Untitled

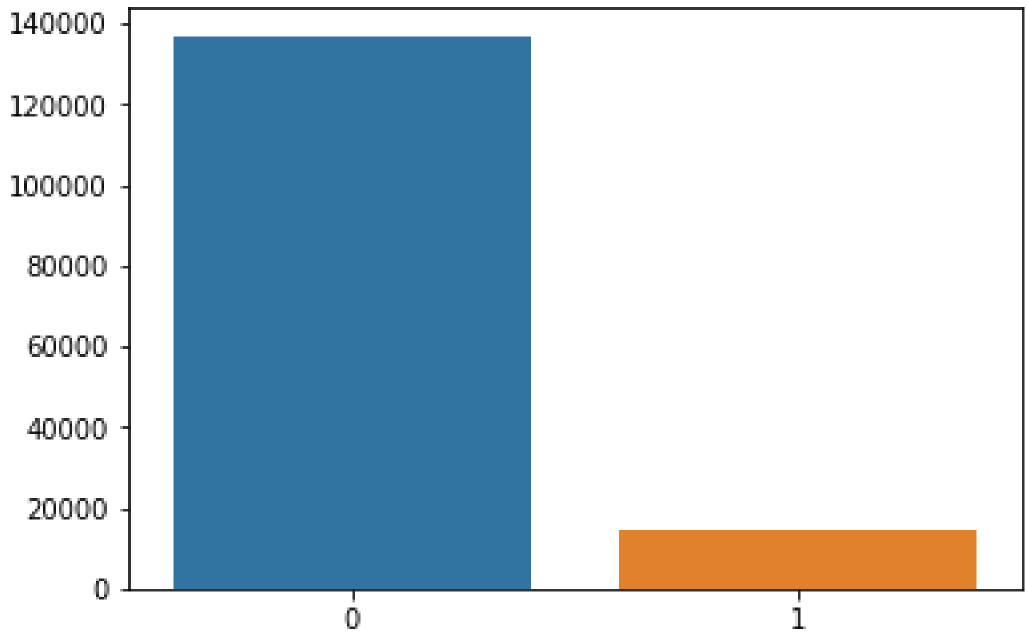
February 7, 2018

```
In [1]: import pandas as pd
        import numpy as np
        from matplotlib import pyplot as plt
        import seaborn as sns
        import datetime,re

In [26]: fraud_data = pd.read_csv('/home/nikit/Desktop/Take_home_Challenges/Fraudulent_Activity/
         ip_address = pd.read_csv('/home/nikit/Desktop/Take_home_Challenges/Fraudulent_Activity/

In [7]: if len(fraud_data)==len(np.unique(fraud_data.user_id)):
            print 'ok'
        len(fraud_data)

ok

Out[7]: 151112

In [4]: none = 'Not Found'
        country = []
        for i, ip_add in enumerate(fraud_data['ip_address']):
            temp = ip_address[(ip_add>=ip_address.lower_bound_ip_address) & (ip_add<=ip_address.
            if len(temp)==1:
                t = temp.country.values
                t = t[0]
                country.append(t)
            else:
                country.append(none)

        fraud_data['country'] = country
        fraud_data.country.value_counts()

Out[4]: United States                    58049
        Not Found                        21966
        China                            12038
        Japan                             7306
        United Kingdom                    4490
        Korea Republic of                 4162
```

Germany	3646
France	3161
Canada	2975
Brazil	2961
Italy	1944
Australia	1844
Netherlands	1680
Russian Federation	1616
India	1310
Taiwan; Republic of China (ROC)	1237
Mexico	1121
Sweden	1090
Spain	1027
South Africa	838
Switzerland	785
Poland	729
Argentina	661
Indonesia	649
Norway	609
Colombia	602
Turkey	568
Viet Nam	550
Romania	525
Denmark	490
	...
Antigua and Barbuda	3
Virgin Islands (U.S.)	3
Bermuda	2
Lesotho	2
Fiji	2
Liechtenstein	2
Maldives	2
Benin	2
Burkina Faso	2
Gibraltar	2
Bhutan	2
Saint Kitts and Nevis	2
Bonaire; Sint Eustatius; Saba	1
Niger	1
Madagascar	1
Turkmenistan	1
British Indian Ocean Territory	1
Tajikistan	1
Yemen	1
Cape Verde	1
Saint Martin	1
Myanmar	1
Burundi	1

```
Guadeloupe                       1
Gambia                           1
San Marino                       1
Vanuatu                          1
Nauru                            1
Dominica                         1
South Sudan                      1
Name: country, Length: 182, dtype: int64
```

In [6]:
```python
classes = fraud_data['class'].value_counts()
sns.barplot(x=classes.index,y=classes.values)
plt.show()
```



In [8]:
```python
fraud_data.describe()
```

Out[8]:

	user_id	purchase_value	age	ip_address
count	151112.000000	151112.000000	151112.000000	1.511120e+05
mean	200171.040970	36.935372	33.140704	2.152145e+09
std	115369.285024	18.322762	8.617733	1.248497e+09
min	2.000000	9.000000	18.000000	5.209350e+04
25%	100642.500000	22.000000	27.000000	1.085934e+09
50%	199958.000000	35.000000	33.000000	2.154770e+09
75%	300054.000000	49.000000	39.000000	3.243258e+09
max	400000.000000	154.000000	76.000000	4.294850e+09

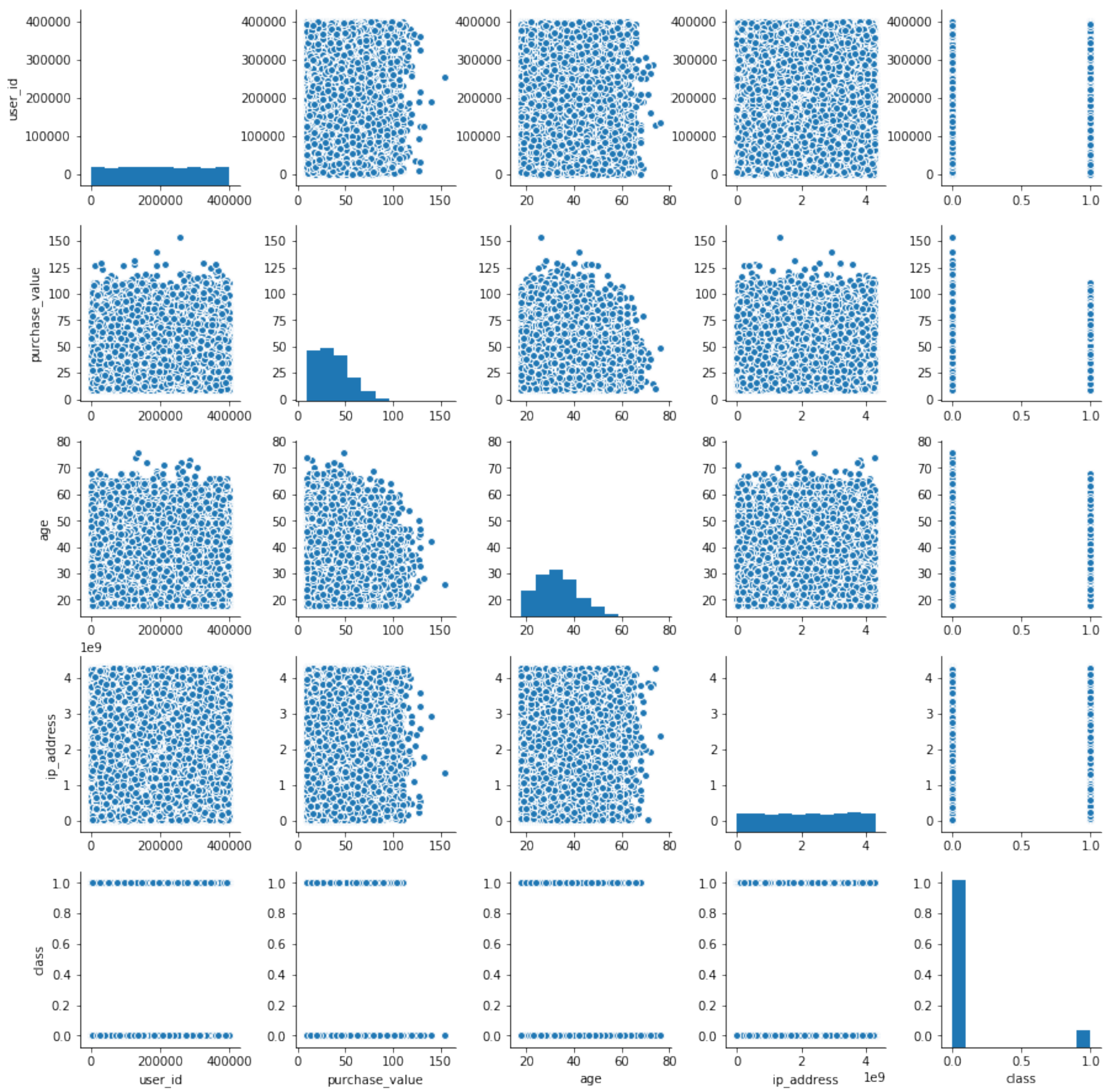
\

class

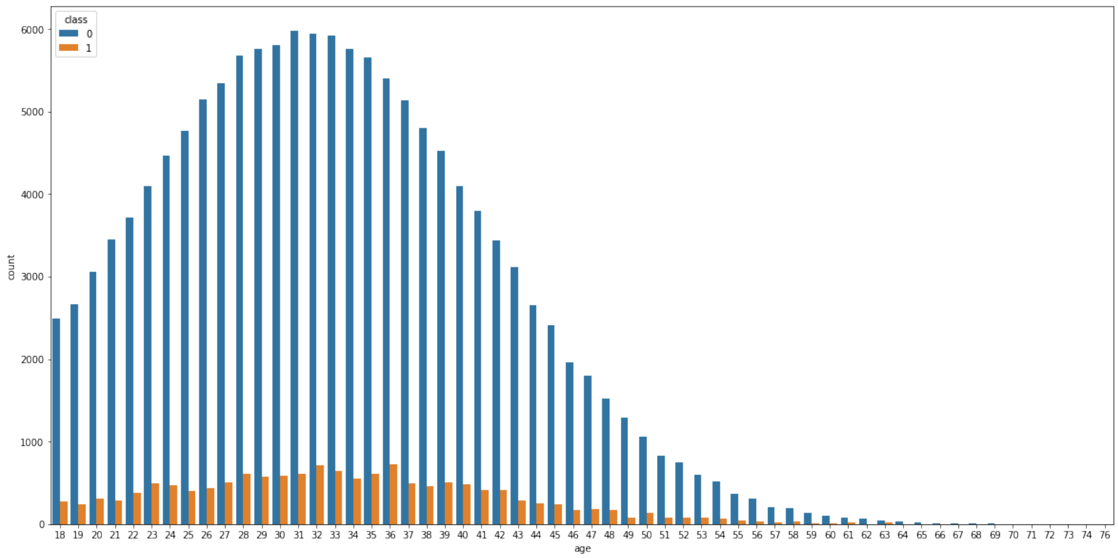
```
count    151112.000000
mean          0.093646
std           0.291336
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max           1.000000
```

In [16]:
```
plt.figure(figsize=(10,10))
sns.pairplot(data=fraud_data)
plt.show()
```

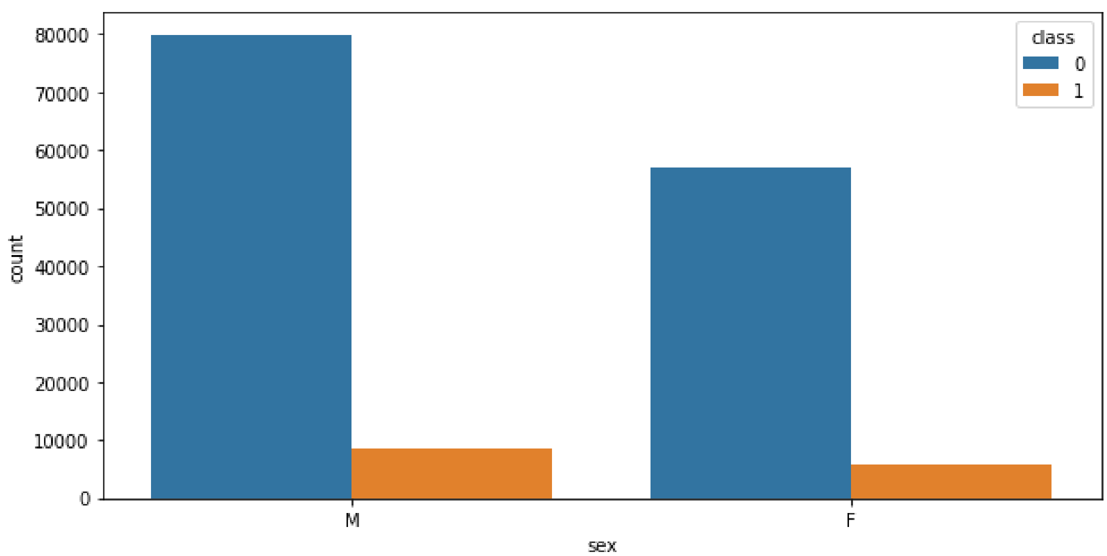
<matplotlib.figure.Figure at 0x7f757d24b890>



In [19]:
```
plt.figure(figsize=(20,10))
sns.countplot(x='age',hue='class',data=fraud_data)
plt.show()
```

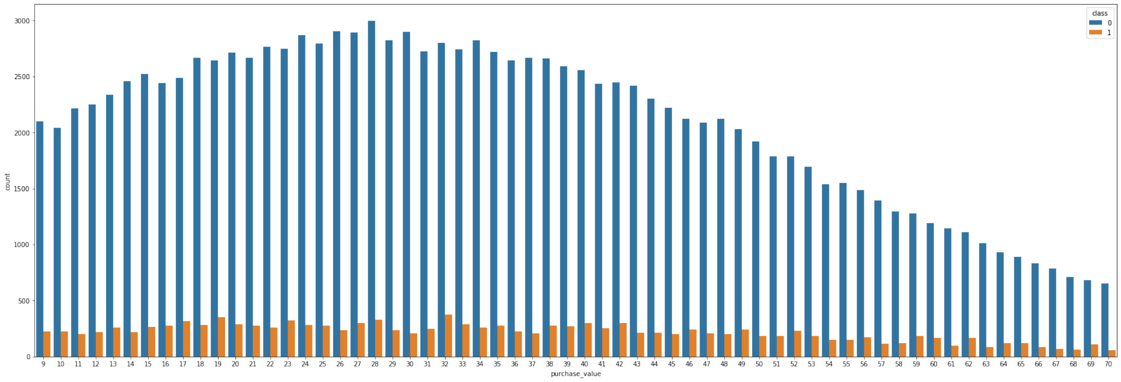


In [22]:
```
plt.figure(figsize=(10,5))
sns.countplot(x='sex',hue='class',data=fraud_data)
plt.show()
```



In [28]:
```
plt.figure(figsize=(30,10))
purchase_value_condition = fraud_data[fraud_data.purchase_value<=70]
```

```
sns.countplot(x='purchase_value',hue='class',data=purchase_value_condition)
plt.show()
```



```
In [38]: fraud_data['device_id'].value_counts()
```

```
Out[38]: ZUSVMDEZRBDTX    20
         NGQCKIADMZORL    20
         CQTUVBYIWWWBC    20
         KIPFSCNUGOLDP    20
         EQYVNEGOFLAWK    20
         ITUMJCKWEYNDD    20
         IGKYVZDBEGALB    19
         CDFXVYHOIHPYP    19
         SDJQRPKXQFBED    19
         BWSMVSLCJXMCM    19
         EGLGSEGYPMMAM    19
         UFBULQADXSSOG    18
         XJWEQEWCBRAKD    18
         OGBNHQHDZLGFZ    18
         FFWAQIABHGYJC    18
         RWZCXZTQUORQL    18
         QVMVTZOIJDKNR    18
         KPAAACGRQWYIK    18
         XHZBVWFWHSGTQ    18
         TAODVYWZTHMTO    18
         GTIYVLCMAYBFA    18
         KGXODJJIWSJJE    17
         XSEQHFFOYFICY    17
         RWCELJOVGBDVR    17
         KYVPIVGZBEXNK    17
         UHCAPOHBEBXJW    17
         SUEKLSZWLASFR    17
         QRMOMDDTIIUVW    17
         FHNLMUKPGJGPZ    17
```

```
DNEKXSIEGFBWD    17
                 ..
KJNITSXBWVWQU     1
YGXBBSOEBKHUW     1
XTBDAYUKQYQRP     1
YRFQDBFJUFLUC     1
UCIJISJKCNHIX     1
VXTRLUMBQDTPX     1
BSQKDBFMFWDBX     1
EMGUDDVXZBRIZ     1
XKOHOBUEXVLWF     1
LPMBAGPOIETUE     1
NIVYEYOMMQUZV     1
WMEQFWGZQSQCW     1
GDCEKHFROERRS     1
VNEVKZZATPSSY     1
IOSMTTEPKRCAB     1
UPNVOEUNHRPDF     1
BJISKIWRXAJJL     1
ZGVYSEGUJEHEY     1
KSXZEJKFBBMRI     1
ZPKLKKBOSGJZE     1
YIXECYJRHLEGC     1
IPDPJPLBTELXU     1
VSNBVIGUNLDCK     1
NULXUXQHKMUVU     1
FTEGATLYLKJSQ     1
QQLBZCZVRKIVA     1
CHTTOXAAOCAGU     1
EFOOYUHDITTMV     1
KRCGIMPSGKDNB     1
SPKIAONPICJEU     1
Name: device_id, Length: 137956, dtype: int64
```

In [39]:
```
fraud_data['ip_address'].value_counts()
```

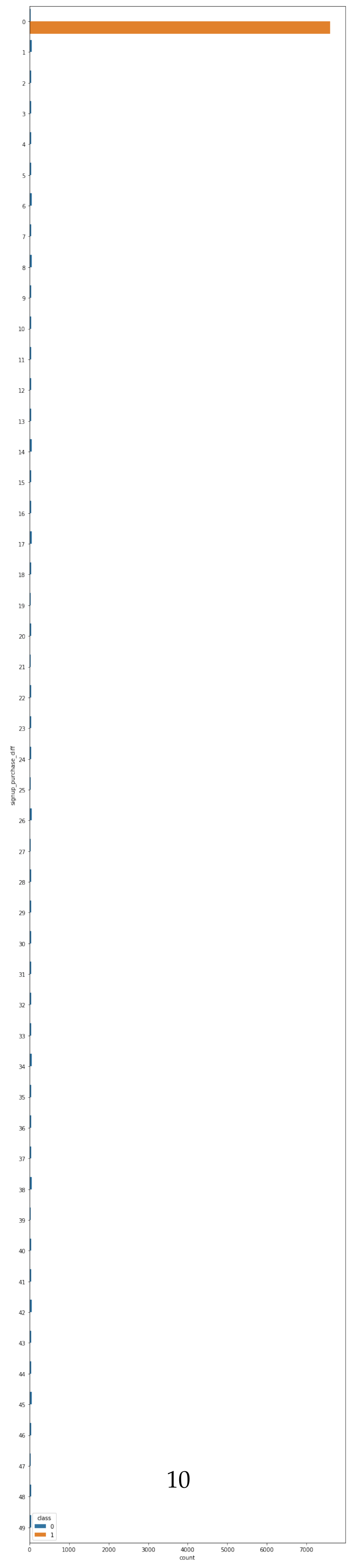
Out[39]:
```
3.874758e+09    20
5.760609e+08    20
2.050964e+09    20
1.502818e+09    20
2.937899e+09    19
1.800550e+09    19
3.503224e+09    19
3.484934e+08    19
2.586669e+09    19
3.058785e+09    19
1.797069e+09    19
1.443896e+09    18
```

```
2.249217e+09    18
2.141692e+09    18
2.354318e+08    18
1.955530e+08    18
1.281304e+09    18
1.687739e+09    18
1.839748e+08    18
9.794124e+08    18
2.470359e+09    17
2.011989e+09    17
1.509973e+09    17
1.235453e+09    17
2.161077e+09    17
2.294137e+09    17
3.445652e+09    17
6.233199e+08    17
2.881396e+09    17
3.645562e+09    17
                ..
1.314423e+09     1
3.896761e+09     1
2.081674e+09     1
1.208879e+09     1
4.187075e+09     1
1.201447e+09     1
1.748791e+08     1
3.694881e+09     1
1.841112e+09     1
1.442817e+09     1
2.625951e+09     1
1.192997e+08     1
2.604958e+09     1
1.494229e+09     1
3.508405e+09     1
3.077081e+09     1
2.976366e+09     1
2.879706e+09     1
1.112672e+09     1
2.619358e+09     1
1.056479e+09     1
3.841902e+09     1
1.209325e+09     1
2.464622e+09     1
9.270926e+08     1
1.101289e+09     1
2.730533e+09     1
3.912052e+09     1
3.192721e+09     1
```

```
2.991295e+09     1
Name: ip_address, Length: 143512, dtype: int64
```

In [80]:
```
times = []
for i, time in enumerate(fraud_data['signup_time']):
    signup_time = time
    purchase_time = fraud_data['purchase_time'][i]
    date_format = '%Y-%m-%d %H:%M:%S'
    t1 = datetime.datetime.strptime(signup_time,date_format)
    t2 = datetime.datetime.strptime(purchase_time,date_format)
    diff = t2-t1
    times.append(diff.days*24+(diff.seconds/3600))
fraud_data['signup_purchase_diff'] = times
```

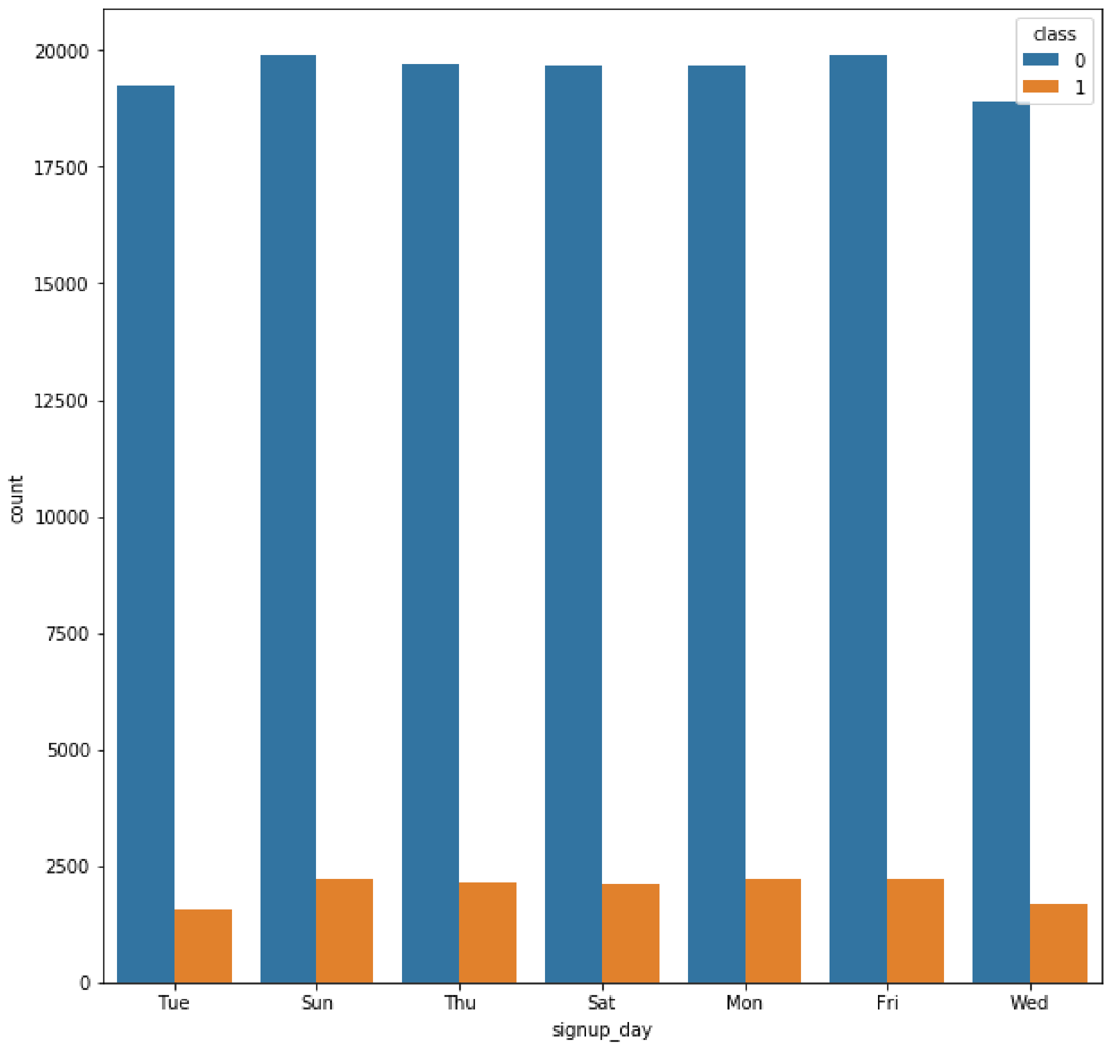
In [85]:
```
plt.figure(figsize=(10,50))
time = fraud_data[fraud_data['signup_purchase_diff']<50]
sns.countplot(y='signup_purchase_diff',hue='class',data=time)
plt.show()
```


signup_purchase_diff
count
class
0
1

In [88]:
```
signup_day = []
purchase_day = []
for i, time in enumerate(fraud_data['signup_time']):
    signup_time = time
    purchase_time = fraud_data['purchase_time'][i]
    date_format = '%Y-%m-%d %H:%M:%S'
    t1 = datetime.datetime.strptime(signup_time,date_format).strftime('%a')
    t2 = datetime.datetime.strptime(purchase_time,date_format).strftime('%a')
    signup_day.append(t1)
    purchase_day.append(t2)
fraud_data['signup_day'] = signup_day
fraud_data['purchase_day'] = purchase_day
fraud_data.head(5)
```

Out[88]:
```
   user_id          signup_time        purchase_time  purchase_value  \
0    22058  2015-02-24 22:55:49  2015-04-18 02:47:11              34
1   333320  2015-06-07 20:39:50  2015-06-08 01:38:54              16
2     1359  2015-01-01 18:52:44  2015-01-01 18:52:45              15
3   150084  2015-04-28 21:13:25  2015-05-04 13:54:50              44
4   221365  2015-07-21 07:09:52  2015-09-09 18:40:53              39

       device_id source browser sex  age    ip_address  class  \
0  QVPSPJUOCKZAR    SEO  Chrome   M   39  7.327584e+08      0
1  EOGFQPIZPYXFZ    Ads  Chrome   F   53  3.503114e+08      0
2  YSSKYOSJHPPLJ    SEO   Opera   M   53  2.621474e+09      1
3  ATGTXKYKUDUQN    SEO  Safari   M   41  3.840542e+09      0
4  NAUITBZFJKHWW    Ads  Safari   M   45  4.155831e+08      0

   signup_purchase_diff signup_day purchase_day
0                  1251        Tue          Sat
1                     4        Sun          Mon
2                     0        Thu          Thu
3                   136        Tue          Mon
4                  1211        Tue          Wed
```

In [91]:
```
plt.figure(figsize=(10,10))
sns.countplot(x="signup_day",hue="class",data=fraud_data)
plt.show()
```

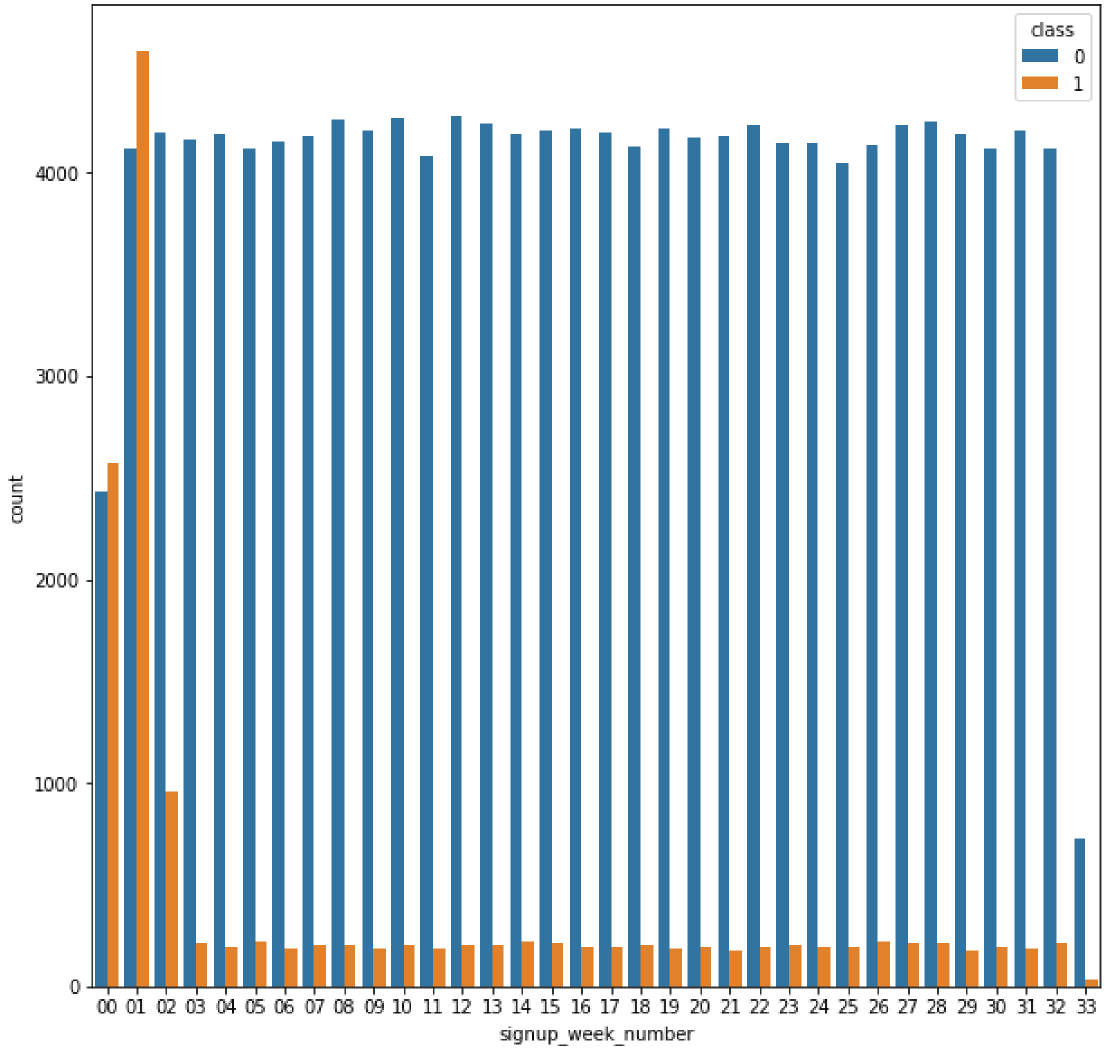


In [93]:
```
signup_week_number = []
purchase_week_number = []
for i, time in enumerate(fraud_data['signup_time']):
    signup_time = time
    purchase_time = fraud_data['purchase_time'][i]
    date_format = '%Y-%m-%d %H:%M:%S'
    t1 = datetime.datetime.strptime(signup_time,date_format).strftime('%W')
    t2 = datetime.datetime.strptime(purchase_time,date_format).strftime('%W')
    signup_week_number.append(t1)
    purchase_week_number.append(t2)
fraud_data['signup_week_number'] = signup_week_number
fraud_data['purchase_week_number'] = purchase_week_number
```

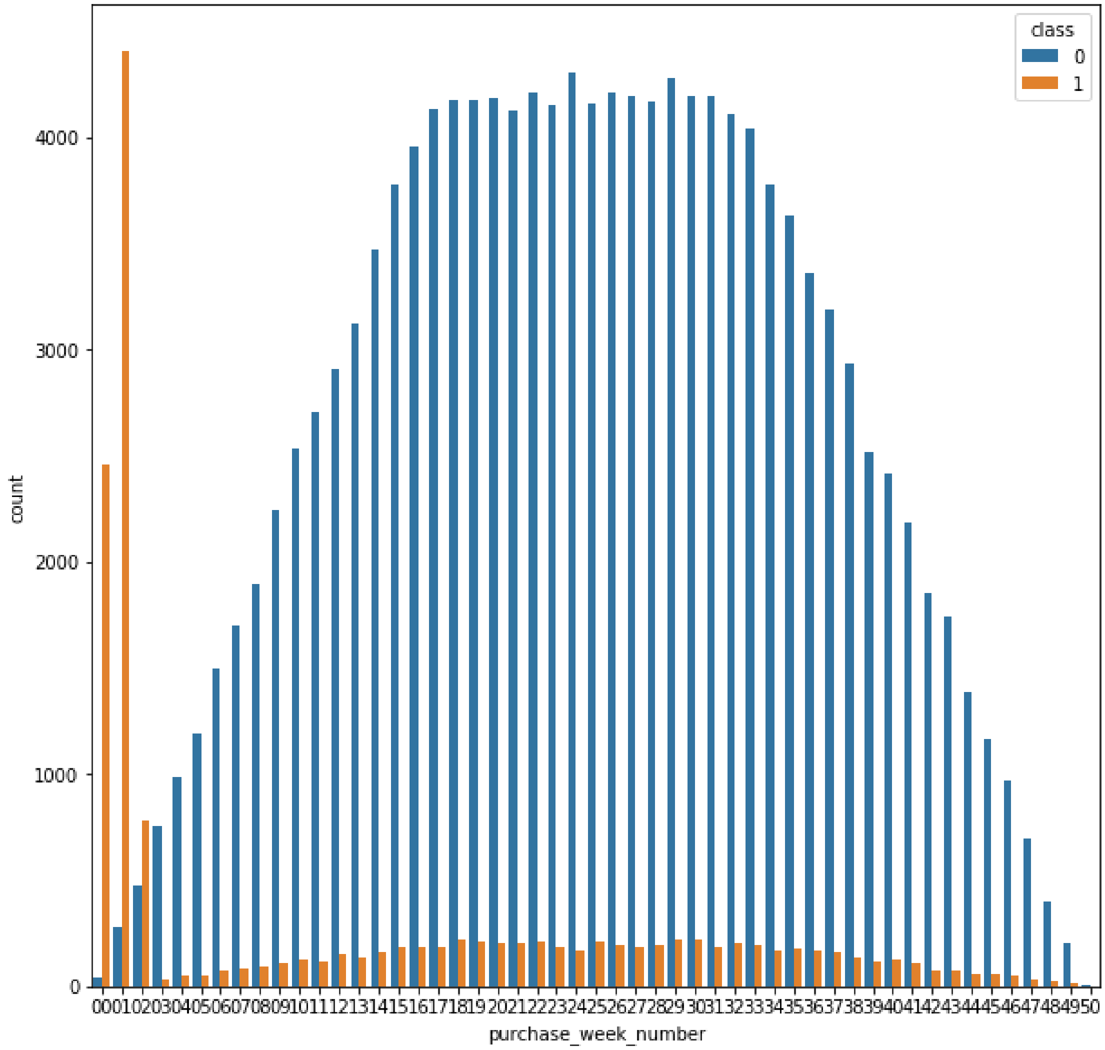
Out[93]:
```
   user_id          signup_time        purchase_time  purchase_value  \
0    22058  2015-02-24 22:55:49  2015-04-18 02:47:11              34
```

```
1   333320  2015-06-07 20:39:50  2015-06-08 01:38:54              16
2     1359  2015-01-01 18:52:44  2015-01-01 18:52:45              15
3   150084  2015-04-28 21:13:25  2015-05-04 13:54:50              44
4   221365  2015-07-21 07:09:52  2015-09-09 18:40:53              39

       device_id source browser sex  age    ip_address  class  \
0  QVPSPJUOCKZAR    SEO  Chrome   M   39  7.327584e+08      0
1  EOGFQPIZPYXFZ    Ads  Chrome   F   53  3.503114e+08      0
2  YSSKYOSJHPPLJ    SEO   Opera   M   53  2.621474e+09      1
3  ATGTXKYKUDUQN    SEO  Safari   M   41  3.840542e+09      0
4  NAUITBZFJKHWW    Ads  Safari   M   45  4.155831e+08      0

   signup_purchase_diff signup_day purchase_day signup_week_number  \
0                  1251        Tue          Sat                 08
1                     4        Sun          Mon                 22
2                     0        Thu          Thu                 00
3                   136        Tue          Mon                 17
4                  1211        Tue          Wed                 29

  purchase_week_number
0                   15
1                   23
2                   00
3                   18
4                   36
```

In [98]:
```
plt.figure(figsize=(10,10))
sns.countplot(x="signup_week_number",hue="class",data=fraud_data)
plt.show()
```



In [99]:
```
plt.figure(figsize=(10,10))
sns.countplot(x="purchase_week_number",hue="class",data=fraud_data)
plt.show()
```



In [100]: `fraud_data.head(5)`

Out[100]:
```
   user_id          signup_time        purchase_time  purchase_value  \
0    22058  2015-02-24 22:55:49  2015-04-18 02:47:11              34
1   333320  2015-06-07 20:39:50  2015-06-08 01:38:54              16
2     1359  2015-01-01 18:52:44  2015-01-01 18:52:45              15
3   150084  2015-04-28 21:13:25  2015-05-04 13:54:50              44
4   221365  2015-07-21 07:09:52  2015-09-09 18:40:53              39

       device_id source browser sex  age    ip_address  class  \
0  QVPSPJUOCKZAR    SEO  Chrome   M   39  7.327584e+08      0
1  EOGFQPIZPYXFZ    Ads  Chrome   F   53  3.503114e+08      0
2  YSSKYOSJHPPLJ    SEO   Opera   M   53  2.621474e+09      1
3  ATGTXKYKUDUQN    SEO  Safari   M   41  3.840542e+09      0
4  NAUITBZFJKHWW    Ads  Safari   M   45  4.155831e+08      0
```

```
   signup_purchase_diff signup_day purchase_day signup_week_number  \
0                  1251        Tue          Sat                 08
1                     4        Sun          Mon                 22
2                     0        Thu          Thu                 00
3                   136        Tue          Mon                 17
4                  1211        Tue          Wed                 29

  purchase_week_number
0                   15
1                   23
2                   00
3                   18
4                   36
```

In [122]:
```
from sklearn.model_selection import train_test_split
columns = ['purchase_value','device_id','source','browser','sex','age','ip_address','s
          'signup_week_number','purchase_week_number']
labels = ['class']
fraud_data['signup_day'] = pd.factorize(fraud_data['signup_day'])[0]
fraud_data['purchase_day'] = pd.factorize(fraud_data['purchase_day'])[0]
fraud_data['sex'] = pd.factorize(fraud_data['sex'])[0]
fraud_data['browser'] = pd.factorize(fraud_data['browser'])[0]
fraud_data['source'] = pd.factorize(fraud_data['source'])[0]
fraud_data['device_id'] = pd.factorize(fraud_data['device_id'])[0]
variables = np.array(fraud_data[columns])
target = np.array(fraud_data[labels])
X_train,X_test,y_train,y_test = train_test_split(variables,target,test_size=0.33,rando
target.shape
```

Out[122]:
```
(151112, 1)
```

In [123]:
```
from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(n_estimators=50)
clf.fit(X_train,y_train)
```

```
/home/nikit/anaconda2/lib/python2.7/site-packages/ipykernel_launcher.py:3: DataConversionWarning
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[123]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=50, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [124]:
```
pred = clf.predict(X_test)
from sklearn.metrics import confusion_matrix,accuracy_score
print confusion_matrix(y_test,pred)
```

```
[[45229     2]
 [ 2125  2511]]
```

In [125]:
```
print accuracy_score(y_test,pred)
```

```
0.957346541801
```

In [132]:
```
var_imp = clf.feature_importances_
v_imp = pd.DataFrame(list(zip(columns,var_imp)),columns=['feature','imp_level'])
v_imp
```

Out[132]:

	feature	imp_level
0	purchase_value	0.054123
1	device_id	0.096252
2	source	0.010057
3	browser	0.018701
4	sex	0.007664
5	age	0.046894
6	ip_address	0.075172
7	signup_purchase_diff	0.325328
8	signup_day	0.025814
9	purchase_day	0.026082
10	signup_week_number	0.089893
11	purchase_week_number	0.224021