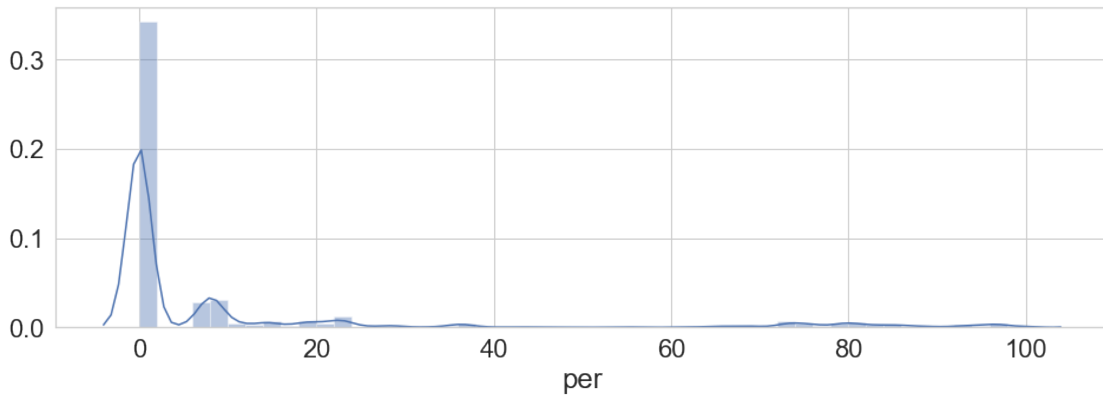
report-2

September 30, 2019

0.1 Distrbution of `null-count` in `training` dataset

```
In [13]: plt.figure(figsize=(16,5))
         sns.distplot(nulls['per'], bins=50, hist=True)
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe0fc623ac8>
```



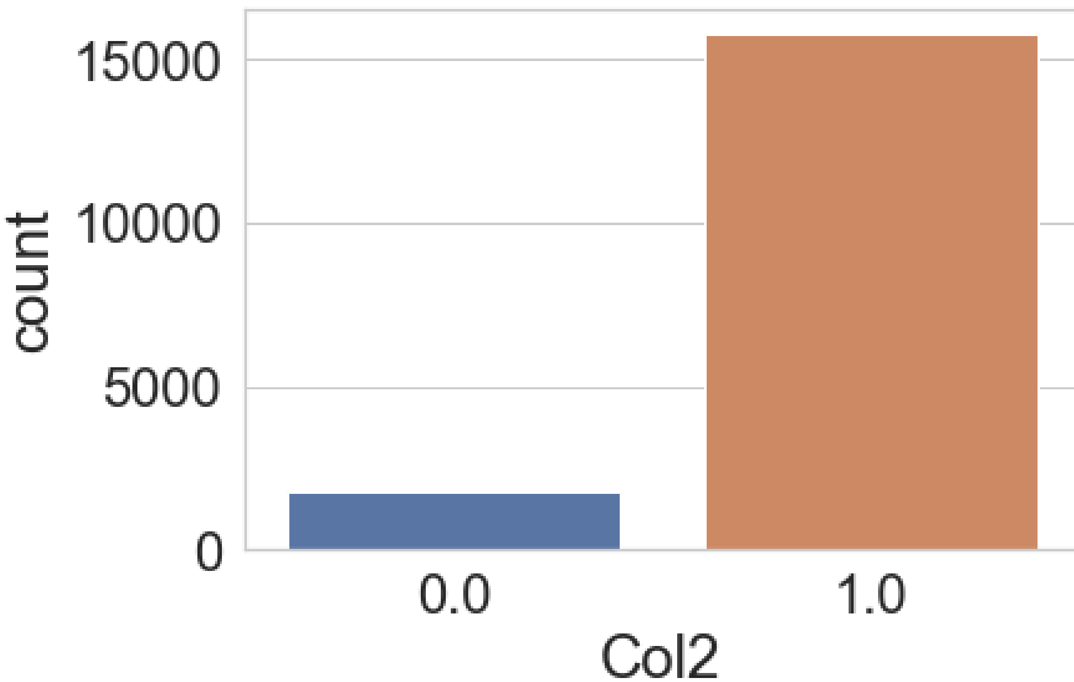
0.2 Null handling

1. We have `150` numerical feature with null percentage 50%
2. We have `148` categorical feature with null percentage > 0
3. To handle num value, i use two tech
   - 50% use generalized rank model to fill those value
   - Use MICE for all
   - use SVD on >50% and low feature impotance
4. For Cat feature,
   - make a new catgory(factorize them)
   - Use for encoding based feature(target encoding)

1 Target variable countplot

```
In [15]: gc.collect()
         sns.countplot(df[df['flag'] == 'train']['Col2'])
         df[df['flag'] == 'train']['Col2'].value_counts()
```

```
Out[15]: 1.0    15760
         0.0     1761
         Name: Col2, dtype: int64
```



1.1 Correct dtypes of following two columns

```
In [40]: df['Col754']  = df['Col754'].replace('-',0).astype('float')
         df['Col843']  = df['Col843'].replace('-',0).astype('float')
```

1.2 There are some intersting feature, with good importance as well

```
- create qunatile bins
- use them for feature-interaction
```

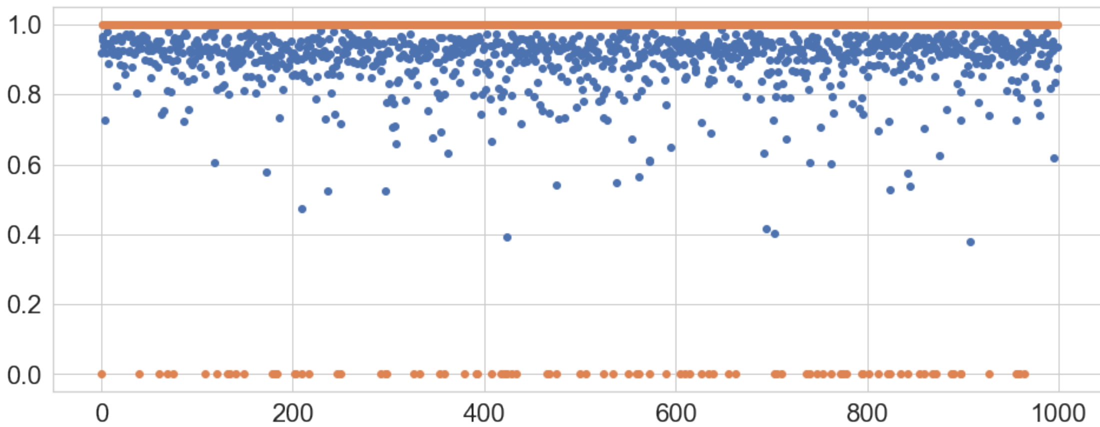
1.3 without considering class weight, while building the model

- this is obvious, as if we don't consider unbalance, while building model, it will shift towards majority class

- here we can see the 99% are choosing `class-1`
- to avoid that i count the weight for each class and assign it to `class-pos-weight`

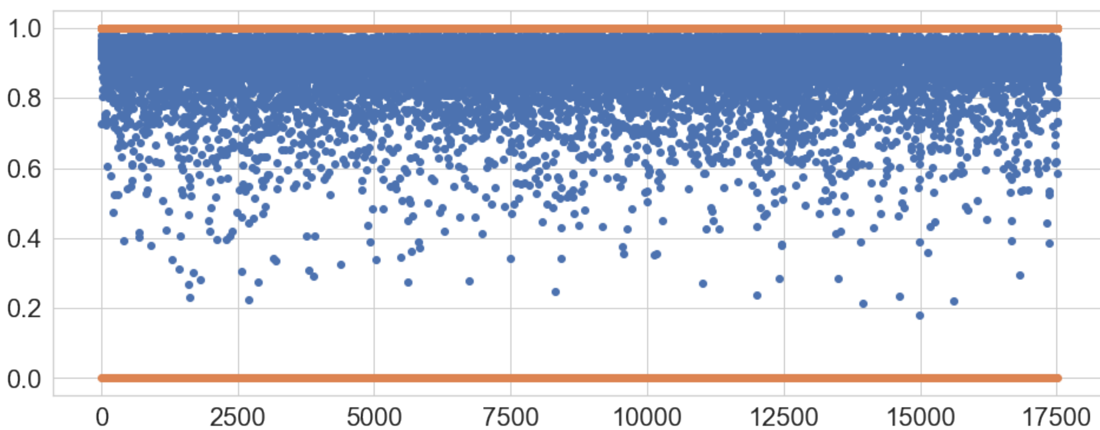
In [69]:

Out[69]: [<matplotlib.lines.Line2D at 0x7efccb9d6eb8>]



In [68]:

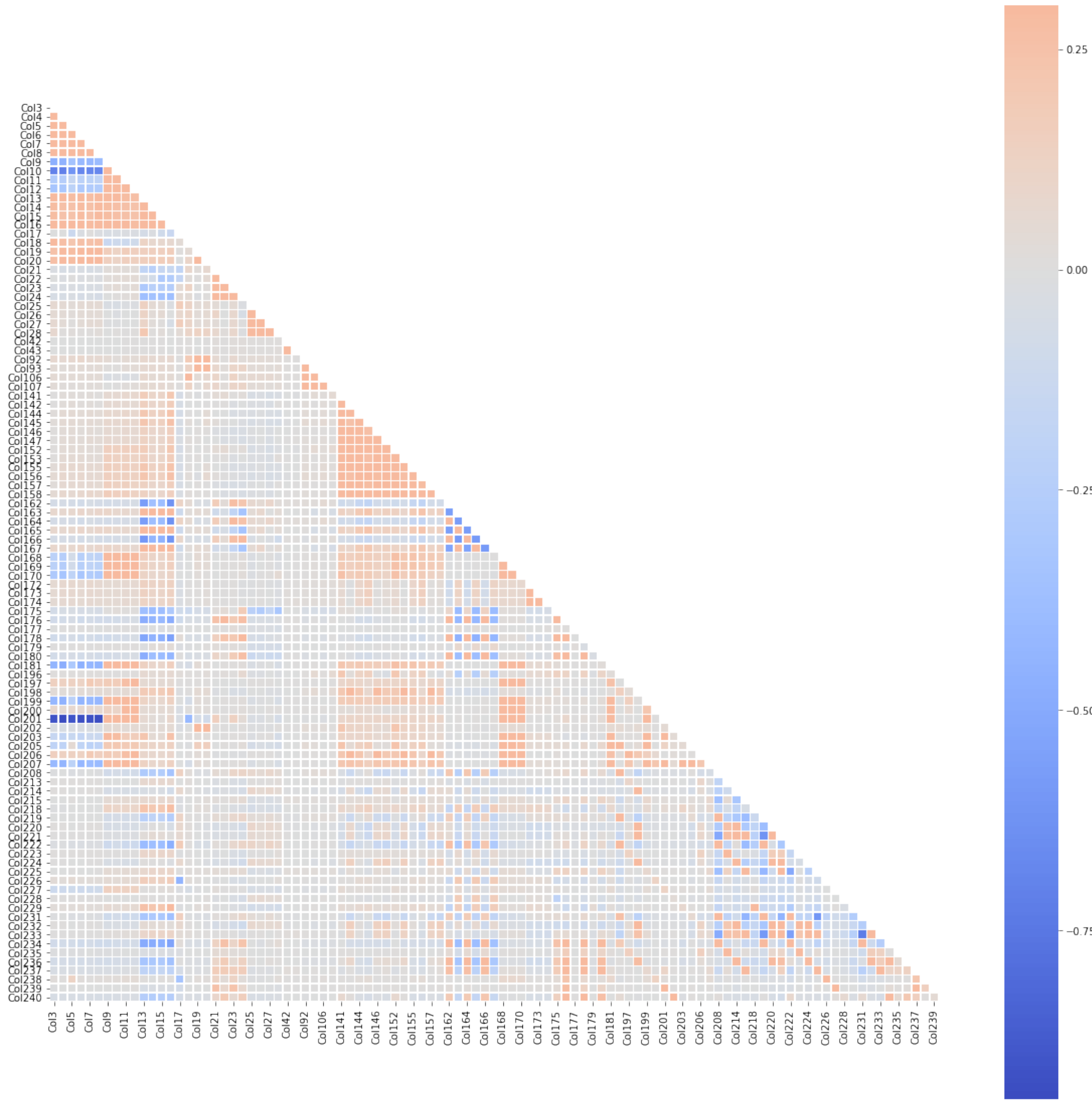
Out[68]: [<matplotlib.lines.Line2D at 0x7efcc7955828>]



1.4 Following feature is chosen by model, i was trying to observe that if the chosen have correlation among them

In [138]:

Out[138]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4cca5358d0>



1.5 some of the variables have `99.9%` missing value.

- I dropped all category variable(I tried to create `NULL` as label, but none of my model find them interesting)
- i found all the categorical feature with NULL percentage more than `34%` are useless

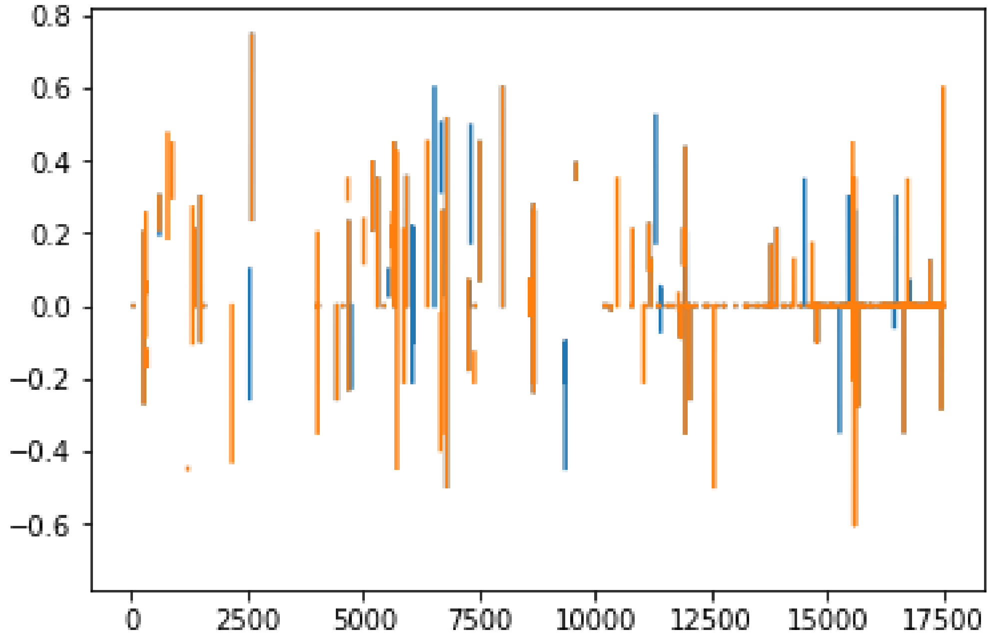
```
In [3]: #             col           type          per
        # 127         Col485        cat           99.960048
        # 126         Col463        cat           99.960048
        # 119         Col266        cat           99.960048
        # 134         Col813        cat           99.960048
        # 132         Col724        cat           99.960048
        # 120         Col288        cat           99.960048
```

```
# 115          Col171        cat         99.372182
# 178          Col930        cat         97.751270
# 13           Col40         cat         97.288968
# 11           Col38         cat         97.226186
# 2375          Col822        num         96.940814
# 2313          Col535        num         96.940814
# 2319          Col556        num         96.940814
# 2360          Col733        num         96.906569
# 2267          Col338        num         96.906569
# 2273          Col359        num         96.906569
# 2380          Col832        num         96.843787
# 2318          Col545        num         96.843787
# 2321          Col566        num         96.843787
# 2275          Col369        num         96.826665
# 2272          Col348        num         96.826665
# 2365          Col743        num         96.826665
# 2394          Col925        num         96.484219
# ...          ...          ...         ...
# 2268          Col340        num         81.616346
# 1836          Col361        num         81.616346
# 2183          Col823        num         81.416586
# 1979          Col557        num         81.416586
# 1965          Col536        num         81.416586
# 1821          Col339        num         81.245363
# 1835          Col360        num         81.245363
```

1.6 Some feature seems to be replica of others

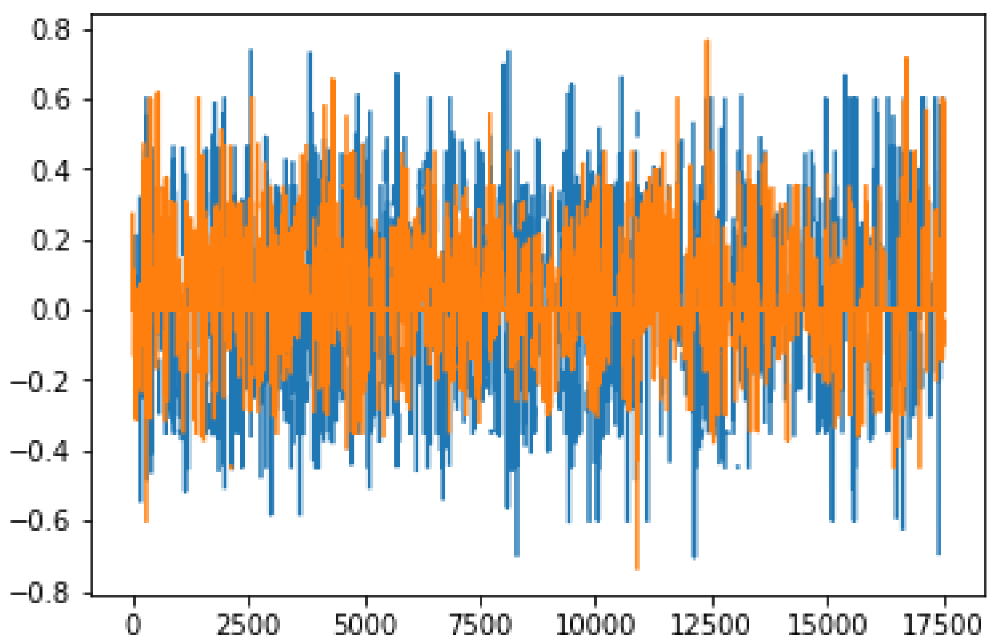
In [35]:
```
train['Col853'].plot(),train['Col857'].plot()
```

Out[35]:
```
(<matplotlib.axes._subplots.AxesSubplot at 0x7f4cf20b7940>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f4cf20b7940>)
```




```
In [36]: train['Col858'].plot(),train['Col859'].plot()
```

```
Out[36]: (<matplotlib.axes._subplots.AxesSubplot at 0x7f4cf21ae860>,
          <matplotlib.axes._subplots.AxesSubplot at 0x7f4cf21ae860>)
```

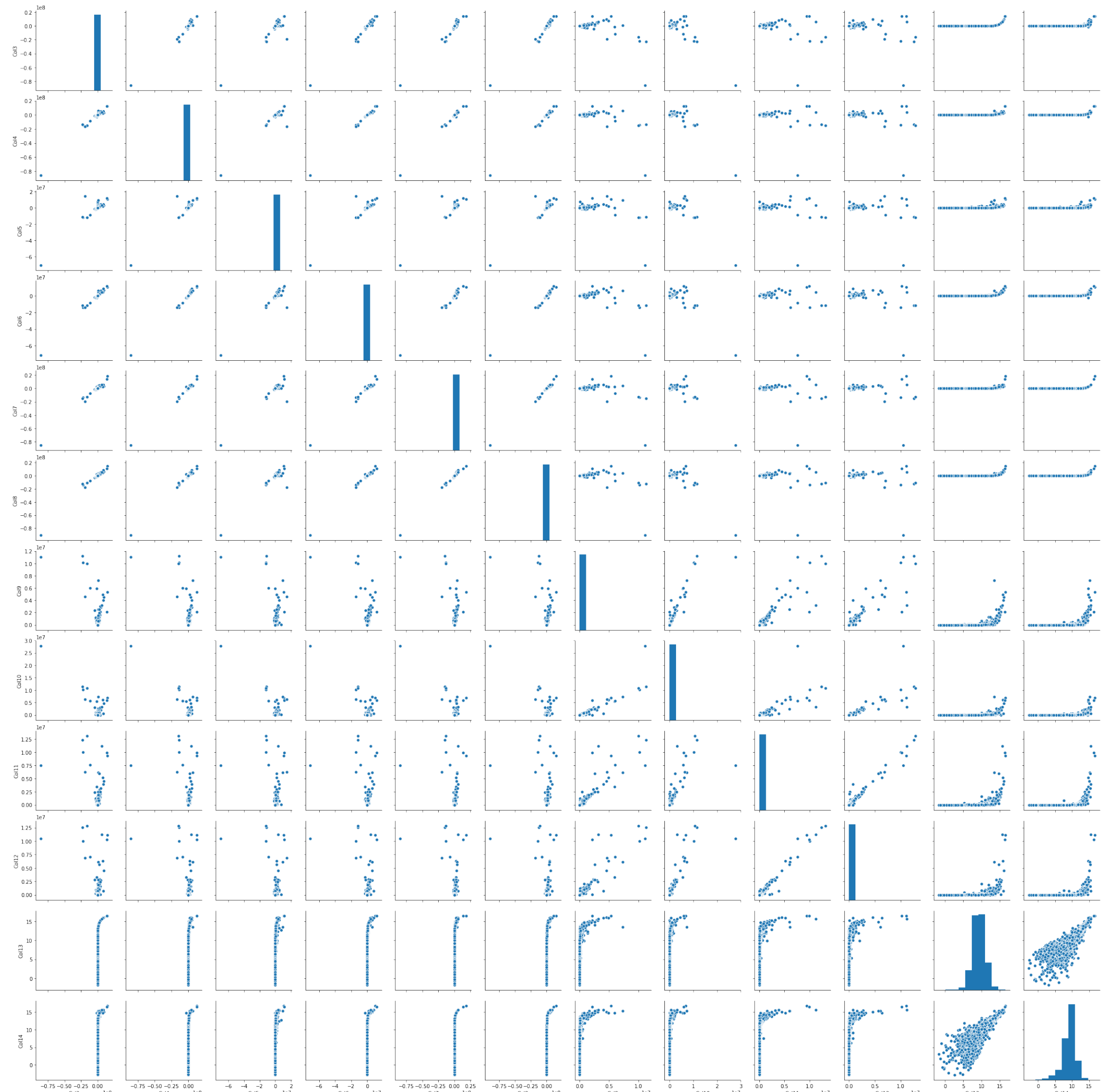


1.7 Joint-plot of few feature

- i tried this to find, which feature could be helpful for `feature engineering`
- i also observe `col3-col14` represents `account` detail such as `saving, loan amount, other`

In [42]:

Out[42]: <seaborn.axisgrid.PairGrid at 0x7f828a0b15f8>



1.8 If we use only following 30 predictors/feature, we will have reasonable score

- most of the `numerical features` have some importance in `gbm model` as well as in `Auto ML`

```
In [1]: # S-no        columns         rel_imp         sca_imp         percentage
        # ---------------------------------------------------------------
        # 0          Col141        2482.739746        4.000000         0.492573
        # 1          Col157        1784.627121        2.785223         0.283858
        # 2          Col770        1518.903397        2.299982         0.202071
        # 3          Col146        1331.083359        1.983335         0.166641
        # 4          Col142        1231.580109        1.805627         0.142803
        # 5          Col152        1189.940491        1.735086         0.135963
        # 6          Col158        1082.997391        1.603169         0.126155
        # 7          Col859        941.143074         1.427708         0.110457
        # 8          Col712        872.583519         1.321074         0.099557
        # 9          Col147        816.666000         1.227485         0.089500
        # 10          Col343        750.114857         1.119430         0.076731
        # 11          Col153        659.452597         0.970077         0.062727
        # 12          Col148        625.814880         0.925868         0.059368
        # 13          Col572        600.625572         0.887249         0.055305
        # 14          Col819        591.438257         0.869824         0.052826
        # 15          Col375        552.594387         0.802067         0.048778
        # 16          Col699        526.582048         0.765085         0.046997
        # 17          Col738        495.478933         0.711484         0.043734
        # 18          Col731        477.591486         0.686355         0.042019
        # 19          Col827        459.398233         0.660391         0.040371
        # 20          Col925        443.199774         0.631364         0.038862
        # 21          Col159        431.078151         0.611178         0.036709
        # 22          Col482        424.444901         0.600768         0.035124
        # 23          Col689        415.684791         0.588512         0.034061
        # 24          Col778        380.638452         0.548187         0.031237
        # 25          Col820        369.445848         0.534114         0.030002
        # 26          Col796        356.842171         0.516208         0.028673
        # 27          Col285        355.060816         0.513935         0.028490
        # 28          Col801        340.458805         0.491252         0.026923
        # 29          Col143        329.762553         0.474782         0.026231
```

1.9 I found a very interesting pattern that most of feature with `null-importance` lie in the columns range of `(1338 - 2385)`

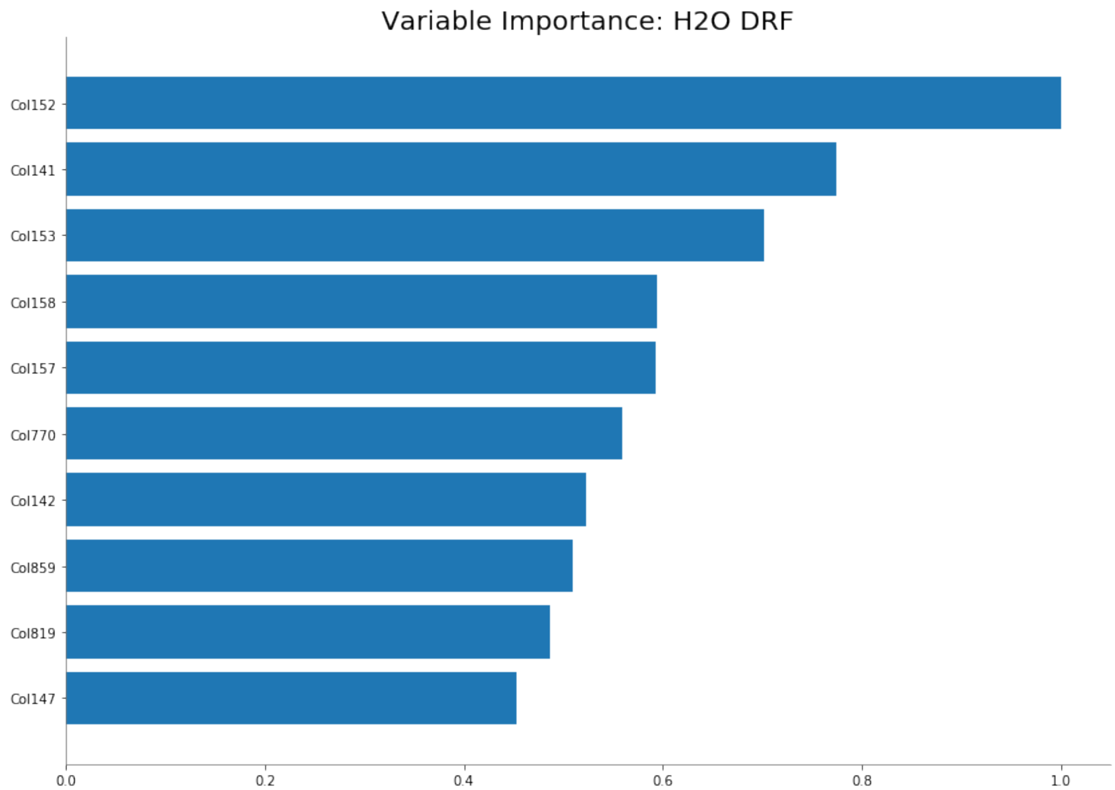
```
In [2]: # array(['Col1338', 'Col1340', 'Col1342', 'Col1343', 'Col1348', 'Col1349',
        #        'Col1351', 'Col1354', 'Col1355', 'Col1356', 'Col1358', 'Col1362',
        #        'Col1363', 'Col1366', 'Col1367', 'Col1368', 'Col1375', 'Col1379',
        #        'Col1380', 'Col1382', 'Col1383', 'Col1384', 'Col1385', 'Col1387',
        #        'Col1388', 'Col1389', 'Col1391', 'Col1397', 'Col1399', 'Col1400',
        #        'Col1402', 'Col1403', 'Col1404', 'Col1406', 'Col1407', 'Col1411',
        #        'Col1414', 'Col1415', 'Col1417', 'Col1419', 'Col1420', 'Col1421',
        #        'Col1422', 'Col1423', 'Col1428', 'Col1430', 'Col1431', 'Col1432',
        #        'Col1433', 'Col1436', 'Col1437', 'Col1438', 'Col1439', 'Col1440',
        #        'Col1442', 'Col1443', 'Col1444', 'Col1446', 'Col1447', 'Col1448',
        #        'Col1451', 'Col1453', 'Col1456', 'Col1457', 'Col1462', 'Col1468',
        #        'Col1469', 'Col1472', 'Col1473', 'Col1474', 'Col1478', 'Col1484',
```

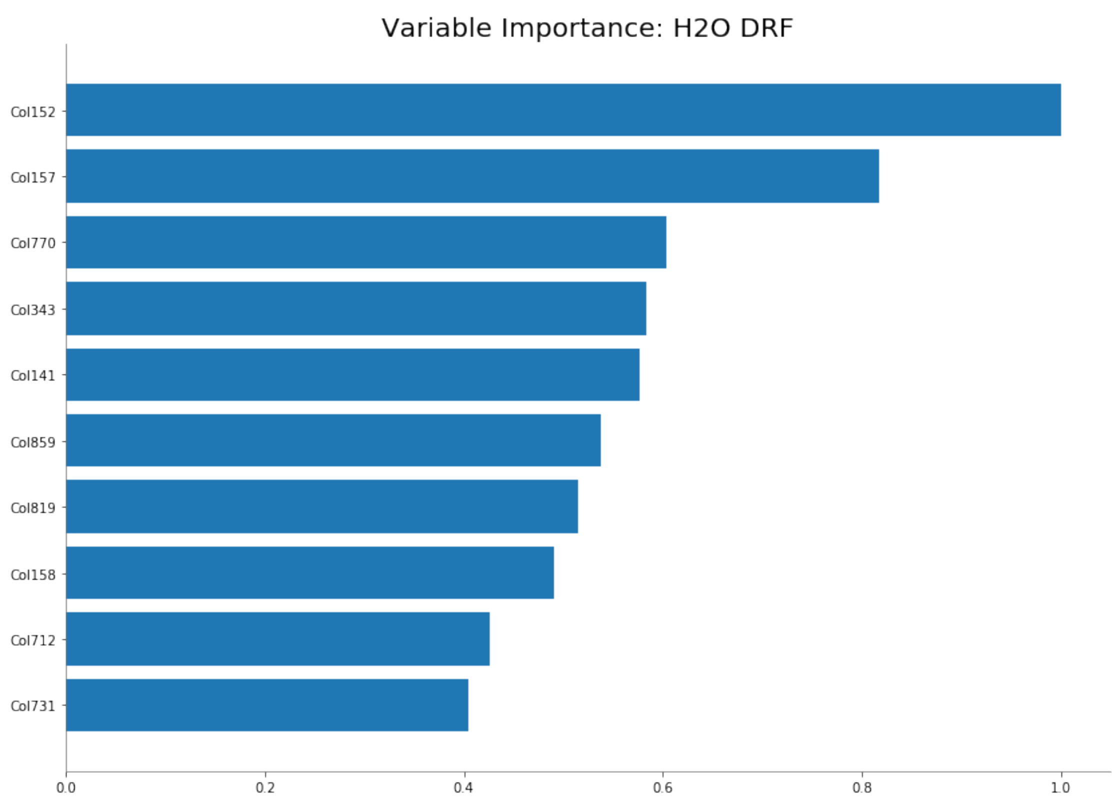
```
#         'Col1487', 'Col1488', 'Col1492', 'Col1493', 'Col1494', 'Col1496',
#         'Col1497', 'Col1499', 'Col1500', 'Col1502', 'Col1503', 'Col1505',
#         'Col1508', 'Col1510', 'Col1512', 'Col1513', 'Col1514', 'Col1515',
#         'Col1516', 'Col1520', 'Col1521', 'Col1527', 'Col1530', 'Col1531',
#         'Col1535', 'Col1538', 'Col1542', 'Col1545', 'Col1546', 'Col1547',
#         'Col1549', 'Col1551', 'Col1552', 'Col1554', 'Col1555', 'Col1560',
#         'Col1561', 'Col1562', 'Col1563', 'Col1565', 'Col1569', 'Col1570',
#         'Col1571', 'Col1576', 'Col1577', 'Col1578', 'Col1579', 'Col1581',
#         'Col1582', 'Col1583', 'Col1584', 'Col1587', 'Col1589', 'Col1590',
#         'Col1591', 'Col1593', 'Col1594', 'Col1595', 'Col1597', 'Col1601',
#         'Col1602', 'Col1603', 'Col1606', 'Col1607', 'Col1608', 'Col1609',
#         'Col1610', 'Col1611', 'Col1612', 'Col1617', 'Col1618', 'Col1619',
#         'Col1620', 'Col1622', 'Col1624', 'Col1626', 'Col1627', 'Col1629',
#         'Col1632', 'Col1633', 'Col1634', 'Col1635', 'Col1636', 'Col1638',
#         'Col1639', 'Col1640', 'Col1642', 'Col1643', 'Col1644', 'Col1645',
#         'Col1646', 'Col1649', 'Col1650', 'Col1652', 'Col1653', 'Col1654',
#         'Col1655', 'Col1656', 'Col1670', 'Col1672', 'Col1676', 'Col1679',
#         'Col1686', 'Col1690', 'Col1691', 'Col1698', 'Col1699', 'Col1704',
#         'Col1705', 'Col1707', 'Col1713', 'Col1715', 'Col1716', 'Col1720',
#         'Col1721', 'Col1722', 'Col1723', 'Col1724', 'Col1725', 'Col1729',
#         'Col1731', 'Col1735', 'Col1737', 'Col1739', 'Col1742', 'Col1743',
#         'Col1747', 'Col1749', 'Col1753', 'Col1758', 'Col1762', 'Col1763',
#         'Col1764', 'Col1765', 'Col1766', 'Col1768', 'Col1782', 'Col1785',
#         'Col1786', 'Col1788', 'Col1790', 'Col1792', 'Col1794', 'Col1796',
#         'Col1797', 'Col1801', 'Col1803', 'Col1804', 'Col1805', 'Col1806',
#         'Col1807', 'Col1808', 'Col1809', 'Col1810', 'Col1811', 'Col1812',
#         'Col1813', 'Col1815', 'Col1817', 'Col1822', 'Col1824', 'Col1826',
#         'Col1827', 'Col1832', 'Col1835', 'Col1837', 'Col1838', 'Col1839',
#         'Col1840', 'Col1841', 'Col1842', 'Col1855', 'Col1860', 'Col1862',
#         'Col1863', 'Col1864', 'Col1865', 'Col1866', 'Col1867', 'Col1868',
#         'Col1870', 'Col1874', 'Col1875', 'Col1877', 'Col1880', 'Col1882',
#         'Col1886', 'Col1887', 'Col1888', 'Col1889', 'Col1891', 'Col1895',
#         'Col1898', 'Col1899', 'Col1902', 'Col1905', 'Col1907', 'Col1909',
#         'Col1911', 'Col1913', 'Col1915', 'Col1918', 'Col1922', 'Col1923',
#         'Col1924', 'Col1925', 'Col1927', 'Col1930', 'Col1931', 'Col1932',
#         'Col1933', 'Col1936', 'Col1937', 'Col1946', 'Col1947', 'Col1949',
#         'Col1950', 'Col1951', 'Col1952', 'Col1955', 'Col1956', 'Col1957',
#         'Col1958', 'Col1959', 'Col1966', 'Col1967', 'Col1970', 'Col1971',
#         'Col1972', 'Col1973', 'Col1974', 'Col1975', 'Col1976', 'Col1977',
#         'Col1978', 'Col1979', 'Col1980', 'Col1981', 'Col1986', 'Col1987',
#         'Col1989', 'Col1991', 'Col1993', 'Col1996', 'Col1997', 'Col1998',
#         'Col1999', 'Col2001', 'Col2003', 'Col2005', 'Col2010', 'Col2011',
#         'Col2014', 'Col2015', 'Col2016', 'Col2019', 'Col2022', 'Col2023',
#         'Col2024', 'Col2025', 'Col2029', 'Col2031', 'Col2036', 'Col2038',
#         'Col2040', 'Col2041', 'Col2043', 'Col2044', 'Col2047', 'Col2049',
#         'Col2050', 'Col2052', 'Col2054', 'Col2057', 'Col2060', 'Col2062',
#         'Col2063', 'Col2068', 'Col2069', 'Col2070', 'Col2071', 'Col2072',
#         'Col2073', 'Col2074', 'Col2078', 'Col2079', 'Col2081', 'Col2085',
```

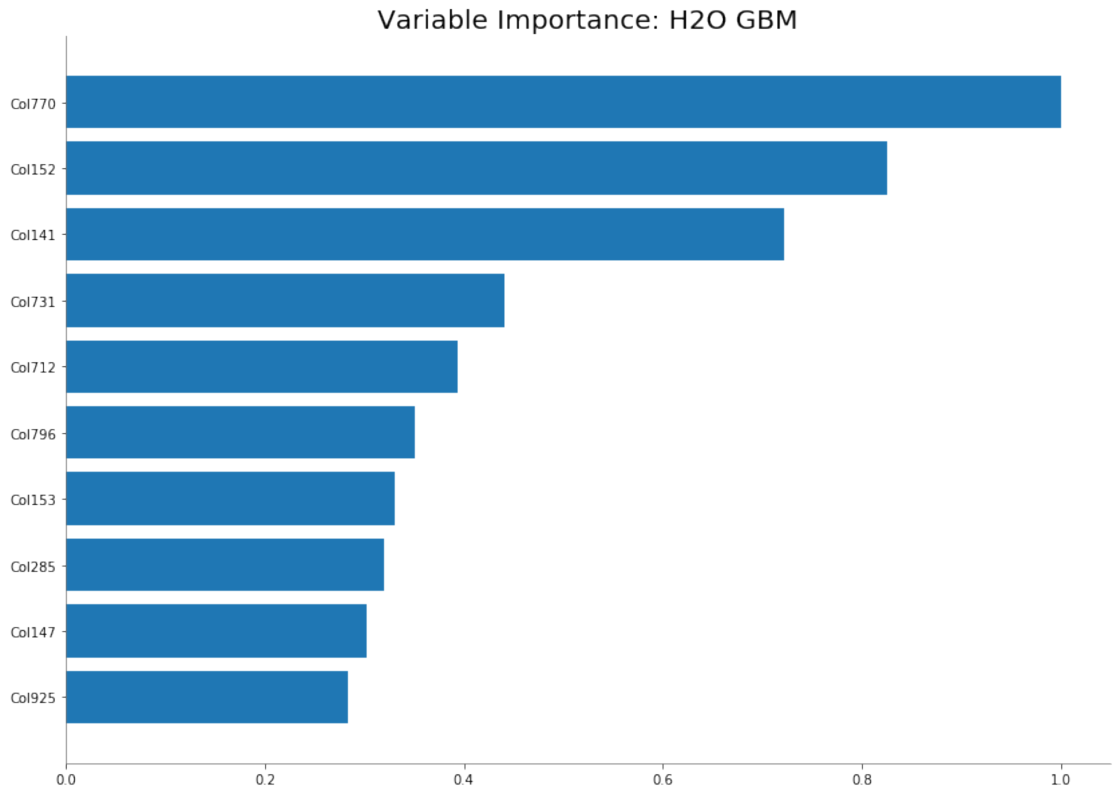
```
#        'Col2087', 'Col2092', 'Col2093', 'Col2094', 'Col2095', 'Col2096',
#        'Col2098', 'Col2099', 'Col2102', 'Col2104', 'Col2105', 'Col2110',
#        'Col2112', 'Col2113', 'Col2114', 'Col2118', 'Col2125', 'Col2126',
#        'Col2127', 'Col2128', 'Col2129', 'Col2130', 'Col2131', 'Col2132',
#        'Col2133', 'Col2134', 'Col2135', 'Col2138', 'Col2139', 'Col2140',
#        'Col2141', 'Col2145', 'Col2150', 'Col2151', 'Col2153', 'Col2158',
#        'Col2159', 'Col2161', 'Col2162', 'Col2167', 'Col2168', 'Col2169',
#        'Col2170', 'Col2172', 'Col2173', 'Col2174', 'Col2175', 'Col2176',
#        'Col2177', 'Col2178', 'Col2179', 'Col2181', 'Col2186', 'Col2188',
#        'Col2189', 'Col2191', 'Col2192', 'Col2193', 'Col2194', 'Col2195',
#        'Col2202', 'Col2203', 'Col2204', 'Col2205', 'Col2207', 'Col2208',
#        'Col2209', 'Col2213', 'Col2214', 'Col2215', 'Col2219', 'Col2220',
#        'Col2221', 'Col2222', 'Col2223', 'Col2224', 'Col2225', 'Col2226',
#        'Col2227', 'Col2230', 'Col2231', 'Col2234', 'Col2236', 'Col2240',
#        'Col2242', 'Col2243', 'Col2244', 'Col2251', 'Col2252', 'Col2254',
#        'Col2258', 'Col2259', 'Col2260', 'Col2262', 'Col2265', 'Col2266',
#        'Col2267', 'Col2269', 'Col2271', 'Col2272', 'Col2275', 'Col2282',
#        'Col2283', 'Col2284', 'Col2285', 'Col2291', 'Col2293', 'Col2294',
#        'Col2295', 'Col2298', 'Col2299', 'Col2305', 'Col2306', 'Col2307',
#        'Col2309', 'Col2310', 'Col2312', 'Col2313', 'Col2315', 'Col2316',
#        'Col2317', 'Col2320', 'Col2321', 'Col2323', 'Col2324', 'Col2325',
#        'Col2326', 'Col2327', 'Col2331', 'Col2333', 'Col2337', 'Col2340',
#        'Col2341', 'Col2343', 'Col2344', 'Col2345', 'Col2348', 'Col2350',
#        'Col2351', 'Col2354', 'Col2355', 'Col2356', 'Col2357', 'Col2358',
#        'Col2359', 'Col2362', 'Col2364', 'Col2366', 'Col2369', 'Col2372',
#        'Col2375', 'Col2377', 'Col2380', 'Col2381', 'Col2382', 'Col2383',
#        'Col2385', 'Col2394'], dtype=object)
```

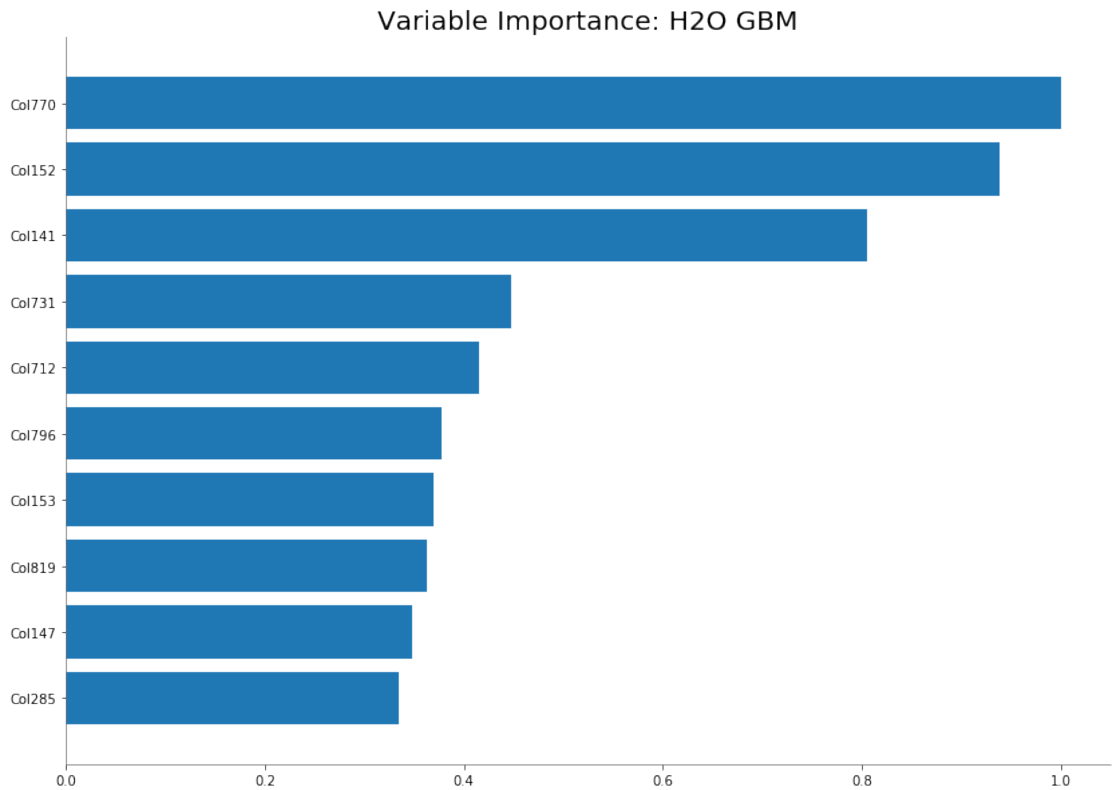
1.10 variable importance of `distributed-random-forest` and `Gradient-boosting-tree`

In [139]:


Variable Importance: H2O DRF
Col152
Col141
Col153
Col158
Col157
Col770
Col142
Col859
Col819
Col147
0.0
0.2
0.4
0.6
0.8
1.0


Variable Importance: H2O DRF
Col152
Col157
Col770
Col343
Col141
Col859
Col819
Col158
Col712
Col731
0.0
0.2
0.4
0.6
0.8
1.0


Variable Importance: H2O GBM
Col770
Col152
Col141
Col731
Col712
Col796
Col153
Col285
Col147
Col925
0.0
0.2
0.4
0.6
0.8
1.0


Variable Importance: H2O GBM
Col770
Col152
Col141
Col731
Col712
Col796
Col153
Col819
Col147
Col285
0.0
0.2
0.4
0.6
0.8
1.0