Financial Analytics - Predicting Fraud in payment Services

In [1]:
```python
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.lines as mlines
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
from sklearn.model_selection import train_test_split, learning_curve
from sklearn.metrics import average_precision_score
from xgboost.sklearn import XGBClassifier
from xgboost import plot_importance, to_graphviz
```

In [ ]:
```python
# Unzipping data on Colab
#local_zip = './archive.zip'
#zip_ref = zipfile.ZipFile(local_zip, 'r')
#zip_ref.extractall('./')
#zip_ref.close()
```

In [2]:
```python
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

Import data and correct spelling of original column headers for consistency

In [3]:
```python
df = pd.read_csv('PS_20174392719_1491204439457_log.csv')
df = df.rename(columns={'oldbalanceOrg':'oldBalanceOrig', 'newbalanceOrig':'newBalanceOrig', \
                        'oldbalanceDest':'oldBalanceDest', 'newbalanceDest':'newBalanceDest'})
print(df.head())
```

```
   step      type    amount     nameOrig  oldBalanceOrig  newBalanceOrig  \
0     1   PAYMENT   9839.64  C1231006815        170136.0       160296.36
1     1   PAYMENT   1864.28  C1666544295         21249.0        19384.72
2     1  TRANSFER    181.00  C1305486145           181.0            0.00
3     1  CASH_OUT    181.00   C840083671           181.0            0.00
4     1   PAYMENT  11668.14  C2048537720         41554.0        29885.86

      nameDest  oldBalanceDest  newBalanceDest  isFraud  isFlaggedFraud
0  M1979787155             0.0             0.0        0               0
1  M2044282225             0.0             0.0        0               0
2   C553264065             0.0             0.0        1               0
3    C38997010         21182.0             0.0        1               0
4  M1230701703             0.0             0.0        0               0
```

In [4]:
```python
df.isnull().values.any()
```

Out[4]:
```
False
```

Exploratory Data Analysis

In [5]:
```python
print('\n The types of fraudulent transactions are {}'.format(\
list(df.loc[df.isFraud == 1].type.drop_duplicates().values))) # only 'CASH_OUT'
                                                             # & 'TRANSFER'

dfFraudTransfer = df.loc[(df.isFraud == 1) & (df.type == 'TRANSFER')]
dfFraudCashout = df.loc[(df.isFraud == 1) & (df.type == 'CASH_OUT')]

print ('\n The number of fraudulent TRANSFERs = {}'.\
       format(len(dfFraudTransfer))) # 4097

print ('\n The number of fraudulent CASH_OUTs = {}'.\
       format(len(dfFraudCashout))) # 4116
```

```
 The types of fraudulent transactions are ['TRANSFER', 'CASH_OUT']

 The number of fraudulent TRANSFERs = 4097

 The number of fraudulent CASH_OUTs = 4116
```

In [6]:
```python
print('\nThe type of transactions in which isFlaggedFraud is set: \
{}'.format(list(df.loc[df.isFlaggedFraud == 1].type.drop_duplicates())))
                                                            # only 'TRANSFER'

dfTransfer = df.loc[df.type == 'TRANSFER']
dfFlagged = df.loc[df.isFlaggedFraud == 1]
dfNotFlagged = df.loc[df.isFlaggedFraud == 0]

print('\nMin amount transacted when isFlaggedFraud is set= {}'\
                                  .format(dfFlagged.amount.min())) # 353874.22

print('\nMax amount transacted in a TRANSFER where isFlaggedFraud is not set=\
 {}'.format(dfTransfer.loc[dfTransfer.isFlaggedFraud == 0].amount.max())) # 92445516.64
```

```
The type of transactions in which isFlaggedFraud is set: ['TRANSFER']

Min amount transacted when isFlaggedFraud is set= 353874.22

Max amount transacted in a TRANSFER where isFlaggedFraud is not set= 92445516.64
```

In [7]:
```python
print('\nThe number of TRANSFERs where isFlaggedFraud = 0, yet oldBalanceDest = 0 and\
 newBalanceDest = 0: {}'.\
format(len(dfTransfer.loc[(dfTransfer.isFlaggedFraud == 0) & \
(dfTransfer.oldBalanceDest == 0) & (dfTransfer.newBalanceDest == 0)]))) # 4158
```

```
The number of TRANSFERs where isFlaggedFraud = 0, yet oldBalanceDest = 0 and newBalanceDest = 0: 4158
```

isFlaggedFraud being set cannot be thresholded on *oldBalanceOrig* since the corresponding range of values overlaps with that for TRANSFERs where *isFlaggedFraud* is not set (see below). Note that we do not need to consider *newBalanceOrig* since it is updated only after the transaction, whereas *isFlaggedFraud* would be set before the transaction takes place.

In [8]:
```python
print('\nMin, Max of oldBalanceOrig for isFlaggedFraud = 1 TRANSFERs: {}'.\
format([round(dfFlagged.oldBalanceOrig.min()), round(dfFlagged.oldBalanceOrig.max())]))

print('\nMin, Max of oldBalanceOrig for isFlaggedFraud = 0 TRANSFERs where \
oldBalanceOrig = \
newBalanceOrig: {}'.format(\
[dfTransfer.loc[(dfTransfer.isFlaggedFraud == 0) & (dfTransfer.oldBalanceOrig \
== dfTransfer.newBalanceOrig)].oldBalanceOrig.min(), \
round(dfTransfer.loc[(dfTransfer.isFlaggedFraud == 0) & (dfTransfer.oldBalanceOrig \
               == dfTransfer.newBalanceOrig)].oldBalanceOrig.max())]))
```

```
Min, Max of oldBalanceOrig for isFlaggedFraud = 1 TRANSFERs: [353874.0, 19585040.0]

Min, Max of oldBalanceOrig for isFlaggedFraud = 0 TRANSFERs where oldBalanceOrig = newBalanceOrig: [0.0, 575668.0]
```

Can *isFlaggedFraud* be set based on seeing a customer transacting more than once? Note that duplicate customer names don't exist within transactions where *isFlaggedFraud* is set, but duplicate customer names exist within transactions where *isFlaggedFraud* is not set. It turns out that originators of transactions that have *isFlaggedFraud* set have transacted only once. Very few destination accounts of transactions that have *isFlaggedFraud* set have transacted more than once.

In [9]:
```python
print('\nHave originators of transactions flagged as fraud transacted more than \
once? {}'\
.format((dfFlagged.nameOrig.isin(pd.concat([dfNotFlagged.nameOrig, \
                                    dfNotFlagged.nameDest]))).any())) # False

print('\nHave destinations for transactions flagged as fraud initiated\
 other transactions? \
{}'.format((dfFlagged.nameDest.isin(dfNotFlagged.nameOrig)).any())) # False

# Since only 2 destination accounts of 16 that have 'isFlaggedFraud' set have been
# destination accounts more than once,
# clearly 'isFlaggedFraud' being set is independent of whether a
# destination account has been used before or not

print('\nHow many destination accounts of transactions flagged as fraud have been \
destination accounts more than once?: {}'\
.format(sum(dfFlagged.nameDest.isin(dfNotFlagged.nameDest)))) # 2
```

```
Have originators of transactions flagged as fraud transacted more than once? False

Have destinations for transactions flagged as fraud initiated other transactions? False

How many destination accounts of transactions flagged as fraud have been destination accounts more than once?: 2
```

It can be easily seen that transactions with *isFlaggedFraud* set occur at all values of *step*, similar to the complementary set of transactions. Thus *isFlaggedFraud* does not correlate with *step* either and is therefore seemingly unrelated to any explanatory variable or feature in the data

Conclusion: Although *isFraud* is always set when *isFlaggedFraud* is set, since *isFlaggedFraud* is set just 16 times in a seemingly meaningless way, we can treat this feature as insignificant and discard it in the dataset without loosing information.

Are expected merchant accounts accordingly labelled?

In [10]:
```python
print('\nAre there any merchants among originator accounts for CASH_IN \
transactions? {}'.format(\
(df.loc[df.type == 'CASH_IN'].nameOrig.str.contains('M')).any())) # False
```

```
Are there any merchants among originator accounts for CASH_IN transactions? False
```

Similarly, it was stated that CASH_OUT involves paying a merchant. However, for CASH_OUT transactions there are no merchants among the destination accounts.

In [11]:
```python
print('\nAre there any merchants among destination accounts for CASH_OUT \
transactions? {}'.format(\
(df.loc[df.type == 'CASH_OUT'].nameDest.str.contains('M')).any())) # False
```

```
Are there any merchants among destination accounts for CASH_OUT transactions? False
```

In fact, there are no merchants among any originator accounts. Merchants are only present in destination accounts for all PAYMENTS.

In [12]:
```python
print('\nAre there merchants among any originator accounts? {}'.format(\
      df.nameOrig.str.contains('M').any())) # False

print('\nAre there any transactions having merchants among destination accounts\
 other than the PAYMENT type? {}'.format(\
(df.loc[df.nameDest.str.contains('M')].type != 'PAYMENT').any())) # False
```

```
Are there merchants among any originator accounts? False

Are there any transactions having merchants among destination accounts other than the PAYMENT type? False
```

Conclusion: Among the account labels *nameOrig* and *nameDest*, for all transactions, the merchant prefix of 'M' occurs in an unexpected way.

Are there account labels common to fraudulent TRANSFERs and CASH_OUTs?

In [13]:
```python
print('\nWithin fraudulent transactions, are there destinations for TRANSFERS \
that are also originators for CASH_OUTs? {}'.format(\
(dfFraudTransfer.nameDest.isin(dfFraudCashout.nameOrig)).any())) # False
dfNotFraud = df.loc[df.isFraud == 0]
```

```
Within fraudulent transactions, are there destinations for TRANSFERS that are also originators for CASH_OUTs? False
```

Could destination accounts for fraudulent TRANSFERs originate CASHOUTs that are not detected and are labeled as genuine? It turns out there are 3 such accounts.

In [14]:
```python
print('\nFraudulent TRANSFERs whose destination accounts are originators of \
genuine CASH_OUTs: \n\n{}'.format(dfFraudTransfer.loc[dfFraudTransfer.nameDest.\
isin(dfNotFraud.loc[dfNotFraud.type == 'CASH_OUT'].nameOrig.drop_duplicates())]))
```

```
Fraudulent TRANSFERs whose destination accounts are originators of genuine CASH_OUTs:

         step      type      amount     nameOrig  oldBalanceOrig  \
1030443    65  TRANSFER  1282971.57  C1175896731      1282971.57
6039814   486  TRANSFER   214793.32  C2140495649       214793.32
6362556   738  TRANSFER   814689.88  C2029041842       814689.88

         newBalanceOrig     nameDest  oldBalanceDest  newBalanceDest  isFraud  \
1030443             0.0  C1714931087             0.0             0.0        1
6039814             0.0   C423543548             0.0             0.0        1
6362556             0.0  C1023330867             0.0             0.0        1

         isFlaggedFraud
1030443               0
6039814               0
6362556               0
```

However, 2 out of 3 of these accounts first make a genuine CASH_OUT and only later (as evidenced by the time step) receive a fraudulent TRANSFER. Thus, fraudulent transactions are not indicated by the *nameOrig* and *nameDest* features.

In [15]:
```python
print('\nFraudulent TRANSFER to C423543548 occured at step = 486 whereas \
genuine CASH_OUT from this account occured earlier at step = {}'.format(\
dfNotFraud.loc[(dfNotFraud.type == 'CASH_OUT') & (dfNotFraud.nameOrig == \
                           'C423543548')].step.values)) # 185
```

```
Fraudulent TRANSFER to C423543548 occured at step = 486 whereas genuine CASH_OUT from this account occured earlier at step = [185]
```

Conclusion: Noting from section 2.3 above that the *nameOrig* and *nameDest* features neither encode merchant accounts in the expected way, below, we drop these features from the data since they are meaningless.

Data cleaning

From the exploratory data analysis (EDA) of section 2, we know that fraud only occurs in 'TRANSFER's and 'CASH_OUT's. So we assemble only the corresponding data in X for analysis.

In [16]:
```python
X = df.loc[(df.type == 'TRANSFER') | (df.type == 'CASH_OUT')]

randomState = 5
np.random.seed(randomState)

#X = X.loc[np.random.choice(X.index, 100000, replace = False)]

Y = X['isFraud']
del X['isFraud']

# Eliminate columns shown to be irrelevant for analysis in the EDA
X = X.drop(['nameOrig', 'nameDest', 'isFlaggedFraud'], axis = 1)

# Binary-encoding of labelled data in 'type'
X.loc[X.type == 'TRANSFER', 'type'] = 0
X.loc[X.type == 'CASH_OUT', 'type'] = 1
X.type = X.type.astype(int) # convert dtype('O') to dtype(int)
```

Imputation of Latent Missing Values

The data has several transactions with zero balances in the destination account both before and after a non-zero amount is transacted. The fraction of such transactions, where zero likely denotes a missing value, is much larger in fraudulent (50%) compared to genuine transactions (0.06%).

In [17]:
```python
Xfraud = X.loc[Y == 1]
XnonFraud = X.loc[Y == 0]
print('\nThe fraction of fraudulent transactions with \'oldBalanceDest\' = \
\'newBalanceDest\' = 0 although the transacted \'amount\' is non-zero is: {}'.\
format(len(Xfraud.loc[(Xfraud.oldBalanceDest == 0) & \
(Xfraud.newBalanceDest == 0) & (Xfraud.amount)]) / (1.0 * len(Xfraud))))

print('\nThe fraction of genuine transactions with \'oldBalanceDest\' = \
newBalanceDest\' = 0 although the transacted \'amount\' is non-zero is: {}'.\
format(len(XnonFraud.loc[(XnonFraud.oldBalanceDest == 0) & \
(XnonFraud.newBalanceDest == 0) & (XnonFraud.amount)]) / (1.0 * len(XnonFraud))))
```

```
The fraction of fraudulent transactions with 'oldBalanceDest' = 'newBalanceDest' = 0 although the transacted 'amount' is non-zero is: 0.4955558261293072

The fraction of genuine transactions with 'oldBalanceDest' = newBalanceDest' = 0 although the transacted 'amount' is non-zero is: 0.0006176245277308345
```

Since the destination account balances being zero is a strong indicator of fraud, we do not impute the account balance (before the transaction is made) with a statistic or from a distribution with a subsequent adjustment for the amount transacted. Doing so would mask this indicator of fraud and make fraudulent transactions appear genuine. Instead, below we replace the value of 0 with -1 which will be more useful to a suitable machine-learning (ML) algorithm detecting fraud.

In [18]:
```python
X.loc[(X.oldBalanceDest == 0) & (X.newBalanceDest == 0) & (X.amount != 0), \
      ['oldBalanceDest', 'newBalanceDest']] = - 1
```

The data also has several transactions with zero balances in the originating account both before and after a non-zero amount is transacted. In this case, the fraction of such transactions is much smaller in fraudulent (0.3%) compared to genuine transactions (47%). Once again, from similar reasoning as above, instead of imputing a numerical value we replace the value of 0 with a null value.

In [19]:
```python
X.loc[(X.oldBalanceOrig == 0) & (X.newBalanceOrig == 0) & (X.amount != 0), \
      ['oldBalanceOrig', 'newBalanceOrig']] = np.nan
```

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Feature-engineering

Motivated by the possibility of zero-balances serving to differentiate between fraudulent and genuine transactions, we take the data-imputation of section 3.1 a step further and create 2 new features (columns) recording errors in the originating and destination accounts for each transaction. These new features turn out to be important in obtaining the best performance from the ML algorithm that we will finally use.

In [20]:
```python
X['errorBalanceOrig'] = X.newBalanceOrig + X.amount - X.oldBalanceOrig
X['errorBalanceDest'] = X.oldBalanceDest + X.amount - X.newBalanceDest
```

Data visualization

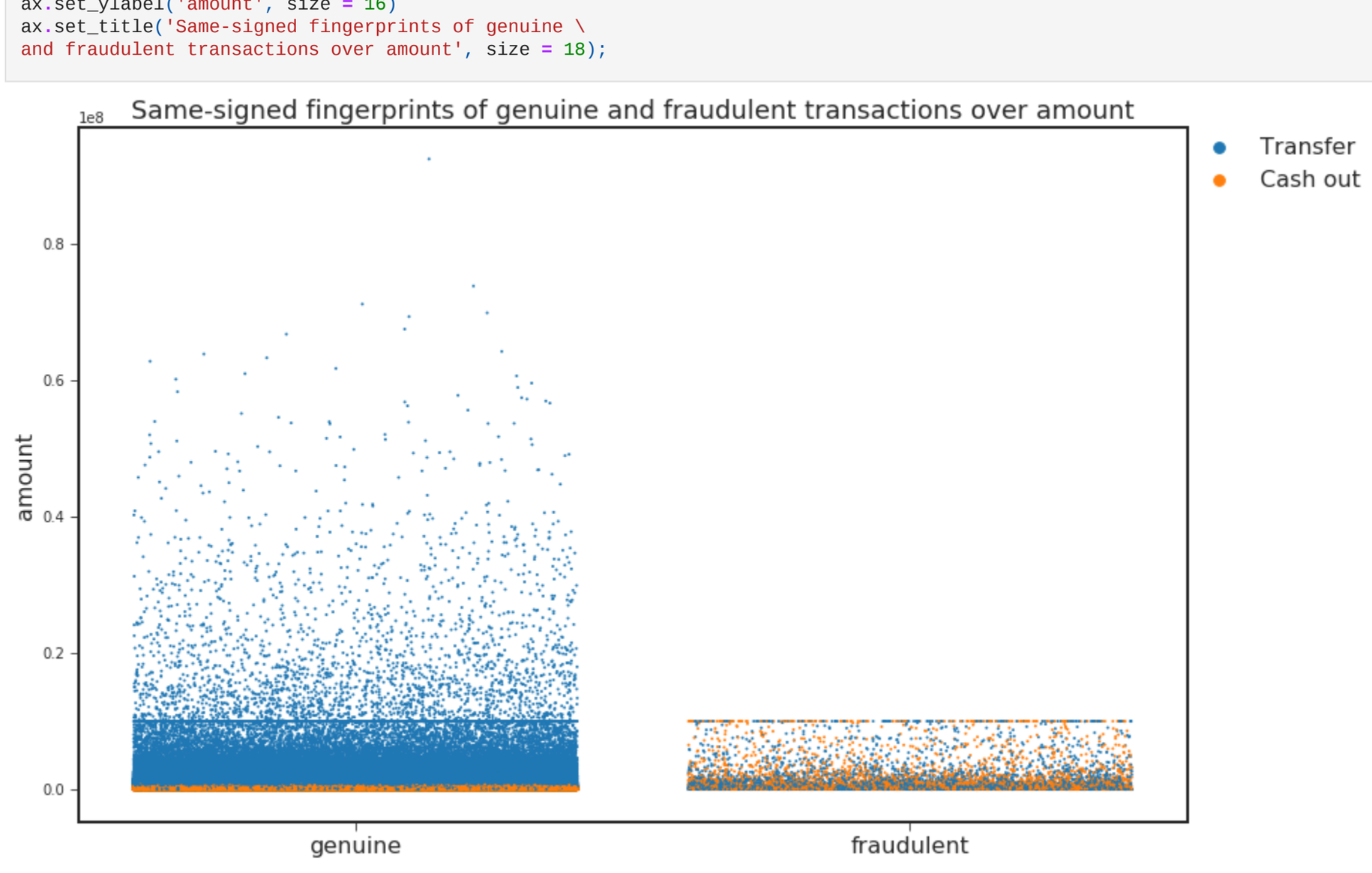
The best way of confirming that the data contains enough information so that a ML algorithm can make strong predictions, is to try and directly visualize the differences between fraudulent and genuine transactions. Motivated by this principle, I visualize these differences in several ways in the plots below.

In [21]:
```python
limit = len(X)

def plotStrip(x, y, hue, figsize = (14, 9)):

    fig = plt.figure(figsize = figsize)
    colours = plt.cm.tab10(np.linspace(0, 1, 9))
    with sns.axes_style('ticks'):
        ax = sns.stripplot(x, y, \
             hue = hue, jitter = 0.4, marker = '.', \
             size = 4, palette = colours)
        ax.set_xlabel('')
        ax.set_xticklabels(['genuine', 'fraudulent'], size = 16)
        for axis in ['top','bottom','left','right']:
            ax.spines[axis].set_linewidth(2)

        handles, labels = ax.get_legend_handles_labels()
        plt.legend(handles, ['Transfer', 'Cash out'], bbox_to_anchor=(1, 1), \
               loc=2, borderaxespad=0, fontsize = 16);
    return ax
```

Dispersion over time

The plot below shows how the fraudulent and genuine transactions yield different fingerprints when their dispersion is viewed over time. It is clear that fradulent transactions are more homogenously distributed over time compared to genuine transactions. Also apparent is that CASH-OUTs outnumber TRANSFERs in genuine transactions, in contrast to a balanced distribution between them in fraudulent transactions. Note that the the width of each 'fingerprint' is set by the 'jitter' parameter in the plotStrip function above which attempts to separate out and plot transactions occuring at the same time with different abscissae.

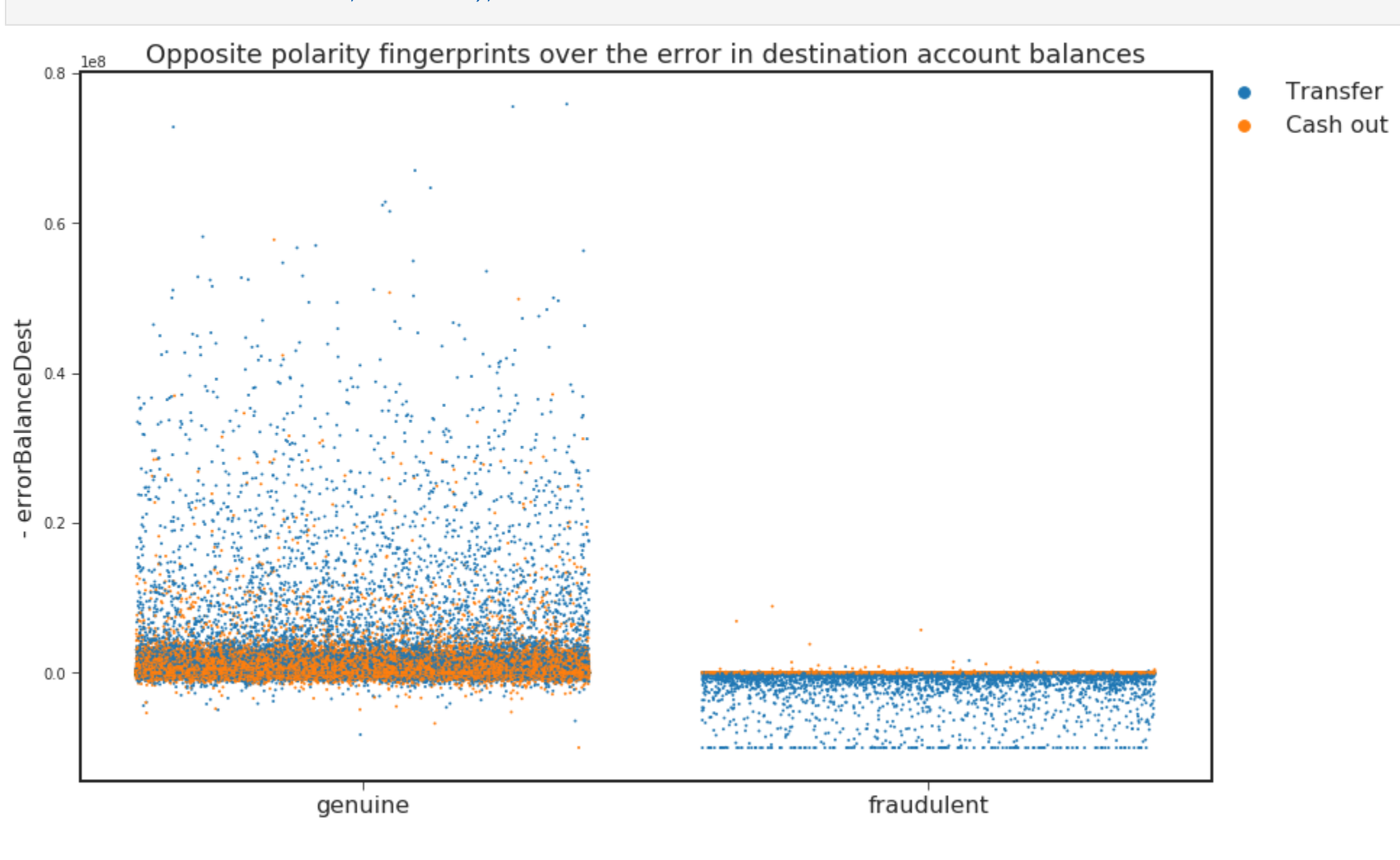
In [22]:
```python
ax = plotStrip(Y[:limit], X.step[:limit], X.type[:limit])
ax.set_ylabel('time [hour]', size = 16)
ax.set_title('Striped vs. homogenous fingerprints of genuine and fraudulent \
transactions over time', size = 20);
```



Dispersion over amount

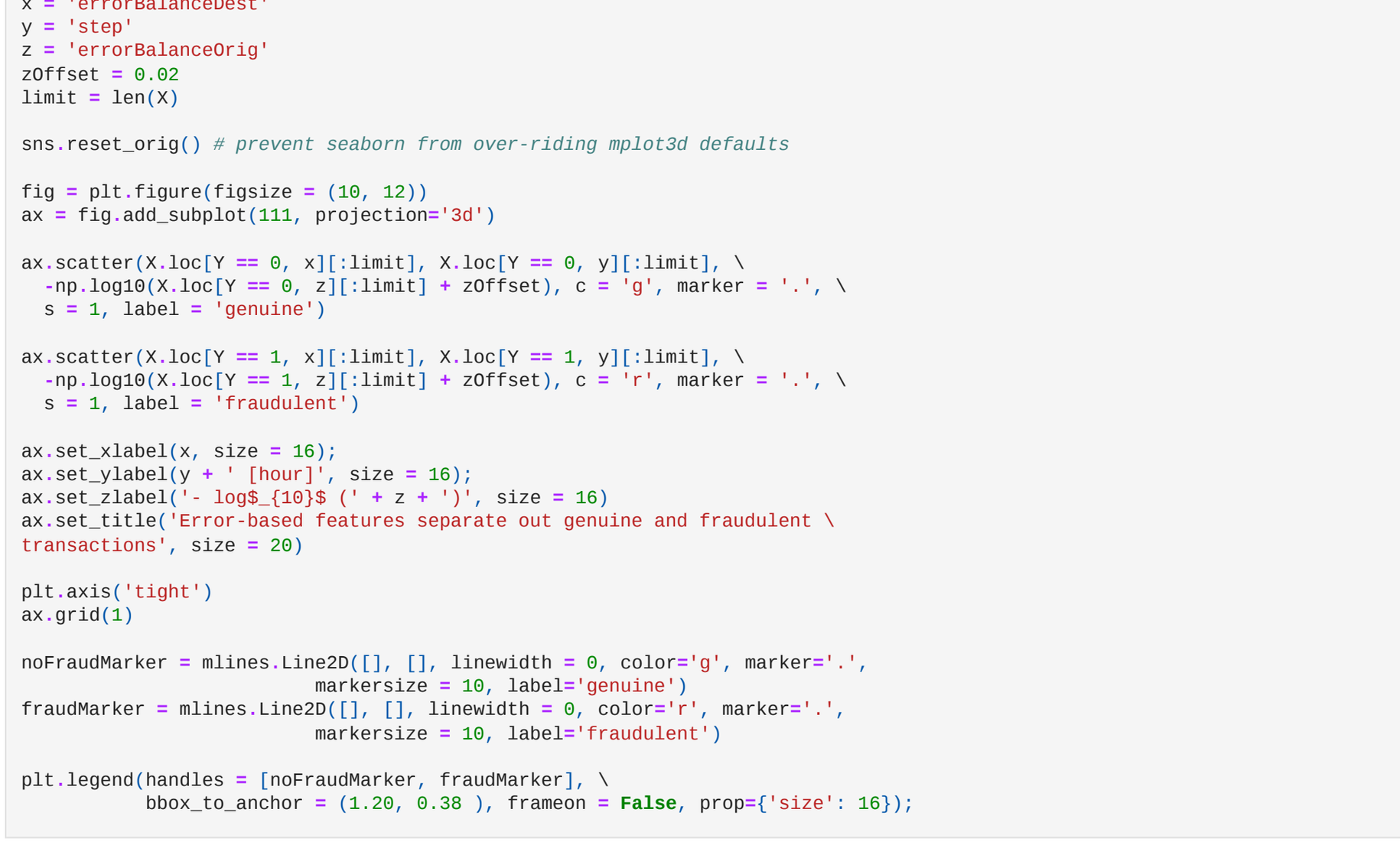
The two plots below shows that although the presence of fraud in a transaction can be discerned by the original *amount* feature, the new *errorBalanceDest* feature is more effective at making a distinction.

In [23]:
```python
limit = len(X)
ax = plotStrip(Y[:limit], X.amount[:limit], X.type[:limit], figsize = (14, 9))
ax.set_ylabel('amount', size = 16)
ax.set_title('Same-signed fingerprints of genuine \
and fraudulent transactions over amount', size = 18);
```



Dispersion over error in balance in destination accounts

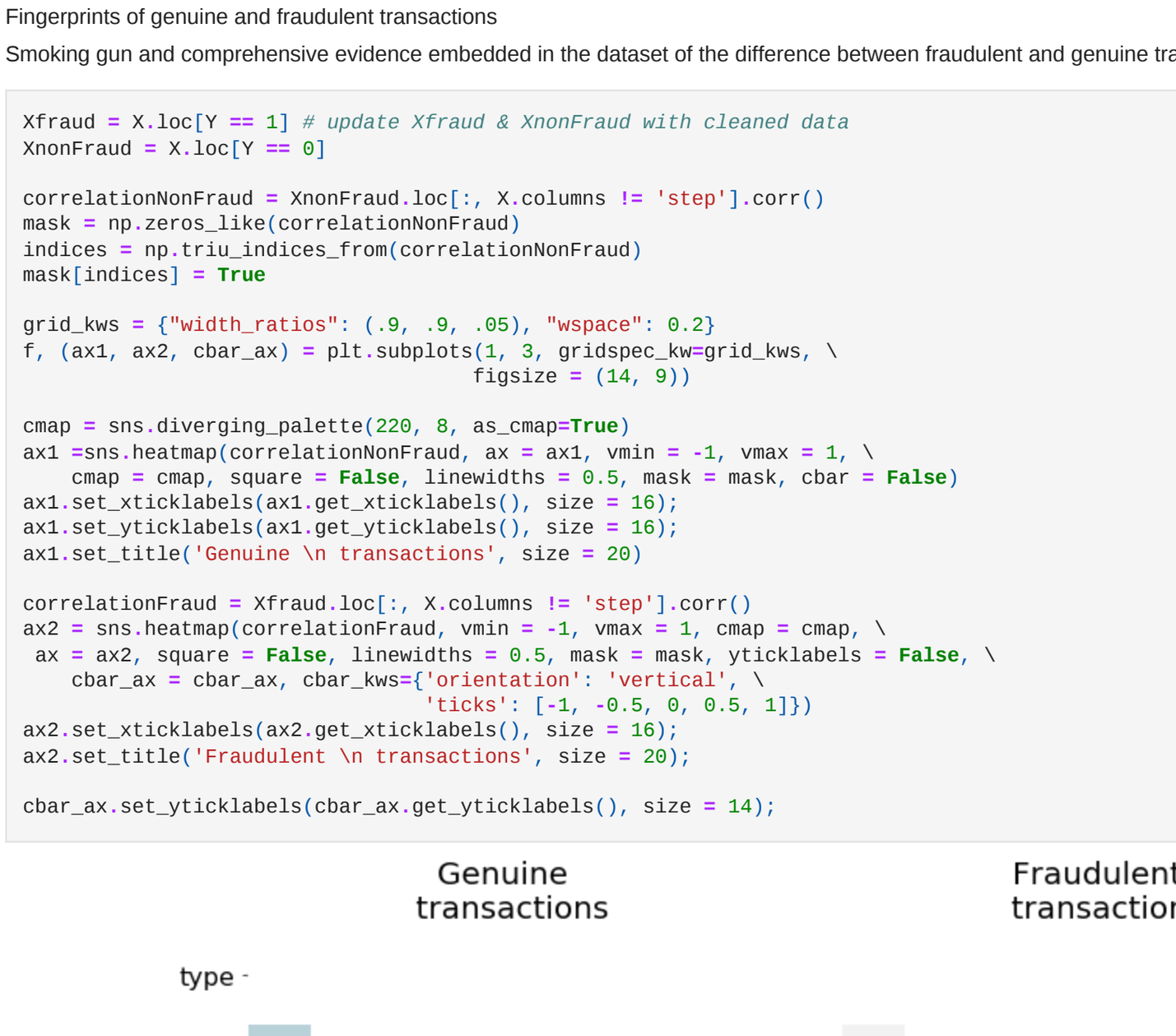
In [24]:
```python
limit = len(X)
ax = plotStrip(Y[:limit], - X.errorBalanceDest[:limit], X.type[:limit], \
              figsize = (14, 9))
ax.set_ylabel('- errorBalanceDest', size = 16)
ax.set_title('Opposite polarity fingerprints over the error in \
destination account balances', size = 18);
```



5. 4. Separating out genuine from fraudulent transactions

The 3D plot below distinguishes best between fraud and non-fraud data by using both of the engineered error-based features. Clearly, the original *step* feature is ineffective in seperating out fraud. Note the striped nature of the genuine data vs time which was aniticipated from the figure in section 5.1.

In [25]:
```python
# Long computation in this cell (~2.5 minutes)
x = 'errorBalanceDest'
y = 'step'
z = 'errorBalanceOrig'
zOffset = 0.02
limit = len(X)

sns.reset_orig() # prevent seaborn from over-riding mplot3d defaults

fig = plt.figure(figsize = (10, 12))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(X.loc[Y == 0, x][:limit], X.loc[Y == 0, y][:limit], \
  -np.log10(X.loc[Y == 0, z][:limit] + zOffset), c = 'g', marker = '.', \
  s = 1, label = 'genuine')

ax.scatter(X.loc[Y == 1, x][:limit], X.loc[Y == 1, y][:limit], \
  -np.log10(X.loc[Y == 1, z][:limit] + zOffset), c = 'r', marker = '.', \
  s = 1, label = 'fraudulent')

ax.set_xlabel(x, size = 16);
ax.set_ylabel(y + ' [hour]', size = 16);
ax.set_zlabel('- log$_{10}$ (' + z + ')', size = 16)
ax.set_title('Error-based features separate out genuine and fraudulent \
transactions', size = 20)

plt.axis('tight')
ax.grid(1)

noFraudMarker = mlines.Line2D([], [], linewidth = 0, color='g', marker='.',
                          markersize = 10, label='genuine')
fraudMarker = mlines.Line2D([], [], linewidth = 0, color='r', marker='.',
                          markersize = 10, label='fraudulent')

plt.legend(handles = [noFraudMarker, fraudMarker], \
           bbox_to_anchor = (1.20, 0.38 ), frameon = False, prop={'size': 16});
```



Fingerprints of genuine and fraudulent transactions

Smoking gun and comprehensive evidence embedded in the dataset of the difference between fraudulent and genuine transactions is obtained by examining their respective correlations in the heatmaps below.

In [26]:
```python
Xfraud = X.loc[Y == 1] # update Xfraud & XnonFraud with cleaned data
XnonFraud = X.loc[Y == 0]

correlationNonFraud = XnonFraud.loc[:, X.columns != 'step'].corr()
mask = np.zeros_like(correlationNonFraud)
indices = np.triu_indices_from(correlationNonFraud)
mask[indices] = True

grid_kws = {"width_ratios": (.9, .9, .05), "wspace": 0.2}
f, (ax1, ax2, cbar_ax) = plt.subplots(1, 3, gridspec_kw=grid_kws, \
                                     figsize = (14, 9))

cmap = sns.diverging_palette(220, 8, as_cmap=True)
ax1 =sns.heatmap(correlationNonFraud, ax = ax1, vmin = -1, vmax = 1, \
    cmap = cmap, square = False, linewidths = 0.5, mask = mask, cbar = False)
ax1.set_xticklabels(ax1.get_xticklabels(), size = 16);
ax1.set_yticklabels(ax1.get_yticklabels(), size = 16);
ax1.set_title('Genuine \n transactions', size = 20)

correlationFraud = Xfraud.loc[:, X.columns != 'step'].corr()
ax2 = sns.heatmap(correlationFraud, vmin = -1, vmax = 1, cmap = cmap, \
 ax = ax2, square = False, linewidths = 0.5, mask = mask, yticklabels = False, \
    cbar_ax = cbar_ax, cbar_kws={'orientation': 'vertical', \
                                 'ticks': [-1, -0.5, 0, 0.5, 1]})
ax2.set_xticklabels(ax2.get_xticklabels(), size = 16);
ax2.set_title('Fraudulent \n transactions', size = 20);

cbar_ax.set_yticklabels(cbar_ax.get_yticklabels(), size = 14);
```

6. Machine Learning to Detect Fraud in Skewed Data

Having obtained evidence from the plots above that the data now contains features that make fraudulent transactions clearly detectable, the remaining obstacle for training a robust ML model is the highly imbalanced nature of the data.

In [27]:
```python
print('skew = {}'.format( len(Xfraud) / float(len(X)) ))
```

```
skew = 0.002964544224336551
```

Split the data into training and test sets in a 80:20 ratio

In [28]:
```python
trainX, testX, trainY, testY = train_test_split(X, Y, test_size = 0.2, \
                                                random_state = randomState)
```

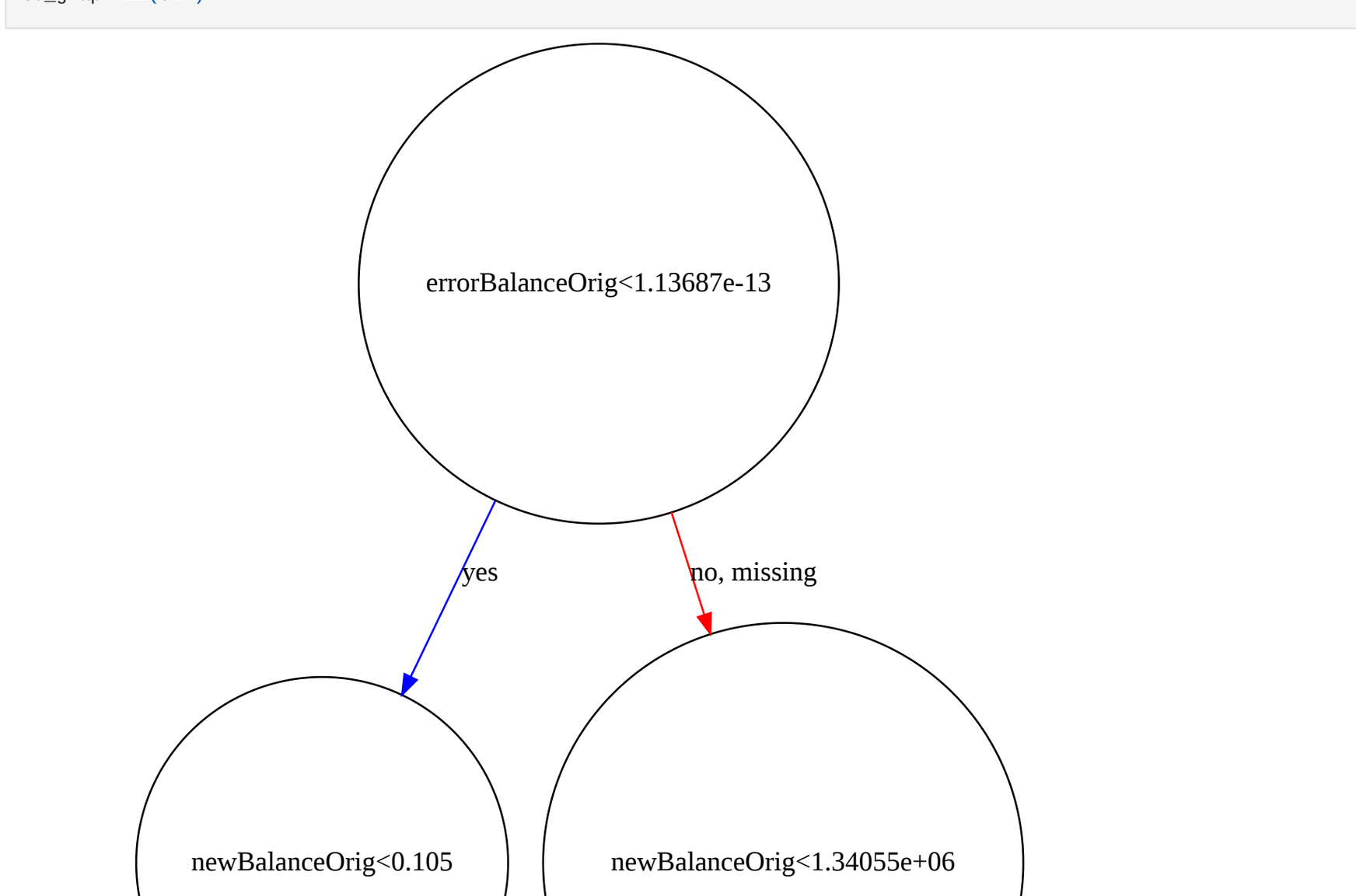
In [29]:
```python
# Long computation in this cell (~1.8 minutes)
weights = (Y == 0).sum() / (1.0 * (Y == 1).sum())
clf = XGBClassifier(max_depth = 3, scale_pos_weight = weights, \
                n_jobs = 4)
probabilities = clf.fit(trainX, trainY).predict_proba(testX)
print('AUPRC = {}'.format(average_precision_score(testY, \
                                              probabilities[:, 1])))
```

```
AUPRC = 0.9986361116985445
```

What are the important features for the ML model?

The figure below shows that the new feature *errorBalanceOrig* that we created is the most relevant feature for the model. The features are ordered based on the number of samples affected by splits on those features.

In [30]:
```python
fig = plt.figure(figsize = (14, 9))
ax = fig.add_subplot(111)

colours = plt.cm.Set1(np.linspace(0, 1, 9))

ax = plot_importance(clf, height = 1, color = colours, grid = False, \
                     show_values = False, importance_type = 'cover', ax = ax);
for axis in ['top','bottom','left','right']:
            ax.spines[axis].set_linewidth(2)

ax.set_xlabel('importance score', size = 16);
ax.set_ylabel('features', size = 16);
ax.set_yticklabels(ax.get_yticklabels(), size = 12);
ax.set_title('Ordering of features by importance to the model learnt', size = 20);
```

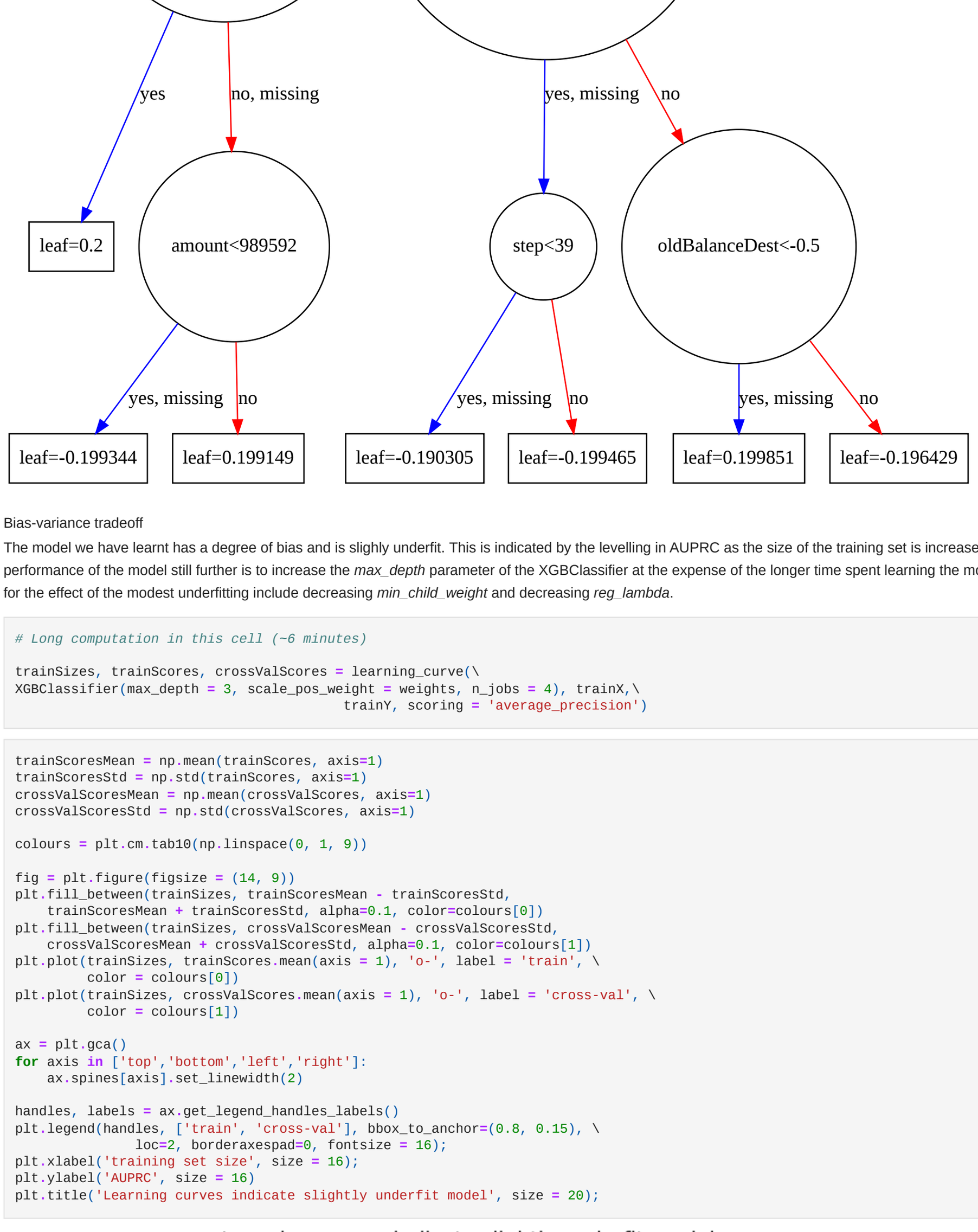


6.2. Visualization of ML model

The root node in the decision tree visualized below is indeed the feature *errorBalanceOrig*, as would be expected from its high significance to the model.

In [31]:
```python
to_graphviz(clf)
```

Out[31]:

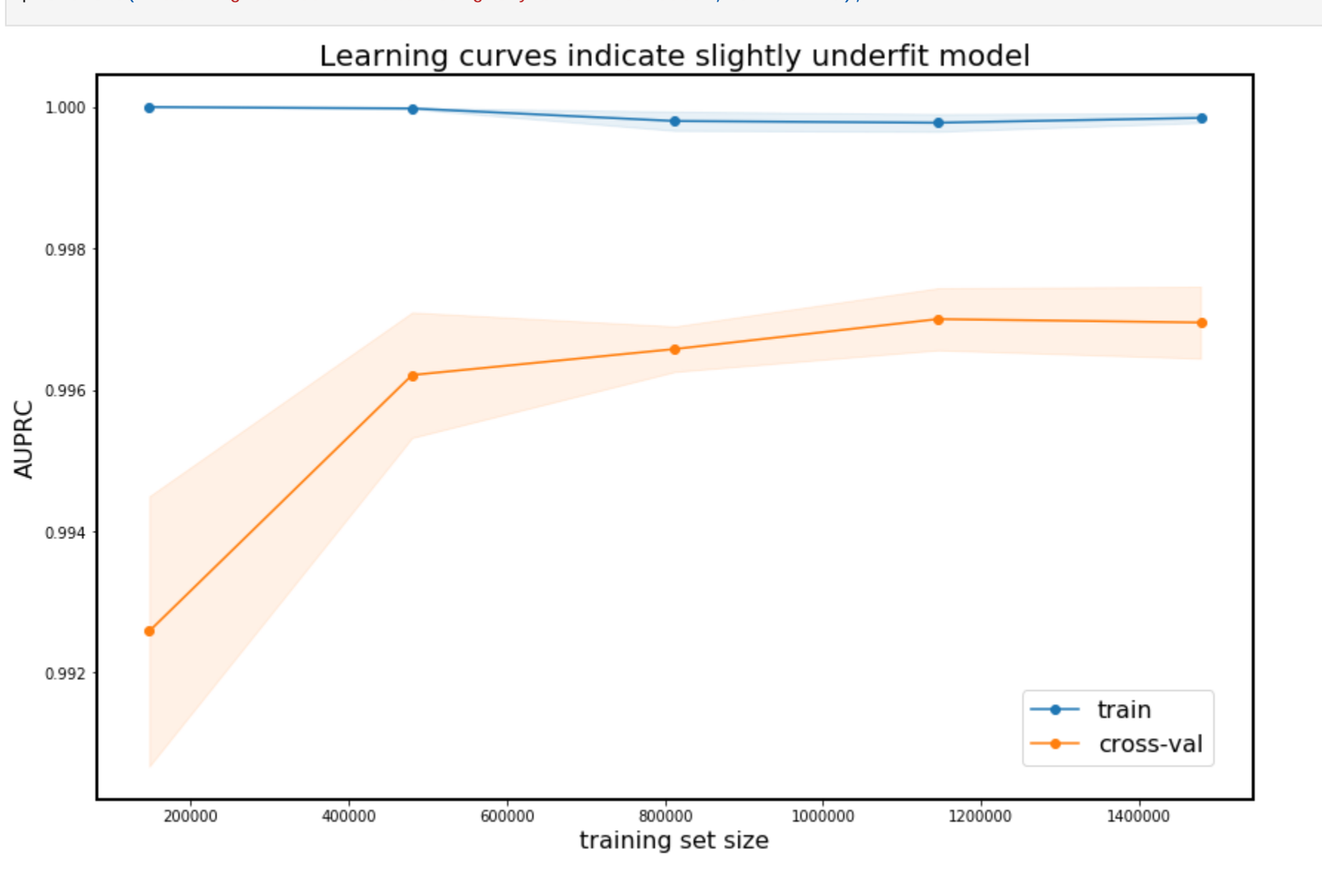


Bias-variance tradeoff

The model we have learnt has a degree of bias and is slighly underfit. This is indicated by the levelling in AUPRC as the size of the training set is increased in the cross-validation curve below. The easiest way to improve the performance of the model still further is to increase the *max_depth* parameter of the XGBClassifier at the expense of the longer time spent learning the model. Other parameters of the classifier that can be adjusted to correct for the effect of the modest underfitting include decreasing *min_child_weight* and decreasing *reg_lambda*.

In [32]:
```python
# Long computation in this cell (~6 minutes)

trainSizes, trainScores, crossValScores = learning_curve(\
XGBClassifier(max_depth = 3, scale_pos_weight = weights, n_jobs = 4), trainX,\
                                         trainY, scoring = 'average_precision')
```

In [33]:
```python
trainScoresMean = np.mean(trainScores, axis=1)
trainScoresStd = np.std(trainScores, axis=1)
crossValScoresMean = np.mean(crossValScores, axis=1)
crossValScoresStd = np.std(crossValScores, axis=1)

colours = plt.cm.tab10(np.linspace(0, 1, 9))

fig = plt.figure(figsize = (14, 9))
plt.fill_between(trainSizes, trainScoresMean - trainScoresStd,
    trainScoresMean + trainScoresStd, alpha=0.1, color=colours[0])
plt.fill_between(trainSizes, crossValScoresMean - crossValScoresStd,
    crossValScoresMean + crossValScoresStd, alpha=0.1, color=colours[1])
plt.plot(trainSizes, trainScores.mean(axis = 1), 'o-', label = 'train', \
         color = colours[0])
plt.plot(trainSizes, crossValScores.mean(axis = 1), 'o-', label = 'cross-val', \
         color = colours[1])

ax = plt.gca()
for axis in ['top','bottom','left','right']:
    ax.spines[axis].set_linewidth(2)

handles, labels = ax.get_legend_handles_labels()
plt.legend(handles, ['train', 'cross-val'], bbox_to_anchor=(0.8, 0.15), \
               loc=2, borderaxespad=0, fontsize = 16);
plt.xlabel('training set size', size = 16);
plt.ylabel('AUPRC', size = 16)
plt.title('Learning curves indicate slightly underfit model', size = 20);
```



7. Conclusion

We thoroughly interrogated the data at the outset to gain insight into which features could be discarded and those which could be valuably engineered. The plots provided visual confirmation that the data could be indeed be discriminated with the aid of the new features. To deal with the large skew in the data, we chose an appropriate metric and used an ML algorithm based on an ensemble of decision trees which works best with strongly imbalanced classes. The method used in this kernel should therefore be broadly applicable to a range of such problems.