Homework 2 - IEEE Fraud Detection

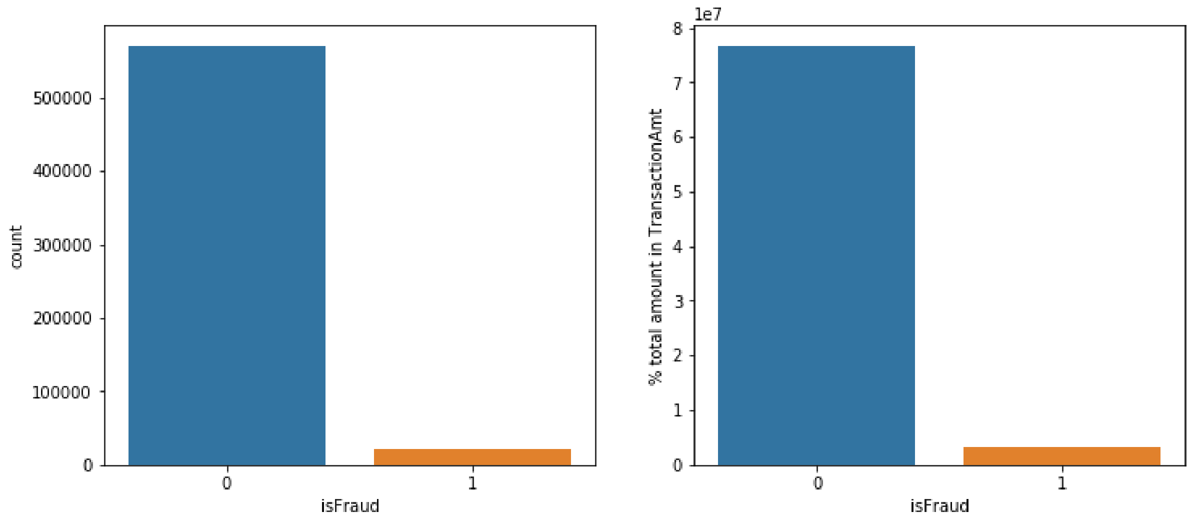
For all parts below, answer all parts as shown in the Google document for Homework 2. Be sure to include both code that justifies your answer as well as text to answer the questions. We also ask that code be commented to make it easier to follow.

Part 1 - Fraudulent vs Non-Fraudulent Transaction

In [3]:
```
# TODO: code and runtime results
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
def myplot(file,col,a,b):
    temp = pd.crosstab(file[col], trainData['isFraud'], normalize='index') * 1
00
    temp = temp.reset_index()
    temp.rename(columns={0:'NoFraud', 1:'Fraud'}, inplace=True)

    plt.figure(figsize=(a,b))
    plt.suptitle(f"{col} Distributions")
    cplot=sns.countplot(x=col,data=file,order=list(temp[col].values))
    pplot=cplot.twinx()
    pplot=sns.pointplot(x=col,y='Fraud',data=temp,color='Black',order=list(tem
p[col].values))
    cplot.set_xticklabels(cplot.get_xticklabels(),rotation=45)
    pplot.set_ylabel('% fof fraud transactions')
    return(cplot,pplot)
fields=['TransactionID','isFraud','TransactionDT','TransactionAmt','ProductCD'
,'card4','card6','P_emaildomain','R_emaildomain','addr1','addr2','dist1','dist
2']
trainData=pd.read_csv("train_transaction.csv",skipinitialspace=True,usecols=fi
elds)
fields1=['TransactionID','DeviceType','DeviceInfo']
trainIdentity=pd.read_csv("train_identity.csv",skipinitialspace=True,usecols=f
ields1)
mergeset=pd.merge(trainData,trainIdentity,how='left',left_on='TransactionID',
right_on='TransactionID')
```

In [4]:
```
plt.figure(figsize=(12,5))
plt.subplot(121)
plot_tc=sns.countplot(x='isFraud', data=trainData)
transactionPercent=(trainData.groupby(['isFraud'])['TransactionAmt'].sum())
transactionPercent=transactionPercent.reset_index()
plt.subplot(122)
plot_tp=sns.barplot(x='isFraud', y='TransactionAmt', data=transactionPercent)
plot_tp.set_ylabel("% total amount in TransactionAmt")
```

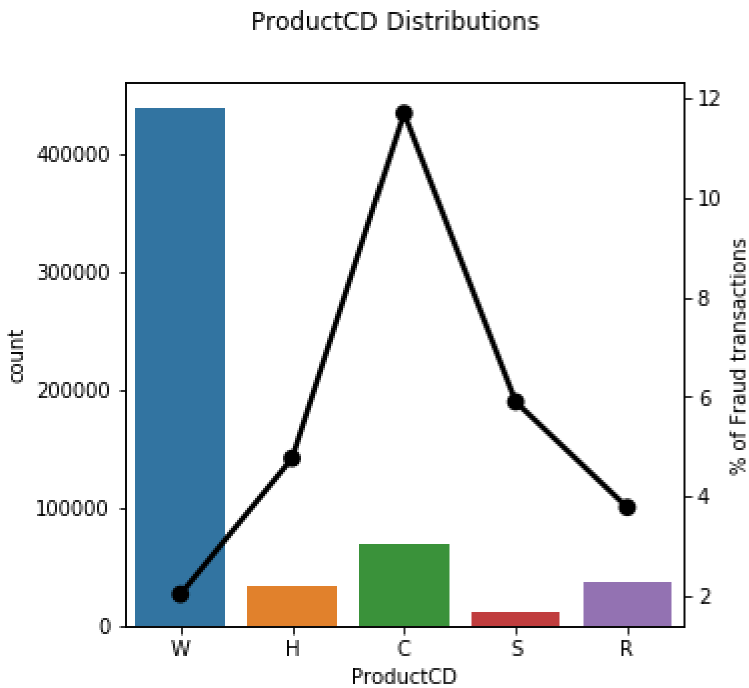
Out[4]:
```
Text(0, 0.5, '% total amount in TransactionAmt')
```



We see that the number of fraudulent transactions are very small compared to the total number of transactions. Also the sum of transaction amounts in the fraudulent transactions is less.

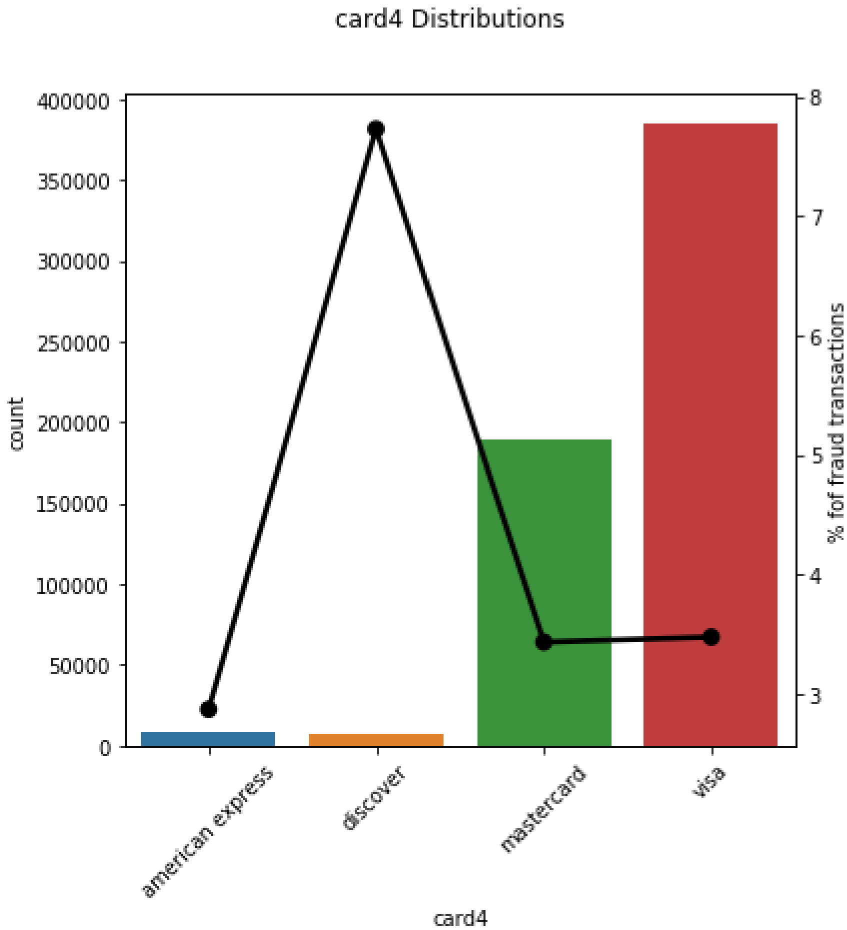
In [5]:
```
tmp = pd.crosstab(mergeset['ProductCD'],mergeset['isFraud'],normalize='index')
*100
tmp = tmp.reset_index()
tmp.rename(columns={0:'NoFraud', 1:'Fraud'},inplace=True)
plt.figure(figsize=(5,5))
plt.suptitle("ProductCD Distributions")
cplot=sns.countplot(x='ProductCD',data=mergeset)

pplot=cplot.twinx()
pplot=sns.pointplot(x='ProductCD',y='Fraud',data=tmp,color='Black',order=['W',
'H','C','S','R'])
pplot.set_ylabel('% of Fraud transactions')
```

Out[5]:
```
Text(0, 0.5, '% of Fraud transactions')
```



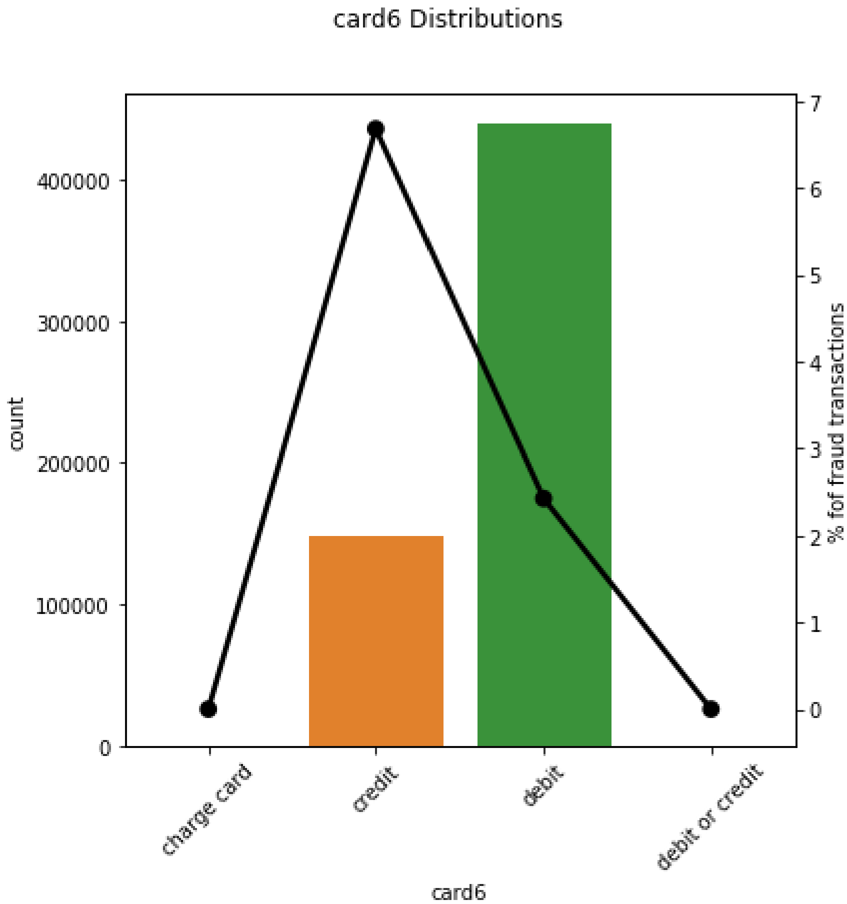
Among all the products available, product c has the highest percentage of fraudulent transactions. Since the number of transactions on Product W are maximum but the fraudulent percentage is minimum, it is least prone to fraudulent transactions.

In [6]:
```
cplotCard4,pplotCard4=myplot(mergeset,'card4',6,6)
```



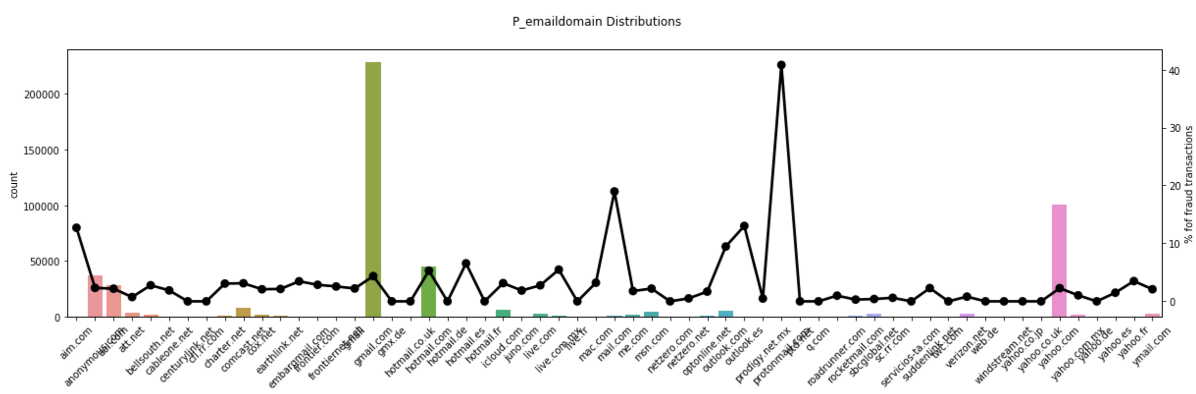
Of all the available cards4 values, the highest percentage of fraudulent transactions are through Discover cards and the least through American Express. But the number of transactions through both of them are very less compared to number of transactions through Visa. Eventhough, the percentage of fraudulent transactions through Visa is less, due to its huge number, it contributes the highest to the number of fraudulent transactions.

In [7]:
```
cplotCard6,pplotCard6=myplot(mergeset,'card6',6,6)
```



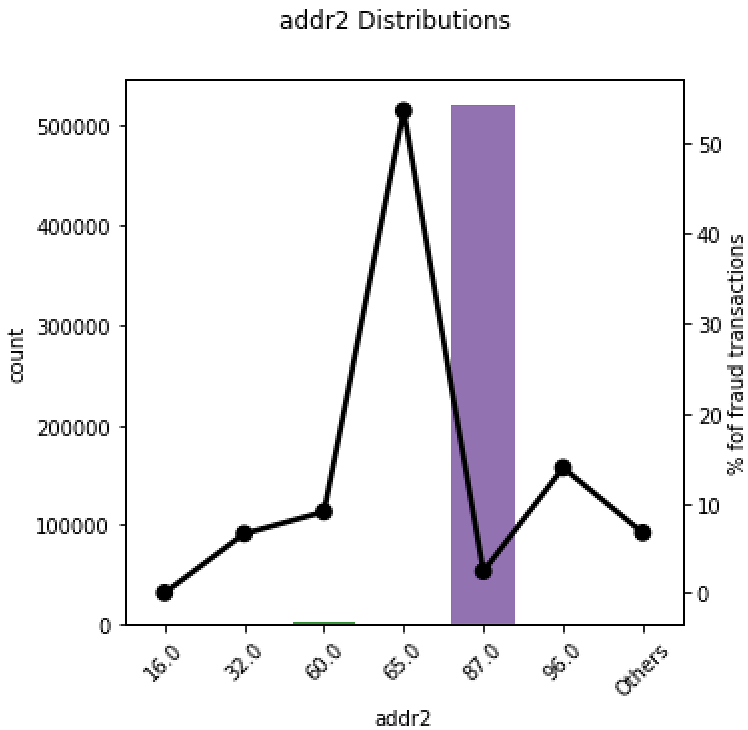
We see that Credit cards have the highest percentage of fraudulent transactions while the number of fraudulent ones through debit are comparitively lesser.

In [8]:
```
cplotPdom,pplotPdom=myplot(mergeset,'P_emaildomain',20,5)
```



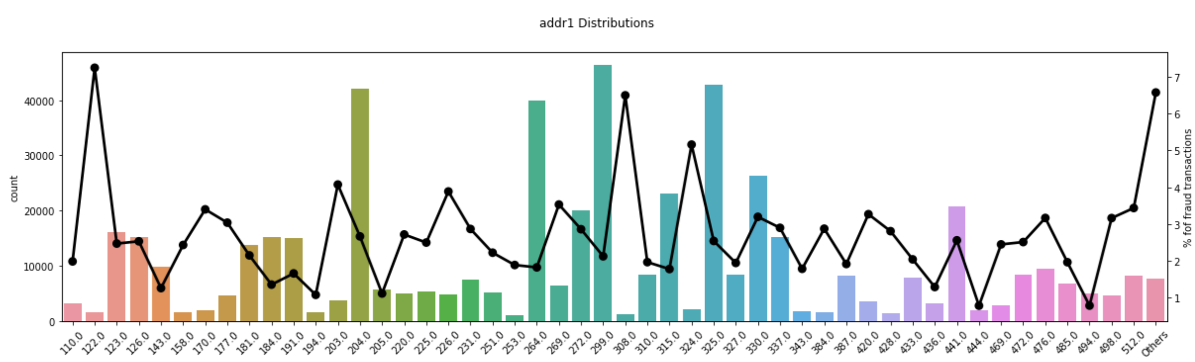
Of all the email domains present, the highest number of transactions are through gmail.com. But when we consider the percentages of errors, we have mail.com and protonmail.com that have the highest fraudulent transaction percentages.

In [9]:
```
mergeset.loc[mergeset.addr2.isin(mergeset.addr2.value_counts()[mergeset.addr2.
value_counts()<= 50].index), 'addr2'] = "Others"
cplotAddr2,pplotAddr2=myplot(mergeset,'addr2',5,5)
```

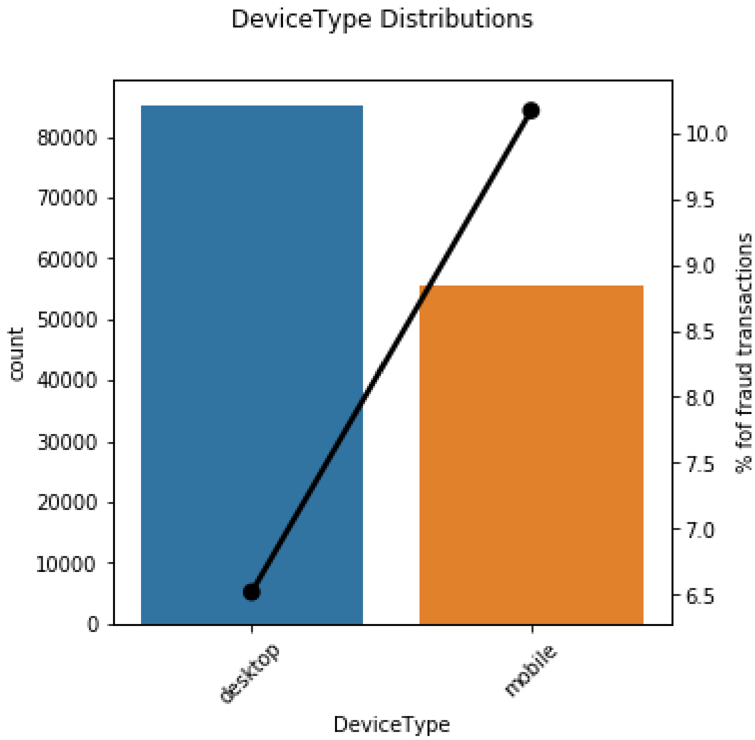


Plotting the graph of all the values in addr2 field after cleaning the data to exclude values with too small transaction frequencies, I see that most of the transactions are from the 87.0 locations, but among the few transactions from the area 65.0, most of the transactions are fraudulent. I think this is an interesting plot as this is the first plot that denotes more than 50% chance of a transaction being fraud given the transaction has a value of 65.0 in addr2 field.

In [10]:
```
mergeset.loc[mergeset.addr1.isin(mergeset.addr1.value_counts()[mergeset.addr1.
value_counts()<= 1000].index), 'addr1'] = "Others"
cplotAddr1,pplotAddr1=myplot(mergeset,'addr1',20,5)
```

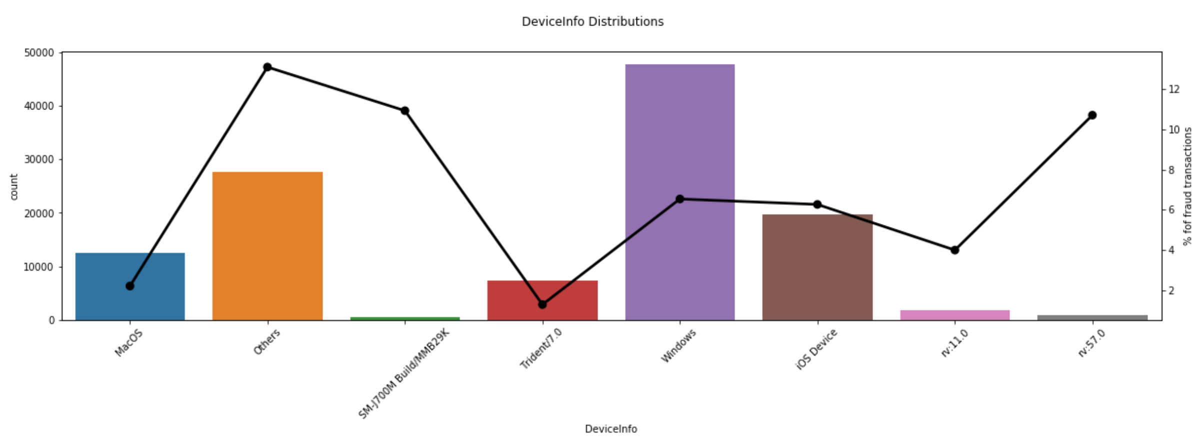


In [11]:
```
cplotDev,pplotDev=myplot(mergeset,'DeviceType',5,5)
```



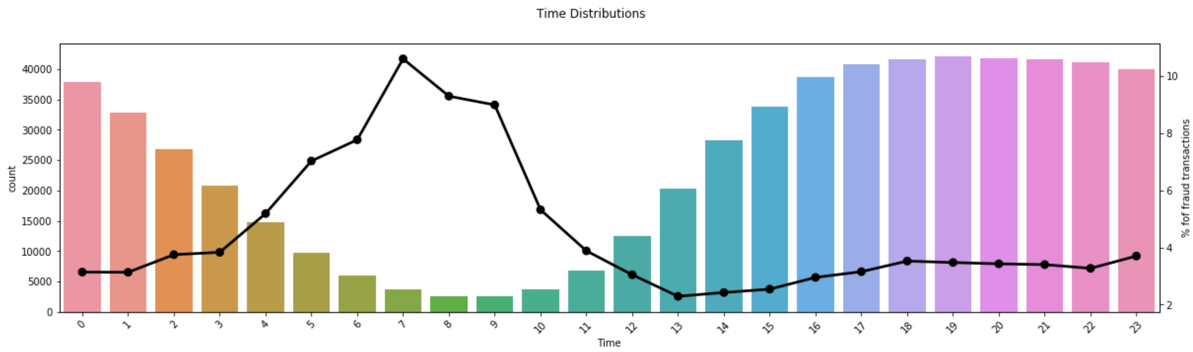
This gives us a relation that most of the fraudulent transactions originate from mobiles.

In [12]:
```
mergeset.loc[mergeset.DeviceInfo.isin(mergeset.DeviceInfo.value_counts()[merge
set.DeviceInfo.value_counts() <500 ].index), 'DeviceInfo'] = "Others"
cplotDevI,pplotDevI=myplot(mergeset,'DeviceInfo',20,5)
```



The above plot suggests that most of the fraudulent transactions come from an unknown operating system rather than from a stable and known Operating System.

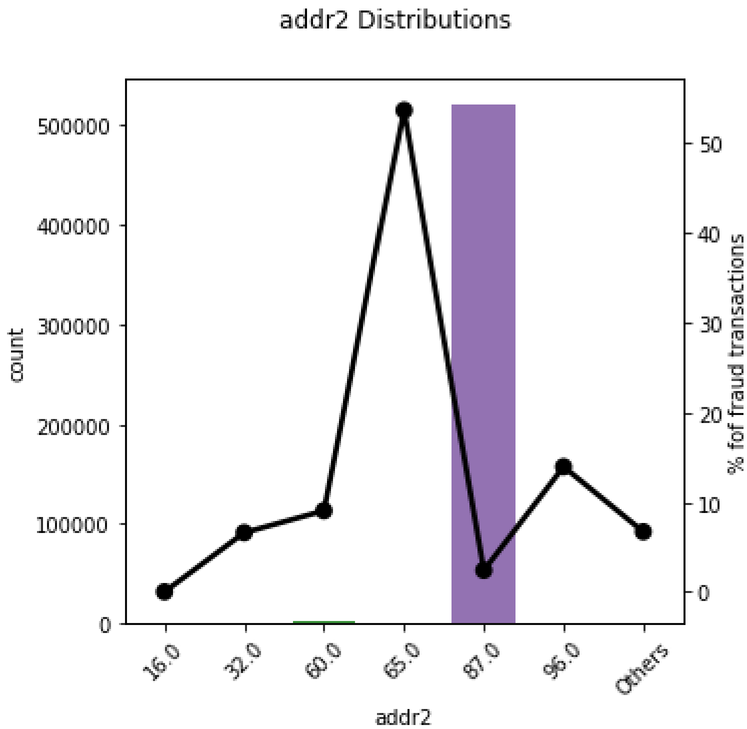
In [13]:
```
mergeset['Day']=(mergeset['TransactionDT']/(24*60*60)-1).astype(int)
mergeset['Time']=((mergeset['TransactionDT']%(24*60*60))/3600).astype(int)
cplotTime,pplotTime=myplot(mergeset,'Time',20,5)
```

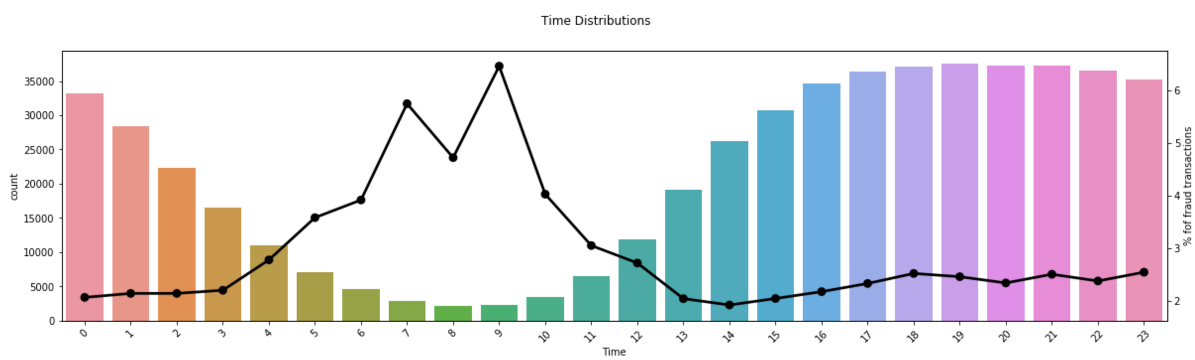


From the above plot, the waking hours of the general populations can be estimated. Since we see a gradual decrease inn the initial hours followed by an increase, we can estimmate that the general population wakes up around the 12th hour.

Part 2 - Transaction Frequency

In [14]:
```
# TODO: code to generate the frequency graph
cplotAddr2,pplotAddr2=myplot(mergeset,'addr2',5,5)
cplotTime,pplotTime=myplot(mergeset[mergeset.addr2.isin([87.0])],'Time',20,5)
```





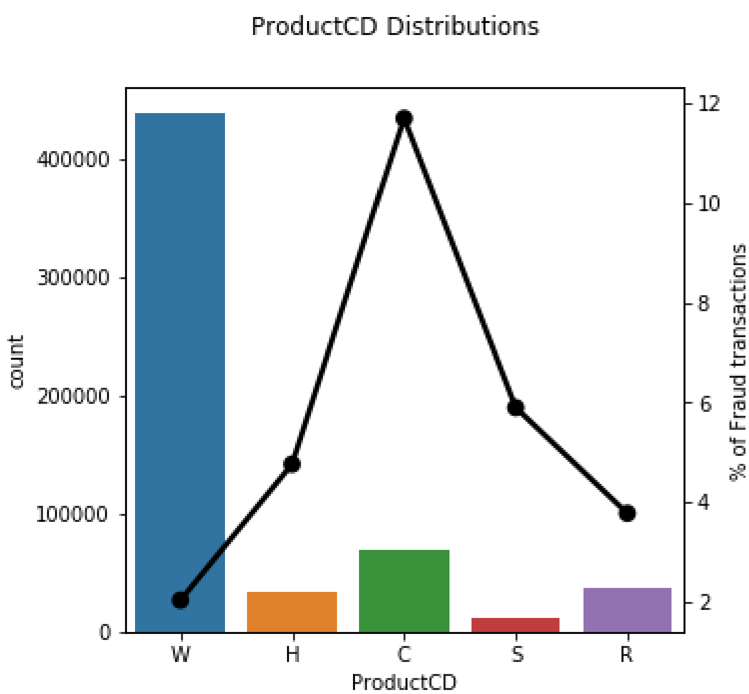
I see that the maximum of the transactions are from the loaction with the Addr2 fiels "87.0". On plotting the countplot of the number of transactions done in each hour of the day, I can see that the number of transactions on average are maximum between 0-4 hours and 13-23 hours. Assuming that a general population sleeps for 8 hours a day, the waking hour at location "87.0" is around 12th hour.

Part 3 - Product Code

In [15]:
```
# TODO: code to analyze prices for different product codes
tmp = pd.crosstab(mergeset['ProductCD'],mergeset['isFraud'],normalize='index')
*100
tmp = tmp.reset_index()
tmp.rename(columns={0:'NoFraud', 1:'Fraud'},inplace=True)
plt.figure(figsize=(5,5))
plt.suptitle("ProductCD Distributions")
cplot=sns.countplot(x='ProductCD',data=mergeset)

pplot=cplot.twinx()
pplot=sns.pointplot(x='ProductCD',y='Fraud',data=tmp,color='Black',order=['W',
'H','C','S','R'])
pplot.set_ylabel('% of Fraud transactions')
tmp1=mergeset.groupby('ProductCD')['TransactionAmt']
tmp1.describe()
```

Out[15]:

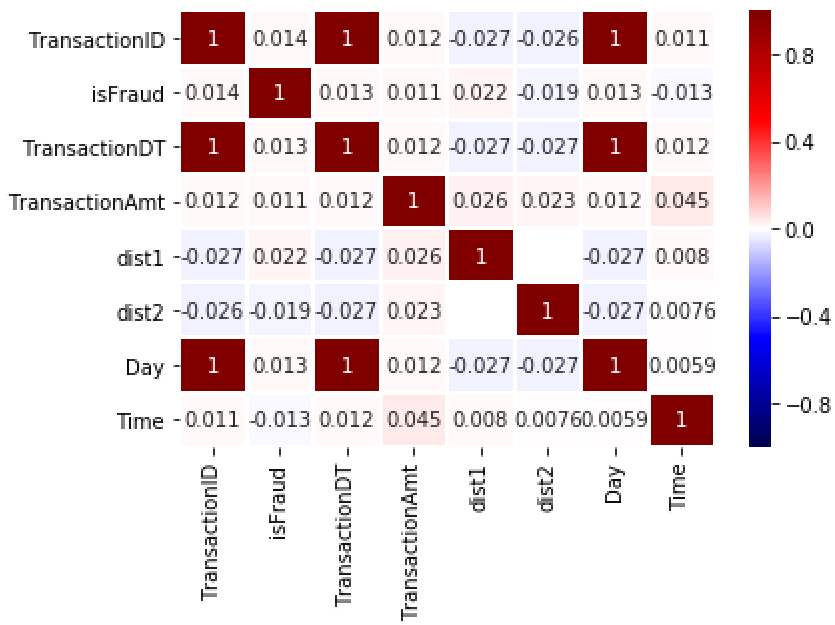
ProductCD	count	mean	std	min	25%	50%	75%	max
C	68519.0	42.872353	38.943070	0.251	18.423	31.191	54.102	712.896
H	33024.0	73.170058	61.950955	15.000	35.000	50.000	100.000	500.000
R	37699.0	168.306188	142.035568	25.000	100.000	125.000	200.000	1800.000
S	11628.0	60.269487	80.546775	5.000	20.000	35.000	80.000	1550.000
W	439670.0	153.158554	268.733692	1.000	49.000	78.500	146.000	31937.391

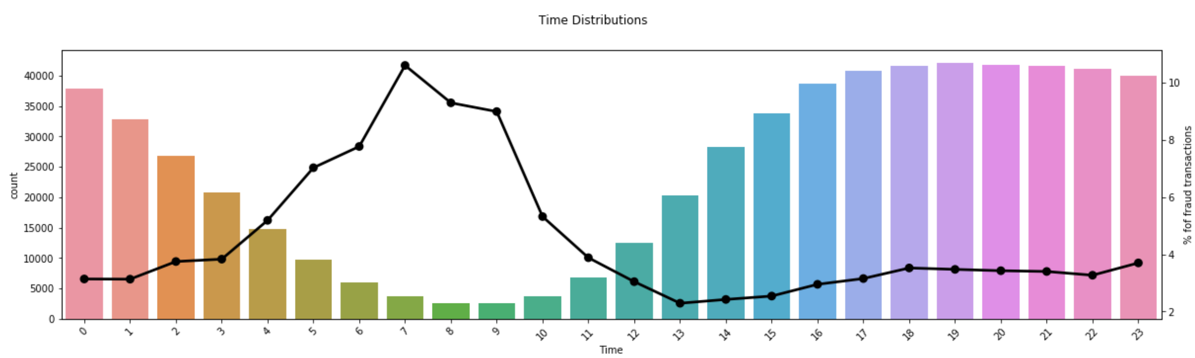


By grouping the dataset with ProductCD, it is see that every metric like the mean, min, first quartile etc are least for product C. So this can be considered as the cheapest product. For the most expensive product, both Product R and W have similar values in each of the above metrics except fro the max. Since Product W has the highest number of transactions, it can be considered the most frequently bought product. The highest value of a transaction on Product W is comparitively higher than the max of Product R. But that could be an outlier as other metrics on Product R are higher. So I would consider Product R to be the most expensive product.

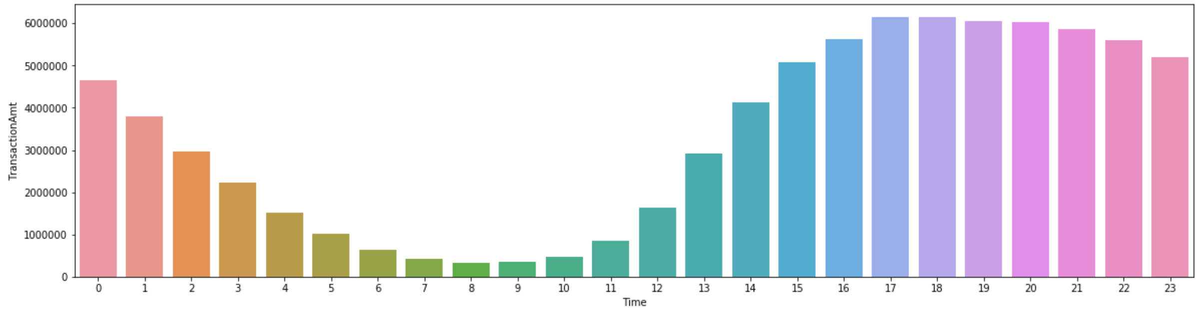
Part 4 - Correlation Coefficient

In [16]:
```
# TODO: code to calculate correlation coefficient
sns.heatmap(mergeset.corr(), vmin=-1, vmax=1, cmap='seismic', linewidths=1, an
not=True);
cplotTime,pplotTime=myplot(mergeset,'Time',20,5);
```





In [40]:
```
y=mergeset.groupby(['Time'])['TransactionAmt'].sum()
y=y.reset_index()
plt.figure(111,figsize=(20,5))
cplot=sns.barplot(x=y['Time'],y=y['TransactionAmt'])
```



The purchase amount follows a trend with the hour of the day. It gradually decreases for a few hours and then starts increasing. This usually signifies the sleeping hours and the waking hours of the general population. The Transaction amount is a feature that has the highest correlation in the complete data set with the hour of the day(Time) and has a value of "0.045".

Part 5 - Interesting Plot

In [41]:
```
# TODO: code to generate the plot here.
interesting=mergeset.copy()
interesting.sort_values('TransactionAmt').head(50)
```

Out[41]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card4	card6	
374299	3361299	0	9324090	0.251	C	visa	debit	
367961	3354961	0	9147032	0.272	C	mastercard	credit	
205872	3192872	1	4734702	0.292	C	visa	debit	
205865	3192865	1	4734545	0.292	C	visa	debit	
29976	3016976	1	757661	0.292	C	visa	debit	
205382	3192382	1	4724798	0.292	C	visa	debit	
205370	3192370	1	4724487	0.292	C	visa	debit	
205393	3192393	1	4725018	0.350	C	visa	debit	
492354	3479354	0	12851308	0.364	C	visa	credit	
41962	3028962	1	1021983	0.424	C	visa	credit	(
41932	3028932	1	1021670	0.424	C	visa	credit	(
42219	3029219	1	1024699	0.424	C	visa	credit	(
42265	3029265	1	1025159	0.424	C	visa	credit	(
22794	3009794	1	590558	0.467	C	visa	debit	
22733	3009733	1	589789	0.467	C	visa	debit	
47125	3034125	1	1119268	0.467	C	mastercard	debit	
31567	3018567	1	777309	0.467	C	visa	debit	
47265	3034265	1	1121075	0.467	C	mastercard	debit	
42215	3029215	1	1024643	0.467	C	visa	credit	(
20640	3007640	1	526865	0.484	C	visa	credit	(
307933	3294933	0	7664404	0.498	C	visa	debit	
548148	3535148	0	14483222	0.499	C	visa	debit	
361693	3348693	0	8971992	0.543	C	mastercard	credit	
309509	3296509	0	7691556	0.570	C	visa	debit	
169055	3156055	1	3625468	0.583	C	visa	credit	
170545	3157545	1	3688788	0.583	C	visa	debit	
169847	3156847	1	3647463	0.583	C	visa	credit	
169046	3156046	1	3625343	0.583	C	visa	credit	
171176	3158176	1	3699772	0.583	C	visa	credit	
542730	3529730	0	14320719	0.588	C	mastercard	debit	(
451774	3438774	0	11542573	0.615	C	visa	credit	
552252	3539252	0	14590490	0.615	C	visa	credit	(
489687	3476687	0	12770179	0.615	C	mastercard	debit	(
489681	3476681	0	12770004	0.615	C	mastercard	credit	(
380839	3367839	0	9522443	0.687	C	visa	debit	

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card4	card6
520640	3507640	0	13661590	0.755	C	visa	debit
520637	3507637	0	13661524	0.755	C	visa	debit
583480	3570480	0	15607182	0.758	C	visa	debit
353386	3340386	0	8719275	0.770	C	visa	debit
290060	3277060	0	7149914	0.786	C	visa	credit
390363	3377363	0	9806790	0.861	C	mastercard	credit
547551	3534551	0	14451641	0.878	C	mastercard	debit
547550	3534550	0	14451589	0.878	C	mastercard	debit
547547	3534547	0	14451520	0.878	C	mastercard	debit
547545	3534545	0	14451457	0.878	C	mastercard	debit
547541	3534541	0	14451382	0.878	C	visa	debit
550551	3537551	0	14540839	0.878	C	mastercard	debit
547540	3534540	0	14451331	0.878	C	visa	debit
547539	3534539	0	14451279	0.878	C	visa	debit
534641	3521641	0	14076767	0.878	C	visa	debit

On sorting the dataset by "TransactionAmt" column, I see that most of the times when the first transaction of a specific amount is a fraudulent transaction, the following transactions of the same amount are also fraudulent.

I also observed that dist1 and dist2 valus for a specific transaction are exclusively present,i.e if one is present, the other is filled with NaN.

Part 6 - Prediction Model

In [116]:

```
# TODO: code for your final model
import pandas as pd
from catboost import CatBoostRegressor
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder


trainData=pd.read_csv("train_transaction.csv",skipinitialspace=True)
trainIdentity=pd.read_csv("train_identity.csv",skipinitialspace=True)
mergetrainset=pd.merge(trainData,trainIdentity,how='left',left_on='Transaction
ID', right_on='TransactionID')
testData=pd.read_csv("test_transaction.csv",skipinitialspace=True)
testIdentity=pd.read_csv("test_identity.csv",skipinitialspace=True)
mergetestset=pd.merge(testData,testIdentity,how='left',left_on='TransactionID'
, right_on='TransactionID')
fields=['ProductCD','card1','card2','card3','card4','card5','card6','addr1','a
ddr2','dist1','dist2','P_emaildomain','R_emaildomain','C1','C2','C3','C4','C5'
,'C6','C7','C8','C9','C10','C11','C12','C13','C14','D1','D2','D3','D4','D5','D
6','D7','D8','D9','D10','D11','D12','D13','D14','D15','M1','M2','M3','M4','M5'
,'M6','M7','M8','M9','V1','V2','V3','V4','V5','V6','V7','V8','V9','V10','V11',
'V12','V13','V14','V15','V16','V17','V18','V19','V20','V21','V22','V23','V24',
'V25','V26','V27','V28','V29','V30','V31','V32','V33','V34','V35','V36','V37',
'V38','V39','V40','V41','V42','V43','V44','V45','V46','V47','V48','V49','V50',
'V51','V52','V53','V54','V55','V56','V57','V58','V59','V60','V61','V62','V63',
'V64','V65','V66','V67','V68','V69','V70','V71','V72','V73','V74','V75','V76',
'V77','V78','V79','V80','V81','V82','V83','V84','V85','V86','V87','V88','V89',
'V90','V91','V92','V93','V94','V95','V96','V97','V98','V99','V100','V101','V10
2','V103','V104','V105','V106','V107','V108','V109','V110','V111','V112','V11
3','V114','V115','V116','V117','V118','V119','V120','V121','V122','V123','V12
4','V125','V126','V127','V128','V129','V130','V131','V132','V133','V134','V13
5','V136','V137','V138','V139','V140','V141','V142','V143','V144','V145','V14
6','V147','V148','V149','V150','V151','V152','V153','V154','V155','V156','V15
7','V158','V159','V160','V161','V162','V163','V164','V165','V166','V167','V16
8','V169','V170','V171','V172','V173','V174','V175','V176','V177','V178','V17
9','V180','V181','V182','V183','V184','V185','V186','V187','V188','V189','V19
0','V191','V192','V193','V194','V195','V196','V197','V198','V199','V200','V20
1','V202','V203','V204','V205','V206','V207','V208','V209','V210','V211','V21
2','V213','V214','V215','V216','V217','V218','V219','V220','V221','V222','V22
3','V224','V225','V226','V227','V228','V229','V230','V231','V232','V233','V23
4','V235','V236','V237','V238','V239','V240','V241','V242','V243','V244','V24
5','V246','V247','V248','V249','V250','V251','V252','V253','V254','V255','V25
6','V257','V258','V259','V260','V261','V262','V263','V264','V265','V266','V26
7','V268','V269','V270','V271','V272','V273','V274','V275','V276','V277','V27
8','V279','V280','V281','V282','V283','V284','V285','V286','V287','V288','V28
9','V290','V291','V292','V293','V294','V295','V296','V297','V298','V299','V30
0','V301','V302','V303','V304','V305','V306','V307','V308','V309','V310','V31
1','V312','V313','V314','V315','V316','V317','V318','V319','V320','V321','V32
2','V323','V324','V325','V326','V327','V328','V329','V330','V331','V332','V33
3','V334','V335','V336','V337','V338','V339','id_01','id_02','id_03','id_04',
'id_05','id_06','id_07','id_08','id_09','id_10','id_11','id_12','id_13','id_1
4','id_15','id_16','id_17','id_18','id_19','id_20','id_21','id_22','id_23','id
_24','id_25','id_26','id_27','id_28','id_29','id_30','id_31','id_32','id_33',
'id_34','id_35','id_36','id_37','id_38','DeviceType','DeviceInfo']
for cl in fields:
    x=mergetrainset[cl].mode()[0]
```

```
    y=mergetestset[cl].mode()[0]
    mergetrainset[cl].fillna(x,inplace=True)
    mergetestset[cl].fillna(y,inplace=True)
mergetrainset['Time']=((mergetrainset['TransactionDT']%(24*60*60))/3600).astyp
e(int)
mergetestset['Time']=((mergetestset['TransactionDT']%(24*60*60))/3600).astype(
int)
mergetrainset1=mergetrainset.drop(['isFraud','TransactionDT'], axis=1)
mergetestset=mergetestset.drop(['TransactionDT'],axis=1)
enc=LabelEncoder()
for cl in fields:
    cols=list(mergetrainset1[cl].values.astype(str))+list(mergetestset[cl].val
ues.astype(str))
    enc.fit(cols)
    mergetrainset1[cl]=enc.transform(mergetrainset1[cl].astype(str))
    mergetestset[cl]=enc.transform(mergetestset[cl].astype(str))
X_train, X_test, y_train, y_test = train_test_split(mergetrainset1, mergetrain
set['isFraud'], test_size=0.1,random_state = 42)

clf = CatBoostRegressor(iterations=2000,task_type="GPU",devices='0:1')
clf.fit(X_train,y_train,verbose=False)
preds=clf.predict(X_test)
new_preds=clf.predict(mergetestset)
new_preds.round()
output=pd.DataFrame({'TransactionID': mergetestset['TransactionID'], 'isFraud'
: new_preds[:]})
output.to_csv('submission.csv', index=False)
```

```
0.9767670267890406
```

For my prediction model, I am using all the features that were given as a part of the dataset. I am replacing all the NaN values with the most frequent value(mode) of that column. For the regression model, I am using the CatBoostRegressor which makes use of decision tree based learning algorithms. I have tried using other learning models like lightgbm and XGBoostRegressor but I did not get similar results is them.

Part 7 - Final Result

Report the rank, score, number of entries, for your highest rank. Include a snapshot of your best score on the leaderboard as confirmation. Be sure to provide a link to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face and affiliation with SBU.

Kaggle Link: [https://www.kaggle.com/abhinaymadunanthu (https://www.kaggle.com/abhinaymadunanthu)](https://www.kaggle.com/abhinaymadunanthu)

Highest Rank: 4640

Score: 0.9081

Number of entries: 23

INCLUDE IMAGE OF YOUR KAGGLE RANKING

4634	bisman singh	0.9087	1	7d
4635	Nakul Joshi	0.9087	1	1mo
4636	parthipanvajeravelu	0.9086	2	2d
4637	junehyung	0.9082	37	17d
4638	Neil Kloper	0.9082	18	1mo
4639	Sobih	0.9082	8	2mo
4640	**Abhinay Reddy Madunanthu**	0.9081	23	5m

Your Best Entry ↑

Your submission scored 0.9081, which is an improvement of your previous score of 0.8941. Great job! Tweet this!

4641	ChristosGlymidakis	0.9080	3	2d
4642	Anonymous73322	0.9079	2	2mo
4643	Rohan George Thampi	0.9078	2	1mo
4644	amitb0	0.9078	5	2mo
4645	Tharindu Gangoda </> IEEE Fraud Detection	0.9077	3	5d

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