Credit_Ratings_1

April 3, 2019

In [1]:
```
# Mount Google Drive
"""
No need to execute this block when working on local system.
"""
from google.colab import drive
drive.mount("/content/vdrive", force_remount = True)
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/vdrive
```

In [0]:
```
# Files to process
"""
Modify the locations below as per your directory struture.
"""
sp_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/"
root_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/"
data_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/raw/"
prep_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/prep/"
model_dir = "/content/vdrive/My Drive/Colab Notebooks/Projects/Bondai/SP 500/data/model
```

In [0]:
```
# Loading the csv files
import pandas as pd
actual_df = pd.read_csv(model_dir + "actual_data.csv")
pred_df = pd.read_csv(model_dir + "pred_data.csv")
```

In [0]:
```
actual_df["act_short_term"] = actual_df["crr_asst"]/actual_df["crr_libt"]
actual_df["act_long_term"] = actual_df["ncrr_asst"]/actual_df["ncrr_libt"]
actual_df["act_overall"] = (actual_df["crr_asst"] + actual_df["ncrr_asst"])/(actual_df
```

In [0]:
```
actual_df
```

Out[0]:

	Ticker	net_income	op_income	gross_profit	crr_asst	\
0	HSIC	5.358810e+08	7.530520e+08	3.595084e+09	4.175220e+09	
1	ALXN	7.760000e+07	3.861000e+08	3.756900e+09	3.385000e+09	

2	KR	1.907000e+09	2.085000e+09	2.700000e+10	1.111700e+10
3	BBT	3.237000e+09	4.060000e+09	1.099200e+10	0.000000e+00
4	DIS	1.259800e+10	1.480400e+10	2.670800e+10	1.682500e+10
5	MMC	1.650000e+09	2.761000e+09	1.495000e+10	5.934000e+09
6	MAR	1.907000e+09	2.366000e+09	3.674000e+09	2.706000e+09
7	CELG	4.046000e+09	5.191000e+09	1.469400e+10	9.067000e+09
8	VMC	5.158050e+08	7.477130e+08	1.100945e+09	1.079145e+09
9	RHI	4.342880e+08	5.872200e+08	2.410014e+09	1.473610e+09
10	MKC	8.986000e+08	9.033000e+08	2.371600e+09	1.479900e+09
11	PGR	2.615300e+09	3.330100e+09	1.025800e+10	0.000000e+00
12	ILMN	8.260000e+08	8.830000e+08	2.300000e+09	4.490000e+09
13	AMAT	3.313000e+09	4.796000e+09	7.817000e+09	1.060400e+10
14	LEG	3.059000e+08	4.377000e+08	8.887000e+08	1.524600e+09
15	STI	2.775000e+09	3.332000e+09	9.005000e+09	0.000000e+00
16	GS	1.045900e+10	1.315500e+10	3.661600e+10	0.000000e+00
17	RTN	2.909000e+09	4.538000e+09	7.485000e+09	1.213600e+10
18	KMI	1.609000e+09	3.794000e+09	6.856000e+09	5.722000e+09
19	CRM	1.110000e+09	5.350000e+08	9.831000e+09	1.068300e+10
20	STZ	2.318900e+09	2.284500e+09	3.817200e+09	3.474000e+09
21	AAP	4.238470e+08	6.042750e+08	4.219413e+09	6.082454e+09
22	EXC	2.010000e+09	3.898000e+09	8.195000e+09	1.336000e+10
23	MCO	1.309600e+09	1.868200e+09	4.442700e+09	3.386900e+09
24	AGN	-5.096400e+09	-6.247600e+09	1.359600e+10	6.475400e+09
25	C	1.804500e+10	2.344500e+10	6.528600e+10	0.000000e+00
26	NTRS	1.556400e+09	1.957800e+09	5.974700e+09	0.000000e+00
27	TMK	7.014660e+08	9.537470e+08	2.028509e+09	0.000000e+00
28	EW	7.222000e+08	7.496000e+08	2.783400e+09	2.286900e+09
29	NEE	6.638000e+09	4.280000e+09	9.665000e+09	6.393000e+09
..	...	...	...	...	...
50	GT	7.080000e+08	1.158000e+09	3.514000e+09	5.925000e+09
51	CF	2.900000e+08	7.300000e+08	9.170000e+08	1.274000e+09
52	DVA	1.593940e+08	1.530308e+09	3.209338e+09	8.424159e+09
53	CAH	2.560000e+08	1.030000e+08	7.181000e+09	2.455300e+10
54	ADP	1.620800e+09	2.511700e+09	5.483200e+09	3.182330e+10
55	CAG	8.084000e+08	1.033500e+09	2.351500e+09	1.938900e+09
56	YUM	1.542000e+09	2.296000e+09	2.658000e+09	1.207000e+09
57	D	2.447000e+09	3.601000e+09	5.624000e+09	5.161000e+09
58	CL	2.400000e+09	3.694000e+09	9.231000e+09	3.793000e+09
59	PRGO	1.310000e+08	2.365000e+08	1.831500e+09	2.902200e+09
60	AZO	1.337536e+09	1.810856e+09	5.973746e+09	4.635869e+09
61	ETFC	1.052000e+09	1.422000e+09	2.873000e+09	0.000000e+00
62	IP	2.012000e+09	2.933000e+09	7.751000e+09	6.996000e+09
63	COF	6.015000e+09	7.318000e+09	2.222000e+10	0.000000e+00
64	GPS	1.003000e+09	1.362000e+09	6.322000e+09	4.251000e+09
65	FL	2.840000e+08	5.710000e+08	2.456000e+09	2.551000e+09
66	GD	3.345000e+09	4.457000e+09	6.715000e+09	1.818900e+10
67	CVS	-5.940000e+08	4.021000e+09	3.153800e+10	4.524300e+10
68	ED	1.382000e+09	2.664000e+09	6.237000e+09	3.864000e+09

69	CI	2.237000e+09	3.606000e+09	1.375400e+10	0.000000e+00
70	PNC	5.301000e+09	6.836000e+09	1.713200e+10	0.000000e+00
71	BLK	4.305000e+09	5.457000e+09	1.152500e+10	0.000000e+00
72	HUM	1.683000e+09	3.100000e+09	1.103000e+10	1.694800e+10
73	MMM	5.349000e+09	7.207000e+09	1.608300e+10	1.370900e+10
74	ALGN	4.002350e+08	4.665640e+08	1.447867e+09	1.302479e+09
75	AFL	2.920000e+09	4.205000e+09	9.758000e+09	0.000000e+00
76	CSX	3.309000e+09	4.773000e+09	4.773000e+09	2.565000e+09
77	ORLY	1.324487e+09	1.815184e+09	5.039966e+09	3.543102e+09
78	CNC	9.000000e+08	1.458000e+09	8.421000e+09	1.199800e+10
79	MDLZ	3.381000e+09	3.312000e+09	1.035200e+10	7.604000e+09

	ncrr_asst	crr_libt	ncrr_libt	act_short_term	act_long_term	\
0	4.325307e+09	3.218827e+09	1.427756e+09	1.297125	3.029444	
1	1.054690e+10	1.174000e+09	3.592600e+09	2.883305	2.935729	
2	2.608000e+10	1.419700e+10	1.609500e+10	0.783053	1.620379	
3	2.256970e+11	0.000000e+00	1.955190e+11	NaN	1.154348	
4	8.177300e+10	1.786000e+10	2.790600e+10	0.942049	2.930302	
5	1.564400e+10	4.924000e+09	9.070000e+09	1.205118	1.724807	
6	2.099000e+10	6.437000e+09	1.503400e+10	0.420382	1.396169	
7	2.641300e+10	4.057000e+09	2.526200e+10	2.234903	1.045563	
8	8.752985e+09	6.025500e+08	4.026677e+09	1.790963	2.173749	
9	4.294870e+08	8.195360e+08	2.036300e+07	1.798103	21.091539	
10	8.776500e+09	2.001700e+09	5.072500e+09	0.739322	1.730212	
11	4.657500e+10	0.000000e+00	3.553870e+10	NaN	1.310543	
12	2.469000e+09	1.804000e+09	1.310000e+09	2.488914	1.884733	
13	7.029000e+09	3.922000e+09	6.866000e+09	2.703723	1.023740	
14	1.857400e+09	8.157000e+08	1.408700e+09	1.869070	1.318521	
15	2.155430e+11	0.000000e+00	1.912630e+11	NaN	1.126946	
16	9.317960e+11	0.000000e+00	8.416110e+11	NaN	1.107158	
17	1.972800e+10	8.288000e+09	1.210400e+10	1.464286	1.629874	
18	7.314400e+10	7.557000e+09	3.611200e+10	0.757179	2.025476	
19	2.005400e+10	1.125500e+10	3.877000e+09	0.949178	5.172556	
20	1.706470e+10	2.039600e+09	1.050740e+10	1.703275	1.624065	
21	2.958194e+09	3.885950e+09	1.603885e+09	1.565242	1.844393	
22	1.063060e+11	1.140400e+10	7.519200e+10	1.171519	1.413794	
23	6.139300e+09	2.098500e+09	6.771200e+09	1.613962	0.906678	
24	9.531220e+10	5.727900e+09	3.092870e+10	1.130502	3.081675	
25	1.917383e+12	0.000000e+00	1.720309e+12	NaN	1.114557	
26	1.322125e+11	0.000000e+00	1.217042e+11	NaN	1.086343	
27	2.309572e+10	0.000000e+00	1.768054e+10	NaN	1.306279	
28	3.036800e+09	8.766000e+08	1.306700e+09	2.608830	2.324022	
29	9.730900e+10	1.756300e+10	4.872600e+10	0.364004	1.997065	
..	...	...	...	...	...	
50	1.094700e+10	4.781000e+09	7.021000e+09	1.239280	1.559180	
51	1.138700e+10	7.050000e+08	6.225000e+09	1.807092	1.829237	
52	1.068609e+10	4.891161e+09	9.186052e+09	1.722323	1.163296	
53	1.539800e+10	2.289300e+10	1.099900e+10	1.072511	1.399945	

54	7.025800e+09	3.041270e+10	3.700500e+09	1.046382	1.898608
55	8.450600e+09	2.336200e+09	4.296700e+09	0.829938	1.966765
56	2.923000e+09	1.301000e+09	1.075500e+10	0.927748	0.271781
57	7.275300e+10	7.647000e+09	4.821900e+10	0.674905	1.508804
58	8.368000e+09	3.341000e+09	8.623000e+09	1.135289	0.970428
59	8.081200e+09	1.537400e+09	3.777900e+09	1.887733	2.139072
60	4.711111e+09	5.028681e+09	5.838654e+09	0.921886	0.806883
61	6.500300e+10	0.000000e+00	5.844100e+10	NaN	1.112284
62	2.658000e+10	4.694000e+09	2.149900e+10	1.490413	1.236337
63	3.725380e+11	0.000000e+00	3.208700e+11	NaN	1.161025
64	3.798000e+09	2.174000e+09	2.322000e+09	1.955382	1.635659
65	1.410000e+09	6.160000e+08	8.260000e+08	4.141234	1.707022
66	2.721900e+10	1.473900e+10	1.893700e+10	1.234073	1.437345
67	1.512130e+11	4.400900e+10	9.390400e+10	1.028040	1.610293
68	5.005600e+10	6.207000e+09	3.087400e+10	0.622523	1.621299
69	6.175900e+10	0.000000e+00	4.799900e+10	NaN	1.286673
70	3.823150e+11	0.000000e+00	3.345450e+11	NaN	1.142791
71	1.595730e+11	0.000000e+00	1.260330e+11	NaN	1.266121
72	8.465000e+09	1.007700e+10	5.175000e+09	1.681850	1.635749
73	2.279100e+10	7.244000e+09	1.940800e+10	1.892463	1.174310
74	7.499790e+08	6.920730e+08	1.074940e+08	1.881997	6.976938
75	1.404060e+11	0.000000e+00	1.169440e+11	NaN	1.200626
76	3.416400e+10	1.915000e+09	2.223400e+10	1.339426	1.536566
77	4.437687e+09	3.894020e+09	3.733102e+09	0.909883	1.188740
78	1.890300e+10	1.197100e+10	7.907000e+09	1.002255	2.390666
79	5.512500e+10	1.673700e+10	2.027900e+10	0.454323	2.718329

	act_overall
0	1.829415
1	2.922817
2	1.227948
3	1.154348
4	2.154394
5	1.541947
6	1.103628
7	1.210137
8	2.123925
9	2.265864
10	1.449832
11	1.310543
12	2.234746
13	1.634501
14	1.520410
15	1.126946
16	1.107158
17	1.562574
18	1.805995
19	2.031258

```
20     1.636941
21     1.646798
22     1.381888
23     1.074016
24     2.776788
25     1.114557
26     1.086343
27     1.306279
28     2.438373
29     1.564392
..          ...
50     1.429588
51     1.826984
52     1.357531
53     1.178774
54     1.138829
55     1.566359
56     0.342568
57     1.394659
58     1.016466
59     2.066374
60     0.860099
61     1.112284
62     1.281869
63     1.161025
64     1.790258
65     2.746879
66     1.348379
67     1.424492
68     1.454114
69     1.286673
70     1.142791
71     1.266121
72     1.666208
73     1.369503
74     2.566962
75     1.200626
76     1.520933
77     1.046370
78     1.554533
79     1.694646

[80 rows x 11 columns]
```

In [0]:
```
pred_df["pred_short_term"] = pred_df["crr_asst"]/pred_df["crr_libt"]
pred_df["pred_long_term"] = pred_df["ncrr_asst"]/pred_df["ncrr_libt"]
pred_df["pred_overall"] = (pred_df["crr_asst"] + pred_df["ncrr_asst"])/(pred_df["crr_li
```

In [0]:
```
pred_df
```

Out[0]:

	Ticker	net_income	op_income	gross_profit	crr_asst	\
0	HSIC	3.679738e+10	3.015203e+10	4.938941e+10	1.307145e+10	
1	ALXN	5.243959e+09	1.972108e+10	1.880685e+10	1.686743e+10	
2	KR	1.344144e+10	7.161474e+10	1.825964e+10	6.923701e+10	
3	BBT	1.108789e+10	2.837211e+10	4.390100e+10	0.000000e+00	
4	DIS	5.498764e+10	-4.170145e+10	9.421502e+10	6.509739e+10	
5	MMC	3.533200e+10	3.706890e+10	8.949936e+10	2.270157e+10	
6	MAR	4.059627e+11	4.884161e+10	1.451784e+11	5.826403e+10	
7	CELG	8.112943e+09	2.936682e+10	6.024234e+10	6.403268e+10	
8	VMC	6.086551e+08	1.095075e+09	3.728789e+09	4.547371e+09	
9	RHI	-4.794914e+09	1.166562e+10	1.435685e+10	4.605498e+09	
10	MKC	1.989180e+10	3.837449e+10	2.466270e+10	1.117875e+10	
11	PGR	-3.560131e+10	-7.053409e+10	-7.372684e+09	0.000000e+00	
12	ILMN	1.759263e+10	-1.314812e+10	1.163666e+10	2.084097e+10	
13	AMAT	-1.362513e+11	-1.887768e+11	2.303585e+10	5.267963e+10	
14	LEG	2.484128e+10	1.749063e+10	1.348911e+10	4.743122e+09	
15	STI	1.211447e+10	-3.313087e+09	3.385239e+10	0.000000e+00	
16	GS	6.081463e+11	2.265172e+11	2.288748e+11	0.000000e+00	
17	RTN	1.783994e+10	3.512444e+10	3.358674e+10	4.463768e+10	
18	KMI	2.565480e+10	2.331421e+11	5.847301e+10	2.330267e+10	
19	CRM	-1.565162e+09	3.239530e+10	1.474947e+11	1.677793e+11	
20	STZ	2.589921e+10	3.699796e+09	2.320455e+10	1.654650e+10	
21	INFO	-1.233533e+10	-3.858978e+10	-5.501919e+07	3.202947e+09	
22	AAP	-1.130057e+11	-1.989240e+10	2.180606e+09	-2.951941e+10	
23	EXC	3.884696e+11	3.145268e+11	1.453028e+11	1.539482e+11	
24	MCO	2.299357e+11	-4.143122e+11	-9.149749e+09	5.358764e+10	
25	AGN	3.114396e+12	1.300802e+12	-3.868414e+11	1.175146e+09	
26	C	-4.276212e+11	6.654888e+12	1.775843e+12	0.000000e+00	
27	NTRS	9.302524e+09	8.410357e+09	2.517505e+10	0.000000e+00	
28	TMK	-2.075195e+10	-7.592208e+09	7.383677e+09	0.000000e+00	
29	EW	4.069926e+10	5.970158e+10	4.530453e+10	2.014124e+10	
..	...	...	...	...	...	
52	CF	-1.888813e+10	4.289536e+10	3.182591e+09	-1.405933e+10	
53	DVA	4.619785e+10	3.428454e+10	2.635681e+10	5.703395e+10	
54	CAH	6.068954e+10	1.242604e+11	9.367018e+10	2.294272e+11	
55	ADP	1.184946e+10	9.169922e+09	2.588157e+10	1.468140e+11	
56	CAG	-6.061071e+10	1.415264e+10	3.458348e+10	-9.936546e+09	
57	YUM	1.838324e+10	-6.592927e+10	1.076109e+10	1.348748e+10	
58	D	1.991379e+10	1.098076e+10	2.756890e+10	1.973152e+10	
59	CL	6.645780e+09	5.463510e+09	3.780004e+10	1.868348e+10	
60	PRGO	5.900410e+10	6.675063e+11	1.627198e+11	1.714247e+11	
61	AZO	1.342543e+09	-9.508770e+09	2.437120e+10	1.999376e+10	
62	ETFC	2.733586e+08	7.607082e+09	8.907217e+09	0.000000e+00	
63	IP	7.432824e+10	2.836092e+10	4.452969e+10	4.198591e+10	
64	COF	6.467564e+11	1.204292e+12	2.552446e+11	0.000000e+00	
65	GPS	3.531481e+09	4.142954e+09	4.339878e+10	2.078828e+10	
66	FL	2.244281e+07	-2.439203e+08	8.788522e+09	9.803873e+09	
67	GD	-5.693522e+10	-2.703642e+09	8.213421e+09	8.631597e+10	

68	CVS	6.263666e+10	1.361894e+11	1.510604e+11	1.664503e+11
69	ED	1.351862e+10	9.022491e+09	2.357653e+10	1.298504e+10
70	CI	-3.741107e+10	-3.550150e+10	2.985656e+10	0.000000e+00
71	PNC	2.032416e+10	7.044803e+09	6.527898e+10	0.000000e+00
72	BLK	-9.008008e+08	1.666090e+10	4.858452e+10	0.000000e+00
73	HUM	2.490475e+10	-6.662985e+10	2.470837e+10	5.907528e+10
74	MMM	1.296425e+11	1.014334e+11	1.247486e+11	6.245319e+10
75	ALGN	2.165331e+10	-2.137315e+09	2.143563e+10	1.120851e+10
76	AFL	1.601975e+10	2.117093e+10	3.929998e+10	0.000000e+00
77	CHTR	-2.579785e+10	2.772546e+10	2.081055e+11	1.614200e+09
78	CSX	2.547086e+10	-6.940559e+06	1.522572e+10	5.689567e+09
79	ORLY	-1.245861e+09	-1.790187e+10	1.849868e+10	1.450312e+10
80	CNC	3.393864e+10	-6.540140e+10	8.071545e+10	1.139558e+11
81	MDLZ	-9.739358e+10	7.196536e+10	4.339102e+10	4.427963e+10

	ncrr_asst	crr_libt	ncrr_libt	pred_short_term	pred_long_term	\
0	4.686288e+10	2.683307e+10	8.592428e+09	0.487140	5.453974	
1	9.999485e+10	7.131052e+09	6.809464e+10	2.365349	1.468469	
2	2.435666e+11	1.125278e+11	2.372352e+11	0.615288	1.026688	
3	1.516303e+12	0.000000e+00	1.258742e+12	NaN	1.204618	
4	5.387763e+11	1.378007e+11	2.112248e+11	0.472403	2.550725	
5	1.271019e+11	3.313393e+10	6.364128e+10	0.685146	1.997162	
6	8.233906e+11	1.462743e+11	-7.911217e+10	0.398320	-10.407888	
7	1.066248e+11	2.186884e+10	1.407706e+11	2.928032	0.757436	
8	5.404595e+10	3.042625e+09	2.720648e+10	1.494555	1.986510	
9	3.096712e+09	5.344396e+09	1.369185e+08	0.861743	22.617183	
10	7.387642e+10	1.846174e+10	1.469464e+10	0.605509	5.027441	
11	2.382071e+11	0.000000e+00	1.729938e+11	NaN	1.376969	
12	2.991347e+10	7.317870e+09	2.785452e+10	2.847956	1.073918	
13	3.597448e+10	2.351893e+10	3.573044e+10	2.239882	1.006830	
14	2.196176e+10	8.668981e+09	9.166935e+08	0.547137	23.957581	
15	1.415710e+12	0.000000e+00	1.324284e+12	NaN	1.069038	
16	3.633571e+10	0.000000e+00	-1.891878e+12	NaN	-0.019206	
17	1.525268e+11	5.346588e+10	8.033108e+10	0.834882	1.898727	
18	5.500768e+11	4.380246e+10	2.016527e+11	0.531995	2.727843	
19	4.275385e+11	1.004642e+11	2.357299e+11	1.670041	1.813680	
20	1.364186e+11	2.160542e+10	6.484040e+10	0.765849	2.103913	
21	1.267734e+10	8.162686e+09	-5.279317e+09	0.392389	-2.401322	
22	1.136613e+10	1.539376e+10	3.599261e+09	-1.917622	3.157907	
23	-1.082454e+11	1.075830e+11	9.080234e+11	1.430971	-0.119210	
24	9.085430e+10	3.174962e+10	3.051376e+11	1.687820	0.297749	
25	1.342250e+12	2.408042e+11	-5.356027e+11	0.004880	-2.506055	
26	9.017712e+12	0.000000e+00	3.640560e+11	NaN	24.770126	
27	1.129783e+12	0.000000e+00	1.033088e+12	NaN	1.093598	
28	1.369240e+11	0.000000e+00	1.101316e+11	NaN	1.243276	
29	6.326778e+10	1.508601e+10	3.231439e+09	1.335094	19.578825	
..	...	...	...	...	...	
52	-2.043053e+11	-3.068729e+09	3.936326e+10	4.581483	-5.190254	

53	1.122156e+11	2.388978e+10	1.699973e+11	2.387378	0.660102
54	1.465214e+11	2.215300e+11	1.033674e+11	1.035648	1.417481
55	3.214285e+10	2.216783e+11	2.507700e+10	0.662284	1.281766
56	2.351532e+11	5.767953e+09	-6.497465e+10	-1.722716	-3.619153
57	2.239490e+10	1.105592e+10	6.976475e+10	1.219933	0.321006
58	4.679937e+11	7.037090e+10	3.108149e+11	0.280393	1.505699
59	5.373563e+10	2.431704e+10	6.210466e+10	0.768329	0.865243
60	-9.022035e+10	1.755399e+10	1.549307e+10	9.765569	-5.823271
61	3.360889e+10	3.421885e+10	4.759506e+10	0.584291	0.706142
62	4.191905e+11	0.000000e+00	3.510275e+11	NaN	1.194181
63	1.619756e+11	3.767908e+10	1.484967e+11	1.114303	1.090769
64	2.979557e+12	0.000000e+00	8.415989e+11	NaN	3.540353
65	2.109297e+10	1.781110e+10	1.029468e+10	1.167153	2.048919
66	7.264840e+09	4.194192e+09	3.825883e+09	2.337488	1.898866
67	1.128304e+11	9.034529e+10	6.789973e+10	0.955401	1.661722
68	6.002787e+11	2.500084e+11	4.725557e+11	0.665779	1.270281
69	3.339547e+11	3.449317e+10	1.778195e+11	0.376452	1.878055
70	4.376020e+11	0.000000e+00	3.982132e+11	NaN	1.098914
71	2.325419e+12	0.000000e+00	2.516122e+12	NaN	0.924207
72	1.261365e+12	0.000000e+00	1.064594e+12	NaN	1.184832
73	4.747541e+10	5.781358e+10	4.440166e+10	1.021824	1.069226
74	2.097235e+11	6.165196e+10	1.500566e+11	1.012996	1.397629
75	1.309432e+10	6.352539e+09	1.363778e+09	1.764415	9.601509
76	9.249001e+11	0.000000e+00	7.389025e+11	NaN	1.251722
77	1.064686e+11	8.574150e+09	1.567961e+11	0.188264	0.679026
78	2.189348e+11	1.213063e+10	1.267822e+11	0.469025	1.726857
79	2.868826e+10	2.635632e+10	2.249224e+10	0.550271	1.275474
80	2.095046e+11	1.447806e+11	2.626981e+10	0.787093	7.975109
81	2.943311e+11	1.268380e+11	2.920925e+11	0.349104	1.007664

	pred_overall
0	1.691842
1	1.553489
2	0.894330
3	1.204618
4	1.730171
5	1.547953
6	13.127251
7	1.049299
8	1.937027
9	1.405176
10	2.565274
11	1.376969
12	1.443019
13	1.496288
14	2.785916
15	1.069038
16	-0.019206

```
17      1.473609
18      2.335985
19      1.770757
20      1.769491
21      5.507545
22     -0.955787
23      0.045000
24      0.428755
25     -4.557095
26     24.770126
27      1.093598
28      1.243276
29      4.553529
..           ...
52     -6.016462
53      0.872928
54      1.157130
55      0.725240
56     -3.803905
57      0.443975
58      1.279495
59      0.837974
60      2.457232
61      0.655178
62      1.194181
63      1.095532
64      3.540353
65      1.490129
66      2.128248
67      1.258469
68      1.061122
69      1.634098
70      1.098914
71      0.924207
72      1.184832
73      1.042415
74      1.285620
75      3.149538
76      1.251722
77      0.653581
78      1.617016
79      0.884189
80      1.891024
81      0.808274

[82 rows x 11 columns]
```

```
In [0]: actual_rating = actual_df[["Ticker", "act_short_term", "act_long_term", "act_overall"]]
```

```
        actual_rating.set_index("Ticker", inplace = True)
```

```
In [0]: actual_rating
```

Out[0]:

Ticker	act_short_term	act_long_term	act_overall
HSIC	1.297125	3.029444	1.829415
ALXN	2.883305	2.935729	2.922817
KR	0.783053	1.620379	1.227948
BBT	NaN	1.154348	1.154348
DIS	0.942049	2.930302	2.154394
MMC	1.205118	1.724807	1.541947
MAR	0.420382	1.396169	1.103628
CELG	2.234903	1.045563	1.210137
VMC	1.790963	2.173749	2.123925
RHI	1.798103	21.091539	2.265864
MKC	0.739322	1.730212	1.449832
PGR	NaN	1.310543	1.310543
ILMN	2.488914	1.884733	2.234746
AMAT	2.703723	1.023740	1.634501
LEG	1.869070	1.318521	1.520410
STI	NaN	1.126946	1.126946
GS	NaN	1.107158	1.107158
RTN	1.464286	1.629874	1.562574
KMI	0.757179	2.025476	1.805995
CRM	0.949178	5.172556	2.031258
STZ	1.703275	1.624065	1.636941
AAP	1.565242	1.844393	1.646798
EXC	1.171519	1.413794	1.381888
MCO	1.613962	0.906678	1.074016
AGN	1.130502	3.081675	2.776788
C	NaN	1.114557	1.114557
NTRS	NaN	1.086343	1.086343
TMK	NaN	1.306279	1.306279
EW	2.608830	2.324022	2.438373
NEE	0.364004	1.997065	1.564392
...	...	...	...
GT	1.239280	1.559180	1.429588
CF	1.807092	1.829237	1.826984
DVA	1.722323	1.163296	1.357531
CAH	1.072511	1.399945	1.178774
ADP	1.046382	1.898608	1.138829
CAG	0.829938	1.966765	1.566359
YUM	0.927748	0.271781	0.342568
D	0.674905	1.508804	1.394659
CL	1.135289	0.970428	1.016466
PRGO	1.887733	2.139072	2.066374
AZO	0.921886	0.806883	0.860099

```
ETFC              NaN       1.112284     1.112284
IP           1.490413       1.236337     1.281869
COF               NaN       1.161025     1.161025
GPS          1.955382       1.635659     1.790258
FL           4.141234       1.707022     2.746879
GD           1.234073       1.437345     1.348379
CVS          1.028040       1.610293     1.424492
ED           0.622523       1.621299     1.454114
CI                NaN       1.286673     1.286673
PNC               NaN       1.142791     1.142791
BLK               NaN       1.266121     1.266121
HUM          1.681850       1.635749     1.666208
MMM          1.892463       1.174310     1.369503
ALGN         1.881997       6.976938     2.566962
AFL               NaN       1.200626     1.200626
CSX          1.339426       1.536566     1.520933
ORLY         0.909883       1.188740     1.046370
CNC          1.002255       2.390666     1.554533
MDLZ         0.454323       2.718329     1.694646

[80 rows x 3 columns]
```

In [0]:
```
pred_rating = pred_df[["Ticker", "pred_short_term", "pred_long_term", "pred_overall"]]
pred_rating.set_index("Ticker", inplace = True)
pred_rating
```

Out[0]:

Ticker	pred_short_term	pred_long_term	pred_overall
HSIC	0.487140	5.453974	1.691842
ALXN	2.365349	1.468469	1.553489
KR	0.615288	1.026688	0.894330
BBT	NaN	1.204618	1.204618
DIS	0.472403	2.550725	1.730171
MMC	0.685146	1.997162	1.547953
MAR	0.398320	-10.407888	13.127251
CELG	2.928032	0.757436	1.049299
VMC	1.494555	1.986510	1.937027
RHI	0.861743	22.617183	1.405176
MKC	0.605509	5.027441	2.565274
PGR	NaN	1.376969	1.376969
ILMN	2.847956	1.073918	1.443019
AMAT	2.239882	1.006830	1.496288
LEG	0.547137	23.957581	2.785916
STI	NaN	1.069038	1.069038
GS	NaN	-0.019206	-0.019206
RTN	0.834882	1.898727	1.473609
KMI	0.531995	2.727843	2.335985
CRM	1.670041	1.813680	1.770757

```
STZ            0.765849       2.103913      1.769491
INFO           0.392389      -2.401322      5.507545
AAP           -1.917622       3.157907     -0.955787
EXC            1.430971      -0.119210      0.045000
MCO            1.687820       0.297749      0.428755
AGN            0.004880      -2.506055     -4.557095
C                   NaN      24.770126     24.770126
NTRS                NaN       1.093598      1.093598
TMK                 NaN       1.243276      1.243276
EW             1.335094      19.578825      4.553529
...                 ...            ...           ...
CF             4.581483      -5.190254     -6.016462
DVA            2.387378       0.660102      0.872928
CAH            1.035648       1.417481      1.157130
ADP            0.662284       1.281766      0.725240
CAG           -1.722716      -3.619153     -3.803905
YUM            1.219933       0.321006      0.443975
D              0.280393       1.505699      1.279495
CL             0.768329       0.865243      0.837974
PRGO           9.765569      -5.823271      2.457232
AZO            0.584291       0.706142      0.655178
ETFC                NaN       1.194181      1.194181
IP             1.114303       1.090769      1.095532
COF                 NaN       3.540353      3.540353
GPS            1.167153       2.048919      1.490129
FL             2.337488       1.898866      2.128248
GD             0.955401       1.661722      1.258469
CVS            0.665779       1.270281      1.061122
ED             0.376452       1.878055      1.634098
CI                  NaN       1.098914      1.098914
PNC                 NaN       0.924207      0.924207
BLK                 NaN       1.184832      1.184832
HUM            1.021824       1.069226      1.042415
MMM            1.012996       1.397629      1.285620
ALGN           1.764415       9.601509      3.149538
AFL                 NaN       1.251722      1.251722
CHTR           0.188264       0.679026      0.653581
CSX            0.469025       1.726857      1.617016
ORLY           0.550271       1.275474      0.884189
CNC            0.787093       7.975109      1.891024
MDLZ           0.349104       1.007664      0.808274

[82 rows x 3 columns]
```

In [0]:
```
rating_df = pd.concat([actual_rating, pred_rating], axis = 1)
rating_df
```

Out[0]:
```
      act_short_term  act_long_term  act_overall  pred_short_term  \
AAP         1.565242       1.844393     1.646798        -1.917622
```

ABC	0.929123	1.744464	1.088099	0.728736
ADP	1.046382	1.898608	1.138829	0.662284
AFL	NaN	1.200626	1.200626	NaN
AGN	1.130502	3.081675	2.776788	0.004880
ALGN	1.881997	6.976938	2.566962	1.764415
ALXN	2.883305	2.935729	2.922817	2.365349
AMAT	2.703723	1.023740	1.634501	2.239882
AWK	0.372970	1.541048	1.381796	0.206861
AZO	0.921886	0.806883	0.860099	0.584291
BBT	NaN	1.154348	1.154348	NaN
BBY	1.257388	1.987654	1.382749	0.689748
BLK	NaN	1.266121	1.266121	NaN
C	NaN	1.114557	1.114557	NaN
CAG	0.829938	1.966765	1.566359	-1.722716
CAH	1.072511	1.399945	1.178774	1.035648
CELG	2.234903	1.045563	1.210137	2.928032
CF	1.807092	1.829237	1.826984	4.581483
CHTR	NaN	NaN	NaN	0.188264
CI	NaN	1.286673	1.286673	NaN
CL	1.135289	0.970428	1.016466	0.768329
CNC	1.002255	2.390666	1.554533	0.787093
COF	NaN	1.161025	1.161025	NaN
CRM	0.949178	5.172556	2.031258	1.670041
CSX	1.339426	1.536566	1.520933	0.469025
CVS	1.028040	1.610293	1.424492	0.665779
D	0.674905	1.508804	1.394659	0.280393
DG	1.546167	2.265049	1.945591	0.999280
DIS	0.942049	2.930302	2.154394	0.472403
DVA	1.722323	1.163296	1.357531	2.387378
...	...	...	...	...
KR	0.783053	1.620379	1.227948	0.615288
LB	1.641490	0.693069	0.903406	0.678593
LEG	1.869070	1.318521	1.520410	0.547137
LYB	1.916561	1.418662	1.571175	1.418779
MA	1.394893	1.117125	1.283362	0.834593
MAR	0.420382	1.396169	1.103628	0.398320
MCO	1.613962	0.906678	1.074016	1.687820
MDLZ	0.454323	2.718329	1.694646	0.349104
MKC	0.739322	1.730212	1.449832	0.605509
MMC	1.205118	1.724807	1.541947	0.685146
MMM	1.892463	1.174310	1.369503	1.012996
MO	0.202850	2.617067	1.363342	0.438723
NEE	0.364004	1.997065	1.564392	0.430642
NTRS	NaN	1.086343	1.086343	NaN
ORLY	0.909883	1.188740	1.046370	0.550271
PGR	NaN	1.310543	1.310543	NaN
PNC	NaN	1.142791	1.142791	NaN
PRGO	1.887733	2.139072	2.066374	9.765569

RCL	0.174637	2.959765	1.725664	0.192734
RHI	1.798103	21.091539	2.265864	0.861743
RTN	1.464286	1.629874	1.562574	0.834882
STI	NaN	1.126946	1.126946	NaN
STZ	1.703275	1.624065	1.636941	0.765849
TGT	0.833822	1.920756	1.376655	0.667319
TMK	NaN	1.306279	1.306279	NaN
TTWO	1.395064	2.545616	1.662097	0.938342
VIAB	1.498767	1.443819	1.457470	0.928359
VMC	1.790963	2.173749	2.123925	1.494555
WAT	5.932232	0.621926	1.725526	-7.414977
YUM	0.927748	0.271781	0.342568	1.219933

	pred_long_term	pred_overall
AAP	3.157907	-0.955787
ABC	1.798877	0.943251
ADP	1.281766	0.725240
AFL	1.251722	1.251722
AGN	-2.506055	-4.557095
ALGN	9.601509	3.149538
ALXN	1.468469	1.553489
AMAT	1.006830	1.496288
AWK	2.103010	1.745378
AZO	0.706142	0.655178
BBT	1.204618	1.204618
BBY	-2.514415	1.008100
BLK	1.184832	1.184832
C	24.770126	24.770126
CAG	-3.619153	-3.803905
CAH	1.417481	1.157130
CELG	0.757436	1.049299
CF	-5.190254	-6.016462
CHTR	0.679026	0.653581
CI	1.098914	1.098914
CL	0.865243	0.837974
CNC	7.975109	1.891024
COF	3.540353	3.540353
CRM	1.813680	1.770757
CSX	1.726857	1.617016
CVS	1.270281	1.061122
D	1.505699	1.279495
DG	1.386529	1.278439
DIS	2.550725	1.730171
DVA	0.660102	0.872928
...	...	...
KR	1.026688	0.894330
LB	0.549345	0.574302
LEG	23.957581	2.785916

```
LYB          1.138509      1.218294
MA           1.518222      1.111748
MAR        -10.407888     13.127251
MCO          0.297749      0.428755
MDLZ         1.007664      0.808274
MKC          5.027441      2.565274
MMC          1.997162      1.547953
MMM          1.397629      1.285620
MO           1.888355      1.534344
NEE          1.583994      1.410967
NTRS         1.093598      1.093598
ORLY         1.275474      0.884189
PGR          1.376969      1.376969
PNC          0.924207      0.924207
PRGO        -5.823271      2.457232
RCL          0.846695      0.790754
RHI         22.617183      1.405176
RTN          1.898727      1.473609
STI          1.069038      1.069038
STZ          2.103913      1.769491
TGT         -8.385081      3.550473
TMK          1.243276      1.243276
TTWO         6.803204      1.773245
VIAB         1.182516      1.125906
VMC          1.986510      1.937027
WAT          0.090603     -0.717009
YUM          0.321006      0.443975

[82 rows x 6 columns]
```

In [0]:
```
rounded_df = round(rating_df)
rounded_df
```

Out[0]:

	act_short_term	act_long_term	act_overall	pred_short_term	\
AAP	2.0	2.0	2.0	-2.0	
ABC	1.0	2.0	1.0	1.0	
ADP	1.0	2.0	1.0	1.0	
AFL	NaN	1.0	1.0	NaN	
AGN	1.0	3.0	3.0	0.0	
ALGN	2.0	7.0	3.0	2.0	
ALXN	3.0	3.0	3.0	2.0	
AMAT	3.0	1.0	2.0	2.0	
AWK	0.0	2.0	1.0	0.0	
AZO	1.0	1.0	1.0	1.0	
BBT	NaN	1.0	1.0	NaN	
BBY	1.0	2.0	1.0	1.0	
BLK	NaN	1.0	1.0	NaN	
C	NaN	1.0	1.0	NaN	

CAG	1.0	2.0	2.0	-2.0
CAH	1.0	1.0	1.0	1.0
CELG	2.0	1.0	1.0	3.0
CF	2.0	2.0	2.0	5.0
CHTR	NaN	NaN	NaN	0.0
CI	NaN	1.0	1.0	NaN
CL	1.0	1.0	1.0	1.0
CNC	1.0	2.0	2.0	1.0
COF	NaN	1.0	1.0	NaN
CRM	1.0	5.0	2.0	2.0
CSX	1.0	2.0	2.0	0.0
CVS	1.0	2.0	1.0	1.0
D	1.0	2.0	1.0	0.0
DG	2.0	2.0	2.0	1.0
DIS	1.0	3.0	2.0	0.0
DVA	2.0	1.0	1.0	2.0
...	...	...	...	...
KR	1.0	2.0	1.0	1.0
LB	2.0	1.0	1.0	1.0
LEG	2.0	1.0	2.0	1.0
LYB	2.0	1.0	2.0	1.0
MA	1.0	1.0	1.0	1.0
MAR	0.0	1.0	1.0	0.0
MCO	2.0	1.0	1.0	2.0
MDLZ	0.0	3.0	2.0	0.0
MKC	1.0	2.0	1.0	1.0
MMC	1.0	2.0	2.0	1.0
MMM	2.0	1.0	1.0	1.0
MO	0.0	3.0	1.0	0.0
NEE	0.0	2.0	2.0	0.0
NTRS	NaN	1.0	1.0	NaN
ORLY	1.0	1.0	1.0	1.0
PGR	NaN	1.0	1.0	NaN
PNC	NaN	1.0	1.0	NaN
PRGO	2.0	2.0	2.0	10.0
RCL	0.0	3.0	2.0	0.0
RHI	2.0	21.0	2.0	1.0
RTN	1.0	2.0	2.0	1.0
STI	NaN	1.0	1.0	NaN
STZ	2.0	2.0	2.0	1.0
TGT	1.0	2.0	1.0	1.0
TMK	NaN	1.0	1.0	NaN
TTWO	1.0	3.0	2.0	1.0
VIAB	1.0	1.0	1.0	1.0
VMC	2.0	2.0	2.0	1.0
WAT	6.0	1.0	2.0	-7.0
YUM	1.0	0.0	0.0	1.0

	pred_long_term	pred_overall
AAP	3.0	-1.0
ABC	2.0	1.0
ADP	1.0	1.0
AFL	1.0	1.0
AGN	-3.0	-5.0
ALGN	10.0	3.0
ALXN	1.0	2.0
AMAT	1.0	1.0
AWK	2.0	2.0
AZO	1.0	1.0
BBT	1.0	1.0
BBY	-3.0	1.0
BLK	1.0	1.0
C	25.0	25.0
CAG	-4.0	-4.0
CAH	1.0	1.0
CELG	1.0	1.0
CF	-5.0	-6.0
CHTR	1.0	1.0
CI	1.0	1.0
CL	1.0	1.0
CNC	8.0	2.0
COF	4.0	4.0
CRM	2.0	2.0
CSX	2.0	2.0
CVS	1.0	1.0
D	2.0	1.0
DG	1.0	1.0
DIS	3.0	2.0
DVA	1.0	1.0
...	...	...
KR	1.0	1.0
LB	1.0	1.0
LEG	24.0	3.0
LYB	1.0	1.0
MA	2.0	1.0
MAR	-10.0	13.0
MCO	0.0	0.0
MDLZ	1.0	1.0
MKC	5.0	3.0
MMC	2.0	2.0
MMM	1.0	1.0
MO	2.0	2.0
NEE	2.0	1.0
NTRS	1.0	1.0
ORLY	1.0	1.0
PGR	1.0	1.0

```
PNC              1.0          1.0
PRGO            -6.0          2.0
RCL              1.0          1.0
RHI             23.0          1.0
RTN              2.0          1.0
STI              1.0          1.0
STZ              2.0          2.0
TGT             -8.0          4.0
TMK              1.0          1.0
TTWO             7.0          2.0
VIAB             1.0          1.0
VMC              2.0          2.0
WAT              0.0         -1.0
YUM              0.0          0.0

[82 rows x 6 columns]
```

In [0]:
```
# rounded_df.to_csv(model_dir + "credit_ratings_1.0.csv")
rounded_df = pd.read_csv(model_dir + "credit_ratings_1.0.csv")
```

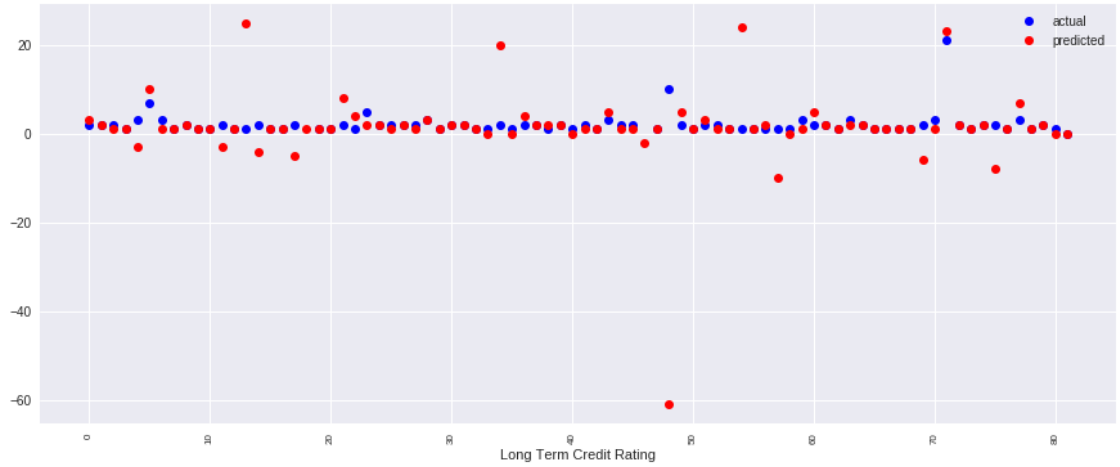
In [34]:
```
import matplotlib.pyplot as plt
plt.figure(figsize = (15, 6))
plt.plot(rounded_df["act_short_term"], "b", label = "actual")
plt.plot(rounded_df["pred_short_term"], "r", label = "predicted")
plt.legend(loc='upper right')
plt.yticks(rotation = 0)
plt.xticks(rotation = 90, fontsize = 8)
plt.xlabel("Short Term Credit Rating")
plt.show()
```

In [35]:
```
import matplotlib.pyplot as plt
plt.figure(figsize = (15, 6))
```

```
plt.plot(rounded_df["act_short_term"], "b", label = "actual", marker = "o", linestyle
plt.plot(rounded_df["pred_short_term"], "r", label = "predicted", marker = "o", lines
plt.legend(loc='upper right')
plt.yticks(rotation = 0)
plt.xticks(rotation = 90, fontsize = 8)
plt.xlabel("Short Term Credit Rating")
plt.show()
```

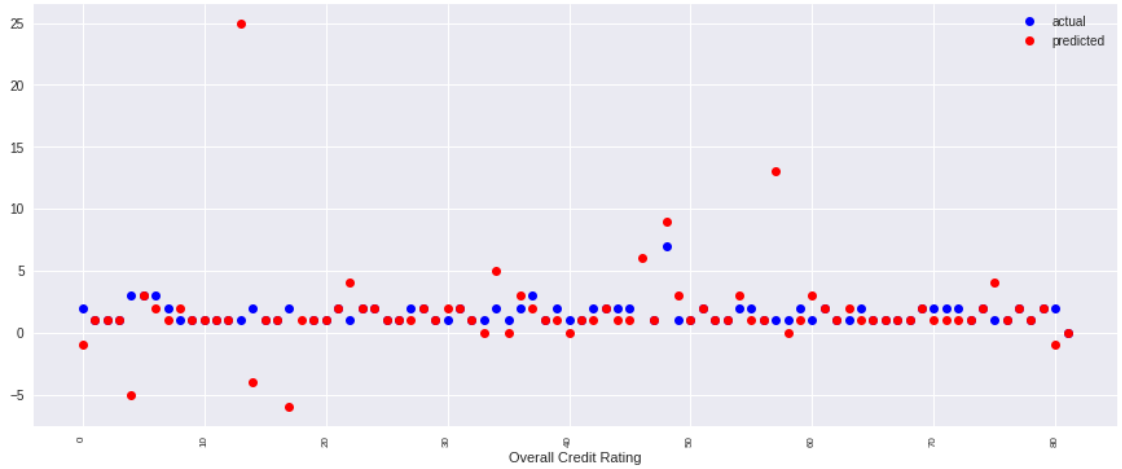
In [36]:
```
plt.figure(figsize = (15, 6))
plt.plot(rounded_df["act_long_term"], "b", label = "actual")
plt.plot(rounded_df["pred_long_term"], "r", label = "predicted")
plt.legend(loc='upper right')
plt.yticks(rotation = 0)
plt.xticks(rotation = 90, fontsize = 8)
plt.xlabel("Long Term Credit Rating")
plt.show()
```

In [37]:
```
plt.figure(figsize = (15, 6))
plt.plot(rounded_df["act_long_term"], "b", label = "actual", marker = "o", linestyle =
plt.plot(rounded_df["pred_long_term"], "r", label = "predicted", marker = "o", linesty
plt.legend(loc='upper right')
plt.yticks(rotation = 0)
plt.xticks(rotation = 90, fontsize = 8)
plt.xlabel("Long Term Credit Rating")
plt.show()
```



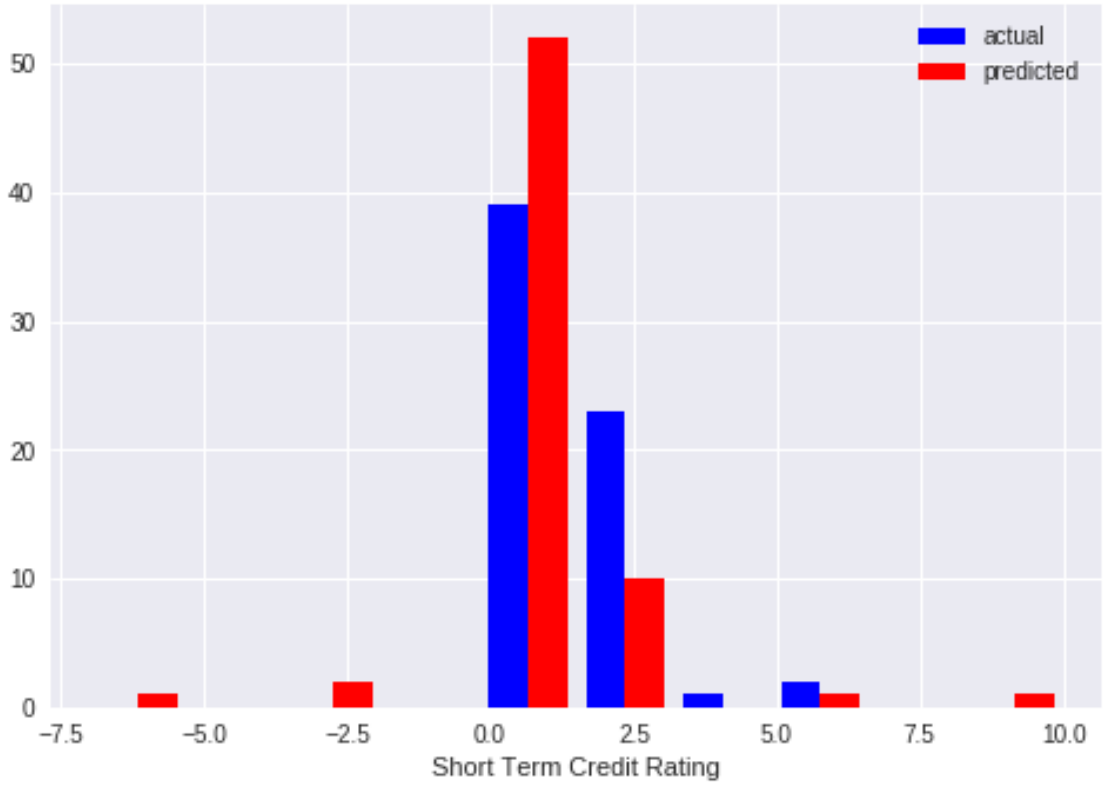
In [38]:
```
plt.figure(figsize = (15, 6))
plt.plot(rounded_df["act_overall"], "b", label = "actual")
plt.plot(rounded_df["pred_overall"], "r", label = "predicted")
plt.legend(loc='upper right')
plt.yticks(rotation = 0)
plt.xticks(rotation = 90, fontsize = 8)
plt.xlabel("Overall Credit Rating")
plt.show()
```

In [39]:
```
plt.figure(figsize = (15, 6))
plt.plot(rounded_df["act_overall"], "b", label = "actual", marker = "o", linestyle = '
plt.plot(rounded_df["pred_overall"], "r", label = "predicted", marker = "o", linestyle
plt.legend(loc='upper right')
plt.yticks(rotation = 0)
plt.xticks(rotation = 90, fontsize = 8)
plt.xlabel("Overall Credit Rating")
plt.show()
```



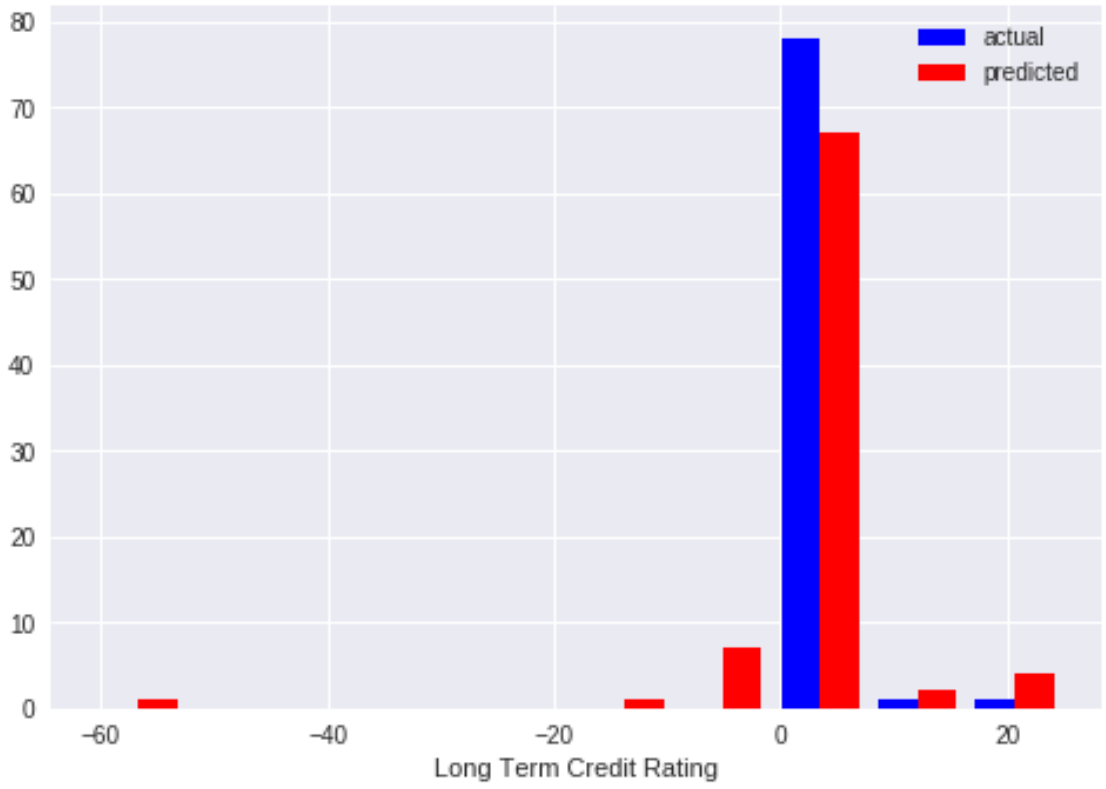
In [0]:
```
import numpy as np
plt.hist([rounded_df["act_short_term"], rounded_df["pred_short_term"]], label=['actual
plt.legend(loc='upper right')
plt.xlabel("Short Term Credit Rating")
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/function_base.py:780: RuntimeWarning: invalid
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/function_base.py:781: RuntimeWarning: invalid
  keep &= (tmp_a <= last_edge)
```




```
In [0]: plt.hist([rounded_df["act_long_term"], rounded_df["pred_long_term"]], label=['actual',
        plt.legend(loc='upper right')
        plt.xlabel("Long Term Credit Rating")
        plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/function_base.py:780: RuntimeWarning: invalid
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/function_base.py:781: RuntimeWarning: invalid
  keep &= (tmp_a <= last_edge)
```




```
In [0]: plt.hist([rounded_df["act_overall"], rounded_df["pred_overall"]], label=['actual', 'pre
        plt.legend(loc='upper right')
        plt.xlabel("Overall Credit Rating")
        plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/function_base.py:780: RuntimeWarning: invalid
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/function_base.py:781: RuntimeWarning: invalid
  keep &= (tmp_a <= last_edge)
```


actual
predicted
80
70
60
50
40
30
20
10
0
−5
0
5
10
15
20
25
Overall Credit Rating