375
7.48E+05	0
8.15E+06	3.287194
0.00E+00	NaN
1.09E+06	0
9.65E+04	30.444123
4.35E+04	0
4.81E+04	0
7.72E+01	100
3.00E+04	0

broker_type	fund_category
Inter-dealer broker	Emerging-Markets Local-Currency Bond
Inter-dealer broker	Utilities

_call", "firm_sales_x", "global_sales_x", "loyalty_Category", "loyalty_Per"]]

state	broker_type
FL	Inter-dealer broker
CT	Inter-dealer broker
GA	Inter-dealer broker

VA	Inter-dealer broker
OH	full-service broker

broker_id', ascending = False)

email_opened	webex_meet	sales_call	firm_sales
NaN	NaN	NaN	174.62
NaN	NaN	NaN	0
NaN	NaN	NaN	0
Y	NaN	NaN	0
Y	NaN	Y	0

	email_opened	webex_meet	sales_call	firm_sales
N	N	N		174.62
N	N	N		0
N	N	N		0
Y	N	N		0
Y	N	Y		0

	email_opened	webex_meet	sales_call	firm_sales
N	N	N		174.62
N	N	N		0
N	N	N		0
Y	N	N		0
Y	N	Y		0

	email_opened	webex_meet	sales_call	firm_sales
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0

	email_opened	webex_meet	sales_call	firm_sales
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
Y	Y	N		0
N	N	N		0
Y	N	N		0

	email_opened	webex_meet	sales_call	firm_sales
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		160313.6
N	N	N		1684.01
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		446.01
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		686.65
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		141.02
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		21907.99
N	N	N		0
N	N	N		32.99
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		548.01

N	N	N	744.67
N	N	N	0

	email_opened	webex_meet	sales_call	firm_sales
--	--------------	------------	------------	------------

	email_opened	webex_meet	sales_call	firm_sales
N	N	N		174.62
N	N	N		0
N	N	N		0
N	N	N		0
N	N	N		0

loyality_Category
Less Inclined Brokers
Non-Committed Brokers
Less Inclined Brokers
Stagnant Brokers
Non-Committed Brokers
Less Inclined Brokers
Non-Committed Brokers
Non-Committed Brokers
Loyal Broker
Non-Committed Brokers

<u>loyality_Catgeory</u>
Less Inclined Brokers
Non-Committed Brokers
Less Inclined Brokers
Stagnant Brokers
Non-Committed Brokers
Less Inclined Brokers
Non-Committed Brokers
Non-Committed Brokers
Loyal Broker
Non-Committed Brokers

<u>email_opened</u>	<u>webex_meet</u>	<u>sales_call</u>	<u>firm_sales</u>
N	N	N	174.62
N	N	N	0

<u>fund_category</u>	<u>email_opened</u>	<u>webex_meet</u>	<u>sales_call</u>
Emerging-Markets Local-Currency Bond	N	N	N
Utilities	N	N	N
Intermediate Government	N	N	N

Intermediate Government	Y	N	N
Target-Date 2050	Y	N	Y

global_sales
174.62
0
0
30709
0

global_sales
174.62
0
0
30709
0

global_sales	state
174.62	FL
0	CT
0	GA
30709	VA
0	OH

global_sales	state
600	TN, TN
0	TN, TN
244.78	TN, TN
75	TN, TN
345.98	TN, TN
0	TN, TN
28803.07	TN, TN
325	TN, TN
25118	TN, TN
4616.81	TN, TN

global_sales	state
600	TNTN
0	TNTN
244.78	TNTN
75	TNTN
345.98	TNTN
0	TNTN
28803.07	TNTN
325	TNTN
25118	TNTN
4616.81	TNTN

global_sales	state
3075.71	WY
12696.61	WY
0	WY
10519.45	WY
40405.09	WY
73.13	WY
5261.12	WY
156791.34	WY
0	WY
450	WY

global_sales	state
0	MO
5110.16	PA
0	MO
0	PA
0	MO
670.64	CA
162621.11	PA
1684.01	PA
4117.37	PA
0	MO
0	MO
12786.01	PA
0	MO
0	MO
692287	CA
4500	CA
63404	CA
12590.98	PA
165100	MO
663179.12	CA
947.5	CA
0	PA
600	CA
1569.25	PA
62.5	CA
16148.94	PA
60875	CA
25197.99	PA
0	PA
32.99	PA
0	MO
0	MO
8933.8	PA
168.8	PA
548.01	PA

744.67	PA
0	PA

global_sales	state
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global_sales	state
174.62	FL
0	CT
0	GA
4807.68	MD
600	TX

global_sales	state
174.62	FL
0	CT

firm_sales_x	global_sales_x	loyality_Category	loyality_Per
174.62	174.62	Less Inclined Brokers	10.46375
0	0	Less Inclined Brokers	10.46375
0	0	Less Inclined Brokers	10.46375

0	30709	Non-Committed Brokers	0
0	0	Less Inclined Brokers	2.472971