

9 - Integrated Project 2

January 3, 2024

Prepare a prototype of a machine learning model for Zyfra. The company develops efficiency solutions for heavy industry. The model should predict the amount of gold recovered from gold ore. You have the data on extraction and purification. The model will help to optimize the production and eliminate unprofitable parameters.

Mined ore undergoes primary processing to get the ore mixture or rougher feed, which is the raw material for flotation (also known as the rougher process). After flotation, the material is sent to two-stage purification.

```
[ ]: import pandas as pd
     from sklearn.metrics import mean_absolute_error
     import numpy as np
     import matplotlib.pyplot as plt
```

```
[ ]: gold_train = pd.read_csv('/datasets/gold_recovery_train.csv')
     gold_test = pd.read_csv('/datasets/gold_recovery_test.csv')
     gold_full = pd.read_csv('/datasets/gold_recovery_full.csv')
```

```
[ ]: gold_train
```

```
[ ]:
      date  final.output.concentrate_ag \
0    2016-01-15 00:00:00                6.055403
1    2016-01-15 01:00:00                6.029369
2    2016-01-15 02:00:00                6.055926
3    2016-01-15 03:00:00                6.047977
4    2016-01-15 04:00:00                6.148599
...
16855 2018-08-18 06:59:59                3.224920
16856 2018-08-18 07:59:59                3.195978
16857 2018-08-18 08:59:59                3.109998
16858 2018-08-18 09:59:59                3.367241
16859 2018-08-18 10:59:59                3.598375

      final.output.concentrate_pb  final.output.concentrate_sol \
0                        9.889648                5.507324
1                        9.968944                5.257781
2                       10.213995                5.383759
3                        9.977019                4.858634
4                       10.142511                4.939416
```

...
16855	11.356233	6.803482
16856	11.349355	6.862249
16857	11.434366	6.886013
16858	11.625587	6.799433
16859	11.737832	6.717509

	final.output.concentrate_au	final.output.recovery \
0	42.192020	70.541216
1	42.701629	69.266198
2	42.657501	68.116445
3	42.689819	68.347543
4	42.774141	66.927016
...
16855	46.713954	73.755150
16856	46.866780	69.049291
16857	46.795691	67.002189
16858	46.408188	65.523246
16859	46.299438	70.281454

	final.output.tail_ag	final.output.tail_pb	final.output.tail_sol \
0	10.411962	0.895447	16.904297
1	10.462676	0.927452	16.634514
2	10.507046	0.953716	16.208849
3	10.422762	0.883763	16.532835
4	10.360302	0.792826	16.525686
...
16855	8.769645	3.141541	10.403181
16856	8.897321	3.130493	10.549470
16857	8.529606	2.911418	11.115147
16858	8.777171	2.819214	10.463847
16859	8.406690	2.517518	10.652193

	final.output.tail_au	...	secondary_cleaner.state.floatbank4_a_air \
0	2.143149	...	14.016835
1	2.224930	...	13.992281
2	2.257889	...	14.015015
3	2.146849	...	14.036510
4	2.055292	...	14.027298
...
16855	1.529220	...	23.031497
16856	1.612542	...	22.960095
16857	1.596616	...	23.015718
16858	1.602879	...	23.024963
16859	1.389434	...	23.018622

secondary_cleaner.state.floatbank4_a_level \

0	-502.488007
1	-505.503262
2	-502.520901
3	-500.857308
4	-499.838632
...	...
16855	-501.167942
16856	-501.612783
16857	-501.711599
16858	-501.153409
16859	-500.492702

	secondary_cleaner.state.floatbank4_b_air \
0	12.099931
1	11.950531
2	11.912783
3	11.999550
4	11.953070
...	...
16855	20.007571
16856	20.035660
16857	19.951231
16858	20.054122
16859	20.020205

	secondary_cleaner.state.floatbank4_b_level \
0	-504.715942
1	-501.331529
2	-501.133383
3	-501.193686
4	-501.053894
...	...
16855	-499.740028
16856	-500.251357
16857	-499.857027
16858	-500.314711
16859	-500.220296

	secondary_cleaner.state.floatbank5_a_air \
0	9.925633
1	10.039245
2	10.070913
3	9.970366
4	9.925709
...	...
16855	18.006038
16856	17.998535

16857	18.019543
16858	17.979515
16859	17.963512

	secondary_cleaner.state.floatbank5_a_level \
0	-498.310211
1	-500.169983
2	-500.129135
3	-499.201640
4	-501.686727
...	...
16855	-499.834374
16856	-500.395178
16857	-500.451156
16858	-499.272871
16859	-499.939490

	secondary_cleaner.state.floatbank5_b_air \
0	8.079666
1	7.984757
2	8.013877
3	7.977324
4	7.894242
...	...
16855	13.001114
16856	12.954048
16857	13.023431
16858	12.992404
16859	12.990306

	secondary_cleaner.state.floatbank5_b_level \
0	-500.470978
1	-500.582168
2	-500.517572
3	-500.255908
4	-500.356035
...	...
16855	-500.155694
16856	-499.895163
16857	-499.914391
16858	-499.976268
16859	-500.080993

	secondary_cleaner.state.floatbank6_a_air \
0	14.151341
1	13.998353
2	14.028663

3	14.005551
4	13.996647
...	...
16855	20.007840
16856	19.968498
16857	19.990885
16858	20.013986
16859	19.990336

	secondary_cleaner.state.floatbank6_a_level
0	-605.841980
1	-599.787184
2	-601.427363
3	-599.996129
4	-601.496691
...	...
16855	-501.296428
16856	-501.041608
16857	-501.518452
16858	-500.625471
16859	-499.191575

[16860 rows x 87 columns]

```
[ ]: gold_train['date'] = pd.to_datetime(gold_train['date'])
```

```
[ ]: gold_test
```

```
[ ]:
      date primary_cleaner.input.sulfate \
0    2016-09-01 00:59:59      210.800909
1    2016-09-01 01:59:59      215.392455
2    2016-09-01 02:59:59      215.259946
3    2016-09-01 03:59:59      215.336236
4    2016-09-01 04:59:59      199.099327
...
5851 2017-12-31 19:59:59      173.957757
5852 2017-12-31 20:59:59      172.910270
5853 2017-12-31 21:59:59      171.135718
5854 2017-12-31 22:59:59      179.697158
5855 2017-12-31 23:59:59      181.556856
```

	primary_cleaner.input.depressant	primary_cleaner.input.feed_size \
0	14.993118	8.080000
1	14.987471	8.080000
2	12.884934	7.786667
3	12.006805	7.640000
4	10.682530	7.530000

...
5851	15.963399	8.070000
5852	16.002605	8.070000
5853	15.993669	8.070000
5854	15.438979	8.070000
5855	14.995850	8.070000

	primary_cleaner.input.xanthate	primary_cleaner.state.floatbank8_a_air \
0	1.005021	1398.981301
1	0.990469	1398.777912
2	0.996043	1398.493666
3	0.863514	1399.618111
4	0.805575	1401.268123
...
5851	0.896701	1401.930554
5852	0.896519	1447.075722
5853	1.165996	1498.836182
5854	1.501068	1498.466243
5855	1.623454	1498.096303

	primary_cleaner.state.floatbank8_a_level \
0	-500.225577
1	-500.057435
2	-500.868360
3	-498.863574
4	-500.808305
...	...
5851	-499.728848
5852	-494.716823
5853	-501.770403
5854	-500.483984
5855	-499.796922

	primary_cleaner.state.floatbank8_b_air \
0	1399.144926
1	1398.055362
2	1398.860436
3	1397.440120
4	1398.128818
...	...
5851	1401.441445
5852	1448.851892
5853	1499.572353
5854	1497.986986
5855	1501.743791

	primary_cleaner.state.floatbank8_b_level \
--	--

0	-499.919735
1	-499.778182
2	-499.764529
3	-499.211024
4	-499.504543
...	...
5851	-499.193423
5852	-465.963026
5853	-495.516347
5854	-519.200340
5855	-505.146931

	primary_cleaner.state.floatbank8_c_air	...	\
0	1400.102998	...	
1	1396.151033	...	
2	1398.075709	...	
3	1400.129303	...	
4	1402.172226	...	
...	
5851	1399.810313	...	
5852	1443.890424	...	
5853	1502.749213	...	
5854	1496.569047	...	
5855	1499.535978	...	

	secondary_cleaner.state.floatbank4_a_air	\
0	12.023554	
1	12.058140	
2	11.962366	
3	12.033091	
4	12.025367	
...	...	
5851	13.995957	
5852	16.749781	
5853	19.994130	
5854	19.958760	
5855	20.034715	

	secondary_cleaner.state.floatbank4_a_level	\
0	-497.795834	
1	-498.695773	
2	-498.767484	
3	-498.350935	
4	-500.786497	
...	...	
5851	-500.157454	
5852	-496.031539	

5853	-499.791312
5854	-499.958750
5855	-500.728588

	secondary_cleaner.state.floatbank4_b_air \
0	8.016656
1	8.130979
2	8.096893
3	8.074946
4	8.054678
...	...
5851	12.069155
5852	13.365371
5853	15.101425
5854	15.026853
5855	14.914199

	secondary_cleaner.state.floatbank4_b_level \
0	-501.289139
1	-499.634209
2	-500.827423
3	-499.474407
4	-500.397500
...	...
5851	-499.673279
5852	-499.122723
5853	-499.936252
5854	-499.723143
5855	-499.948518

	secondary_cleaner.state.floatbank5_a_air \
0	7.946562
1	7.958270
2	8.071056
3	7.897085
4	8.107890
...	...
5851	7.977259
5852	9.288553
5853	10.989181
5854	11.011607
5855	10.986607

	secondary_cleaner.state.floatbank5_a_level \
0	-432.317850
1	-525.839648
2	-500.801673

3	-500.868509
4	-509.526725
...	...
5851	-499.516126
5852	-496.892967
5853	-498.347898
5854	-499.985046
5855	-500.658027

	secondary_cleaner.state.floatbank5_b_air \
0	4.872511
1	4.878850
2	4.905125
3	4.931400
4	4.957674
...	...
5851	5.933319
5852	7.372897
5853	9.020944
5854	9.009783
5855	8.989497

	secondary_cleaner.state.floatbank5_b_level \
0	-500.037437
1	-500.162375
2	-499.828510
3	-499.963623
4	-500.360026
...	...
5851	-499.965973
5852	-499.942956
5853	-500.040448
5854	-499.937902
5855	-500.337588

	secondary_cleaner.state.floatbank6_a_air \
0	26.705889
1	25.019940
2	24.994862
3	24.948919
4	25.003331
...	...
5851	8.987171
5852	8.986832
5853	8.982038
5854	9.012660
5855	8.988632

```

secondary_cleaner.state.floatbank6_a_level
0          -499.709414
1          -499.819438
2          -500.622559
3          -498.709987
4          -500.856333
...
5851        -499.755909
5852        -499.903761
5853        -497.789882
5854        -500.154284
5855        -500.764937

```

[5856 rows x 53 columns]

```
[ ]: gold_test['date'] = pd.to_datetime(gold_test['date'])
```

```
[ ]: gold_full
```

```
[ ]:
           date  final.output.concentrate_ag  \
0    2016-01-15 00:00:00          6.055403
1    2016-01-15 01:00:00          6.029369
2    2016-01-15 02:00:00          6.055926
3    2016-01-15 03:00:00          6.047977
4    2016-01-15 04:00:00          6.148599
...
22711 2018-08-18 06:59:59          3.224920
22712 2018-08-18 07:59:59          3.195978
22713 2018-08-18 08:59:59          3.109998
22714 2018-08-18 09:59:59          3.367241
22715 2018-08-18 10:59:59          3.598375

```

```

           final.output.concentrate_pb  final.output.concentrate_sol  \
0          9.889648          5.507324
1          9.968944          5.257781
2         10.213995          5.383759
3          9.977019          4.858634
4         10.142511          4.939416
...
22711         11.356233          6.803482
22712         11.349355          6.862249
22713         11.434366          6.886013
22714         11.625587          6.799433
22715         11.737832          6.717509

```

```

final.output.concentrate_au  final.output.recovery  \

```

0	42.192020	70.541216
1	42.701629	69.266198
2	42.657501	68.116445
3	42.689819	68.347543
4	42.774141	66.927016
...
22711	46.713954	73.755150
22712	46.866780	69.049291
22713	46.795691	67.002189
22714	46.408188	65.523246
22715	46.299438	70.281454

	final.output.tail_ag	final.output.tail_pb	final.output.tail_sol \
0	10.411962	0.895447	16.904297
1	10.462676	0.927452	16.634514
2	10.507046	0.953716	16.208849
3	10.422762	0.883763	16.532835
4	10.360302	0.792826	16.525686
...
22711	8.769645	3.141541	10.403181
22712	8.897321	3.130493	10.549470
22713	8.529606	2.911418	11.115147
22714	8.777171	2.819214	10.463847
22715	8.406690	2.517518	10.652193

	final.output.tail_au	... secondary_cleaner.state.floatbank4_a_air \
0	2.143149	14.016835
1	2.224930	13.992281
2	2.257889	14.015015
3	2.146849	14.036510
4	2.055292	14.027298
...
22711	1.529220	23.031497
22712	1.612542	22.960095
22713	1.596616	23.015718
22714	1.602879	23.024963
22715	1.389434	23.018622

	secondary_cleaner.state.floatbank4_a_level \
0	-502.488007
1	-505.503262
2	-502.520901
3	-500.857308
4	-499.838632
...	...
22711	-501.167942
22712	-501.612783

22713	-501.711599
22714	-501.153409
22715	-500.492702

	secondary_cleaner.state.floatbank4_b_air \
0	12.099931
1	11.950531
2	11.912783
3	11.999550
4	11.953070
...	...
22711	20.007571
22712	20.035660
22713	19.951231
22714	20.054122
22715	20.020205

	secondary_cleaner.state.floatbank4_b_level \
0	-504.715942
1	-501.331529
2	-501.133383
3	-501.193686
4	-501.053894
...	...
22711	-499.740028
22712	-500.251357
22713	-499.857027
22714	-500.314711
22715	-500.220296

	secondary_cleaner.state.floatbank5_a_air \
0	9.925633
1	10.039245
2	10.070913
3	9.970366
4	9.925709
...	...
22711	18.006038
22712	17.998535
22713	18.019543
22714	17.979515
22715	17.963512

	secondary_cleaner.state.floatbank5_a_level \
0	-498.310211
1	-500.169983
2	-500.129135

3	-499.201640
4	-501.686727
...	...
22711	-499.834374
22712	-500.395178
22713	-500.451156
22714	-499.272871
22715	-499.939490

	secondary_cleaner.state.floatbank5_b_air \
0	8.079666
1	7.984757
2	8.013877
3	7.977324
4	7.894242
...	...
22711	13.001114
22712	12.954048
22713	13.023431
22714	12.992404
22715	12.990306

	secondary_cleaner.state.floatbank5_b_level \
0	-500.470978
1	-500.582168
2	-500.517572
3	-500.255908
4	-500.356035
...	...
22711	-500.155694
22712	-499.895163
22713	-499.914391
22714	-499.976268
22715	-500.080993

	secondary_cleaner.state.floatbank6_a_air \
0	14.151341
1	13.998353
2	14.028663
3	14.005551
4	13.996647
...	...
22711	20.007840
22712	19.968498
22713	19.990885
22714	20.013986
22715	19.990336

	secondary_cleaner.state.floatbank6_a_level
0	-605.841980
1	-599.787184
2	-601.427363
3	-599.996129
4	-601.496691
...	...
22711	-501.296428
22712	-501.041608
22713	-501.518452
22714	-500.625471
22715	-499.191575

[22716 rows x 87 columns]

```
[ ]: gold_full['date'] = pd.to_datetime(gold_full['date'])
```

```
[ ]: col_mapping_dict = {c[0]:c[1] for c in enumerate(gold_train.columns)}
col_mapping_dict
```

```
[ ]: {0: 'date',
      1: 'final.output.concentrate_ag',
      2: 'final.output.concentrate_pb',
      3: 'final.output.concentrate_sol',
      4: 'final.output.concentrate_au',
      5: 'final.output.recovery',
      6: 'final.output.tail_ag',
      7: 'final.output.tail_pb',
      8: 'final.output.tail_sol',
      9: 'final.output.tail_au',
      10: 'primary_cleaner.input.sulfate',
      11: 'primary_cleaner.input.depressant',
      12: 'primary_cleaner.input.feed_size',
      13: 'primary_cleaner.input.xanthate',
      14: 'primary_cleaner.output.concentrate_ag',
      15: 'primary_cleaner.output.concentrate_pb',
      16: 'primary_cleaner.output.concentrate_sol',
      17: 'primary_cleaner.output.concentrate_au',
      18: 'primary_cleaner.output.tail_ag',
      19: 'primary_cleaner.output.tail_pb',
      20: 'primary_cleaner.output.tail_sol',
      21: 'primary_cleaner.output.tail_au',
      22: 'primary_cleaner.state.floatbank8_a_air',
      23: 'primary_cleaner.state.floatbank8_a_level',
      24: 'primary_cleaner.state.floatbank8_b_air',
      25: 'primary_cleaner.state.floatbank8_b_level',
```

26: 'primary_cleaner.state.floatbank8_c_air',
27: 'primary_cleaner.state.floatbank8_c_level',
28: 'primary_cleaner.state.floatbank8_d_air',
29: 'primary_cleaner.state.floatbank8_d_level',
30: 'rougher.calculation.sulfate_to_au_concentrate',
31: 'rougher.calculation.floatbank10_sulfate_to_au_feed',
32: 'rougher.calculation.floatbank11_sulfate_to_au_feed',
33: 'rougher.calculation.au_pb_ratio',
34: 'rougher.input.feed_ag',
35: 'rougher.input.feed_pb',
36: 'rougher.input.feed_rate',
37: 'rougher.input.feed_size',
38: 'rougher.input.feed_sol',
39: 'rougher.input.feed_au',
40: 'rougher.input.floatbank10_sulfate',
41: 'rougher.input.floatbank10_xanthate',
42: 'rougher.input.floatbank11_sulfate',
43: 'rougher.input.floatbank11_xanthate',
44: 'rougher.output.concentrate_ag',
45: 'rougher.output.concentrate_pb',
46: 'rougher.output.concentrate_sol',
47: 'rougher.output.concentrate_au',
48: 'rougher.output.recovery',
49: 'rougher.output.tail_ag',
50: 'rougher.output.tail_pb',
51: 'rougher.output.tail_sol',
52: 'rougher.output.tail_au',
53: 'rougher.state.floatbank10_a_air',
54: 'rougher.state.floatbank10_a_level',
55: 'rougher.state.floatbank10_b_air',
56: 'rougher.state.floatbank10_b_level',
57: 'rougher.state.floatbank10_c_air',
58: 'rougher.state.floatbank10_c_level',
59: 'rougher.state.floatbank10_d_air',
60: 'rougher.state.floatbank10_d_level',
61: 'rougher.state.floatbank10_e_air',
62: 'rougher.state.floatbank10_e_level',
63: 'rougher.state.floatbank10_f_air',
64: 'rougher.state.floatbank10_f_level',
65: 'secondary_cleaner.output.tail_ag',
66: 'secondary_cleaner.output.tail_pb',
67: 'secondary_cleaner.output.tail_sol',
68: 'secondary_cleaner.output.tail_au',
69: 'secondary_cleaner.state.floatbank2_a_air',
70: 'secondary_cleaner.state.floatbank2_a_level',
71: 'secondary_cleaner.state.floatbank2_b_air',
72: 'secondary_cleaner.state.floatbank2_b_level',

```

73: 'secondary_cleaner.state.floatbank3_a_air',
74: 'secondary_cleaner.state.floatbank3_a_level',
75: 'secondary_cleaner.state.floatbank3_b_air',
76: 'secondary_cleaner.state.floatbank3_b_level',
77: 'secondary_cleaner.state.floatbank4_a_air',
78: 'secondary_cleaner.state.floatbank4_a_level',
79: 'secondary_cleaner.state.floatbank4_b_air',
80: 'secondary_cleaner.state.floatbank4_b_level',
81: 'secondary_cleaner.state.floatbank5_a_air',
82: 'secondary_cleaner.state.floatbank5_a_level',
83: 'secondary_cleaner.state.floatbank5_b_air',
84: 'secondary_cleaner.state.floatbank5_b_level',
85: 'secondary_cleaner.state.floatbank6_a_air',
86: 'secondary_cleaner.state.floatbank6_a_level'}

```

```
[ ]: gold_train.isna().sum().sort_values(ascending=False)/len(gold_train)
```

```

[ ]: rougher.output.recovery                0.152610
     rougher.output.tail_ag                 0.133452
     rougher.output.tail_sol                0.133393
     rougher.output.tail_au                 0.133393
     secondary_cleaner.output.tail_sol      0.117794
     ...
     rougher.calculation.sulfate_to_au_concentrate 0.001601
     rougher.calculation.floatbank10_sulfate_to_au_feed 0.001601
     rougher.calculation.floatbank11_sulfate_to_au_feed 0.001601
     primary_cleaner.input.feed_size          0.000000
     date                                     0.000000
     Length: 87, dtype: float64

```

```
[ ]: gold_test.isna().sum().sort_values(ascending=False)/len(gold_test)
```

```

[ ]: rougher.input.floatbank11_xanthate      0.060280
     primary_cleaner.input.sulfate            0.051571
     primary_cleaner.input.depressant         0.048497
     rougher.input.floatbank10_sulfate        0.043887
     primary_cleaner.input.xanthate           0.028347
     rougher.input.floatbank10_xanthate       0.021004
     rougher.input.feed_sol                   0.011441
     rougher.input.floatbank11_sulfate        0.009392
     rougher.input.feed_rate                  0.006831
     secondary_cleaner.state.floatbank3_a_air 0.005806
     secondary_cleaner.state.floatbank2_b_air 0.003928
     rougher.input.feed_size                  0.003757
     secondary_cleaner.state.floatbank2_a_air 0.003415
     rougher.state.floatbank10_e_air          0.002903
     rougher.state.floatbank10_d_air          0.002903

```


rougher.state.floatbank10_a_air	0.002903
rougher.state.floatbank10_b_air	0.002903
rougher.state.floatbank10_c_air	0.002903
rougher.state.floatbank10_f_air	0.002903
primary_cleaner.state.floatbank8_a_air	0.002732
primary_cleaner.state.floatbank8_a_level	0.002732
rougher.input.feed_au	0.002732
primary_cleaner.state.floatbank8_d_air	0.002732
primary_cleaner.state.floatbank8_b_air	0.002732
primary_cleaner.state.floatbank8_d_level	0.002732
primary_cleaner.state.floatbank8_b_level	0.002732
rougher.input.feed_pb	0.002732
primary_cleaner.state.floatbank8_c_air	0.002732
rougher.input.feed_ag	0.002732
primary_cleaner.state.floatbank8_c_level	0.002732
secondary_cleaner.state.floatbank6_a_level	0.002732
rougher.state.floatbank10_b_level	0.002732
rougher.state.floatbank10_a_level	0.002732
secondary_cleaner.state.floatbank6_a_air	0.002732
secondary_cleaner.state.floatbank5_b_level	0.002732
secondary_cleaner.state.floatbank5_b_air	0.002732
secondary_cleaner.state.floatbank5_a_level	0.002732
secondary_cleaner.state.floatbank5_a_air	0.002732
secondary_cleaner.state.floatbank4_b_level	0.002732
secondary_cleaner.state.floatbank4_b_air	0.002732
secondary_cleaner.state.floatbank4_a_level	0.002732
secondary_cleaner.state.floatbank4_a_air	0.002732
secondary_cleaner.state.floatbank3_b_level	0.002732
secondary_cleaner.state.floatbank3_b_air	0.002732
secondary_cleaner.state.floatbank3_a_level	0.002732
secondary_cleaner.state.floatbank2_b_level	0.002732
secondary_cleaner.state.floatbank2_a_level	0.002732
rougher.state.floatbank10_f_level	0.002732
rougher.state.floatbank10_e_level	0.002732
rougher.state.floatbank10_d_level	0.002732
rougher.state.floatbank10_c_level	0.002732
primary_cleaner.input.feed_size	0.000000
date	0.000000
dtype: float64	

```
[ ]: gold_full.isna().sum().sort_values(ascending=False)/len(gold_train)
```

[]: rougher.output.recovery	0.184994
rougher.output.tail_ag	0.162337
rougher.output.tail_sol	0.162278
rougher.output.tail_au	0.162278
rougher.input.floatbank11_xanthate	0.133867

```

...
primary_cleaner.state.floatbank8_b_level    0.002550
primary_cleaner.state.floatbank8_c_level    0.002550
primary_cleaner.state.floatbank8_d_level    0.002550
primary_cleaner.input.feed_size             0.000000
date                                         0.000000
Length: 87, dtype: float64

```

```

[ ]: gold_test.fillna(method='ffill', inplace=True)
gold_test

```

```

[ ]:
      date primary_cleaner.input.sulfate \
0  2016-09-01 00:59:59      210.800909
1  2016-09-01 01:59:59      215.392455
2  2016-09-01 02:59:59      215.259946
3  2016-09-01 03:59:59      215.336236
4  2016-09-01 04:59:59      199.099327
...
5851 2017-12-31 19:59:59      173.957757
5852 2017-12-31 20:59:59      172.910270
5853 2017-12-31 21:59:59      171.135718
5854 2017-12-31 22:59:59      179.697158
5855 2017-12-31 23:59:59      181.556856

```

```

      primary_cleaner.input.depressant primary_cleaner.input.feed_size \
0      14.993118      8.080000
1      14.987471      8.080000
2      12.884934      7.786667
3      12.006805      7.640000
4      10.682530      7.530000
...
5851      15.963399      8.070000
5852      16.002605      8.070000
5853      15.993669      8.070000
5854      15.438979      8.070000
5855      14.995850      8.070000

```

```

      primary_cleaner.input.xanthate primary_cleaner.state.floatbank8_a_air \
0      1.005021      1398.981301
1      0.990469      1398.777912
2      0.996043      1398.493666
3      0.863514      1399.618111
4      0.805575      1401.268123
...
5851      0.896701      1401.930554
5852      0.896519      1447.075722
5853      1.165996      1498.836182

```

5854	1.501068	1498.466243
5855	1.623454	1498.096303

	primary_cleaner.state.floatbank8_a_level \
0	-500.225577
1	-500.057435
2	-500.868360
3	-498.863574
4	-500.808305
...	...
5851	-499.728848
5852	-494.716823
5853	-501.770403
5854	-500.483984
5855	-499.796922

	primary_cleaner.state.floatbank8_b_air \
0	1399.144926
1	1398.055362
2	1398.860436
3	1397.440120
4	1398.128818
...	...
5851	1401.441445
5852	1448.851892
5853	1499.572353
5854	1497.986986
5855	1501.743791

	primary_cleaner.state.floatbank8_b_level \
0	-499.919735
1	-499.778182
2	-499.764529
3	-499.211024
4	-499.504543
...	...
5851	-499.193423
5852	-465.963026
5853	-495.516347
5854	-519.200340
5855	-505.146931

	primary_cleaner.state.floatbank8_c_air ... \
0	1400.102998 ...
1	1396.151033 ...
2	1398.075709 ...
3	1400.129303 ...

4	1402.172226	...
...
5851	1399.810313	...
5852	1443.890424	...
5853	1502.749213	...
5854	1496.569047	...
5855	1499.535978	...

	secondary_cleaner.state.floatbank4_a_air \	
0	12.023554	
1	12.058140	
2	11.962366	
3	12.033091	
4	12.025367	
...	...	
5851	13.995957	
5852	16.749781	
5853	19.994130	
5854	19.958760	
5855	20.034715	

	secondary_cleaner.state.floatbank4_a_level \	
0	-497.795834	
1	-498.695773	
2	-498.767484	
3	-498.350935	
4	-500.786497	
...	...	
5851	-500.157454	
5852	-496.031539	
5853	-499.791312	
5854	-499.958750	
5855	-500.728588	

	secondary_cleaner.state.floatbank4_b_air \	
0	8.016656	
1	8.130979	
2	8.096893	
3	8.074946	
4	8.054678	
...	...	
5851	12.069155	
5852	13.365371	
5853	15.101425	
5854	15.026853	
5855	14.914199	

	secondary_cleaner.state.floatbank4_b_level \
0	-501.289139
1	-499.634209
2	-500.827423
3	-499.474407
4	-500.397500
...	...
5851	-499.673279
5852	-499.122723
5853	-499.936252
5854	-499.723143
5855	-499.948518

	secondary_cleaner.state.floatbank5_a_air \
0	7.946562
1	7.958270
2	8.071056
3	7.897085
4	8.107890
...	...
5851	7.977259
5852	9.288553
5853	10.989181
5854	11.011607
5855	10.986607

	secondary_cleaner.state.floatbank5_a_level \
0	-432.317850
1	-525.839648
2	-500.801673
3	-500.868509
4	-509.526725
...	...
5851	-499.516126
5852	-496.892967
5853	-498.347898
5854	-499.985046
5855	-500.658027

	secondary_cleaner.state.floatbank5_b_air \
0	4.872511
1	4.878850
2	4.905125
3	4.931400
4	4.957674
...	...
5851	5.933319

```

5852          7.372897
5853          9.020944
5854          9.009783
5855          8.989497

secondary_cleaner.state.floatbank5_b_level \
0          -500.037437
1          -500.162375
2          -499.828510
3          -499.963623
4          -500.360026
...          ...
5851          -499.965973
5852          -499.942956
5853          -500.040448
5854          -499.937902
5855          -500.337588

secondary_cleaner.state.floatbank6_a_air \
0          26.705889
1          25.019940
2          24.994862
3          24.948919
4          25.003331
...          ...
5851          8.987171
5852          8.986832
5853          8.982038
5854          9.012660
5855          8.988632

secondary_cleaner.state.floatbank6_a_level
0          -499.709414
1          -499.819438
2          -500.622559
3          -498.709987
4          -500.856333
...          ...
5851          -499.755909
5852          -499.903761
5853          -497.789882
5854          -500.154284
5855          -500.764937

```

[5856 rows x 53 columns]

When we look at NA values in the 3 sets, we see that some rows have almost 20% of values missing. We are told that parameters that are close in time tend to be similar, so I have used forward fill

to fill these. In order to manually compute the recovery statistic below, I will drop NA values to avoid dividing by 0.

```
[ ]: gold_train.dropna(inplace=True)
      c = gold_train['rougher.output.concentrate_au']
      f = gold_train['rougher.input.feed_au']
      t = gold_train['rougher.output.tail_au']
      recovery = ((c*(f-t))/(f*(c-t))) *100
      recovery
```

```
[ ]: 0      87.107763
      1      86.843261
      2      86.842308
      3      87.226430
      4      86.688794
      ...
      16855   89.574376
      16856   87.724007
      16857   88.890579
      16858   89.858126
      16859   89.514960
      Length: 11017, dtype: float64
```

```
[ ]: recovery.shape
```

```
[ ]: (11017,)
```

```
[ ]: gold_train['rougher.output.recovery'].shape
```

```
[ ]: (11017,)
```

```
[ ]: mean_absolute_error(gold_train['rougher.output.recovery'], recovery)
```

```
[ ]: 9.555596961987514e-15
```

```
[ ]: sum(np.abs(recovery-gold_train['rougher.output.recovery']))/len(recovery)
```

```
[ ]: 9.555596961987514e-15
```

MAE is confirmed to be reasonably small (very close to zero) for the manually calculated recovery values. This tells us that this equation is a good model to predict the output of the process.

```
[ ]: col_mapping_dict = {c[0]:c[1] for c in enumerate(gold_test.columns)}
      col_mapping_dict
```

```
[ ]: {0: 'date',
      1: 'primary_cleaner.input.sulfate',
      2: 'primary_cleaner.input.depressant',
      3: 'primary_cleaner.input.feed_size',
```

4: 'primary_cleaner.input.xanthate',
5: 'primary_cleaner.state.floatbank8_a_air',
6: 'primary_cleaner.state.floatbank8_a_level',
7: 'primary_cleaner.state.floatbank8_b_air',
8: 'primary_cleaner.state.floatbank8_b_level',
9: 'primary_cleaner.state.floatbank8_c_air',
10: 'primary_cleaner.state.floatbank8_c_level',
11: 'primary_cleaner.state.floatbank8_d_air',
12: 'primary_cleaner.state.floatbank8_d_level',
13: 'rougher.input.feed_ag',
14: 'rougher.input.feed_pb',
15: 'rougher.input.feed_rate',
16: 'rougher.input.feed_size',
17: 'rougher.input.feed_sol',
18: 'rougher.input.feed_au',
19: 'rougher.input.floatbank10_sulfate',
20: 'rougher.input.floatbank10_xanthate',
21: 'rougher.input.floatbank11_sulfate',
22: 'rougher.input.floatbank11_xanthate',
23: 'rougher.state.floatbank10_a_air',
24: 'rougher.state.floatbank10_a_level',
25: 'rougher.state.floatbank10_b_air',
26: 'rougher.state.floatbank10_b_level',
27: 'rougher.state.floatbank10_c_air',
28: 'rougher.state.floatbank10_c_level',
29: 'rougher.state.floatbank10_d_air',
30: 'rougher.state.floatbank10_d_level',
31: 'rougher.state.floatbank10_e_air',
32: 'rougher.state.floatbank10_e_level',
33: 'rougher.state.floatbank10_f_air',
34: 'rougher.state.floatbank10_f_level',
35: 'secondary_cleaner.state.floatbank2_a_air',
36: 'secondary_cleaner.state.floatbank2_a_level',
37: 'secondary_cleaner.state.floatbank2_b_air',
38: 'secondary_cleaner.state.floatbank2_b_level',
39: 'secondary_cleaner.state.floatbank3_a_air',
40: 'secondary_cleaner.state.floatbank3_a_level',
41: 'secondary_cleaner.state.floatbank3_b_air',
42: 'secondary_cleaner.state.floatbank3_b_level',
43: 'secondary_cleaner.state.floatbank4_a_air',
44: 'secondary_cleaner.state.floatbank4_a_level',
45: 'secondary_cleaner.state.floatbank4_b_air',
46: 'secondary_cleaner.state.floatbank4_b_level',
47: 'secondary_cleaner.state.floatbank5_a_air',
48: 'secondary_cleaner.state.floatbank5_a_level',
49: 'secondary_cleaner.state.floatbank5_b_air',
50: 'secondary_cleaner.state.floatbank5_b_level',


```
51: 'secondary_cleaner.state.floatbank6_a_air',
52: 'secondary_cleaner.state.floatbank6_a_level'}
```

```
[ ]: col_mapping_dict = {c[0]:c[1] for c in enumerate(gold_full.columns)}
col_mapping_dict
```

```
[ ]: {0: 'date',
1: 'final.output.concentrate_ag',
2: 'final.output.concentrate_pb',
3: 'final.output.concentrate_sol',
4: 'final.output.concentrate_au',
5: 'final.output.recovery',
6: 'final.output.tail_ag',
7: 'final.output.tail_pb',
8: 'final.output.tail_sol',
9: 'final.output.tail_au',
10: 'primary_cleaner.input.sulfate',
11: 'primary_cleaner.input.depressant',
12: 'primary_cleaner.input.feed_size',
13: 'primary_cleaner.input.xanthate',
14: 'primary_cleaner.output.concentrate_ag',
15: 'primary_cleaner.output.concentrate_pb',
16: 'primary_cleaner.output.concentrate_sol',
17: 'primary_cleaner.output.concentrate_au',
18: 'primary_cleaner.output.tail_ag',
19: 'primary_cleaner.output.tail_pb',
20: 'primary_cleaner.output.tail_sol',
21: 'primary_cleaner.output.tail_au',
22: 'primary_cleaner.state.floatbank8_a_air',
23: 'primary_cleaner.state.floatbank8_a_level',
24: 'primary_cleaner.state.floatbank8_b_air',
25: 'primary_cleaner.state.floatbank8_b_level',
26: 'primary_cleaner.state.floatbank8_c_air',
27: 'primary_cleaner.state.floatbank8_c_level',
28: 'primary_cleaner.state.floatbank8_d_air',
29: 'primary_cleaner.state.floatbank8_d_level',
30: 'rougher.calculation.sulfate_to_au_concentrate',
31: 'rougher.calculation.floatbank10_sulfate_to_au_feed',
32: 'rougher.calculation.floatbank11_sulfate_to_au_feed',
33: 'rougher.calculation.au_pb_ratio',
34: 'rougher.input.feed_ag',
35: 'rougher.input.feed_pb',
36: 'rougher.input.feed_rate',
37: 'rougher.input.feed_size',
38: 'rougher.input.feed_sol',
39: 'rougher.input.feed_au',
40: 'rougher.input.floatbank10_sulfate',
```

```

41: 'rougher.input.floatbank10_xanthate',
42: 'rougher.input.floatbank11_sulfate',
43: 'rougher.input.floatbank11_xanthate',
44: 'rougher.output.concentrate_ag',
45: 'rougher.output.concentrate_pb',
46: 'rougher.output.concentrate_sol',
47: 'rougher.output.concentrate_au',
48: 'rougher.output.recovery',
49: 'rougher.output.tail_ag',
50: 'rougher.output.tail_pb',
51: 'rougher.output.tail_sol',
52: 'rougher.output.tail_au',
53: 'rougher.state.floatbank10_a_air',
54: 'rougher.state.floatbank10_a_level',
55: 'rougher.state.floatbank10_b_air',
56: 'rougher.state.floatbank10_b_level',
57: 'rougher.state.floatbank10_c_air',
58: 'rougher.state.floatbank10_c_level',
59: 'rougher.state.floatbank10_d_air',
60: 'rougher.state.floatbank10_d_level',
61: 'rougher.state.floatbank10_e_air',
62: 'rougher.state.floatbank10_e_level',
63: 'rougher.state.floatbank10_f_air',
64: 'rougher.state.floatbank10_f_level',
65: 'secondary_cleaner.output.tail_ag',
66: 'secondary_cleaner.output.tail_pb',
67: 'secondary_cleaner.output.tail_sol',
68: 'secondary_cleaner.output.tail_au',
69: 'secondary_cleaner.state.floatbank2_a_air',
70: 'secondary_cleaner.state.floatbank2_a_level',
71: 'secondary_cleaner.state.floatbank2_b_air',
72: 'secondary_cleaner.state.floatbank2_b_level',
73: 'secondary_cleaner.state.floatbank3_a_air',
74: 'secondary_cleaner.state.floatbank3_a_level',
75: 'secondary_cleaner.state.floatbank3_b_air',
76: 'secondary_cleaner.state.floatbank3_b_level',
77: 'secondary_cleaner.state.floatbank4_a_air',
78: 'secondary_cleaner.state.floatbank4_a_level',
79: 'secondary_cleaner.state.floatbank4_b_air',
80: 'secondary_cleaner.state.floatbank4_b_level',
81: 'secondary_cleaner.state.floatbank5_a_air',
82: 'secondary_cleaner.state.floatbank5_a_level',
83: 'secondary_cleaner.state.floatbank5_b_air',
84: 'secondary_cleaner.state.floatbank5_b_level',
85: 'secondary_cleaner.state.floatbank6_a_air',
86: 'secondary_cleaner.state.floatbank6_a_level'}

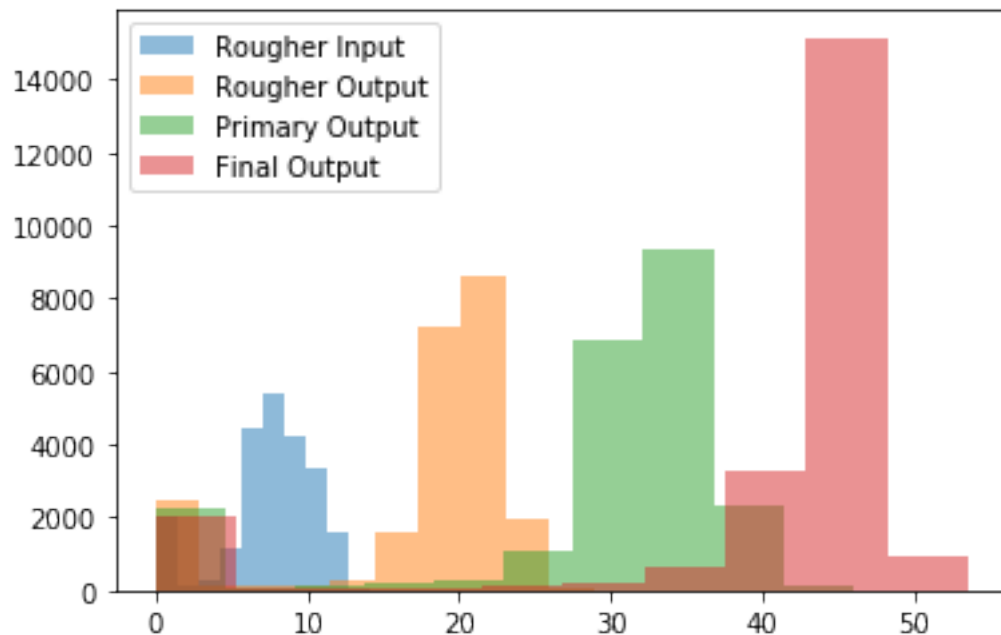
```

The test dataset doesn't include any of the final states, calculations, or the outputs of any of

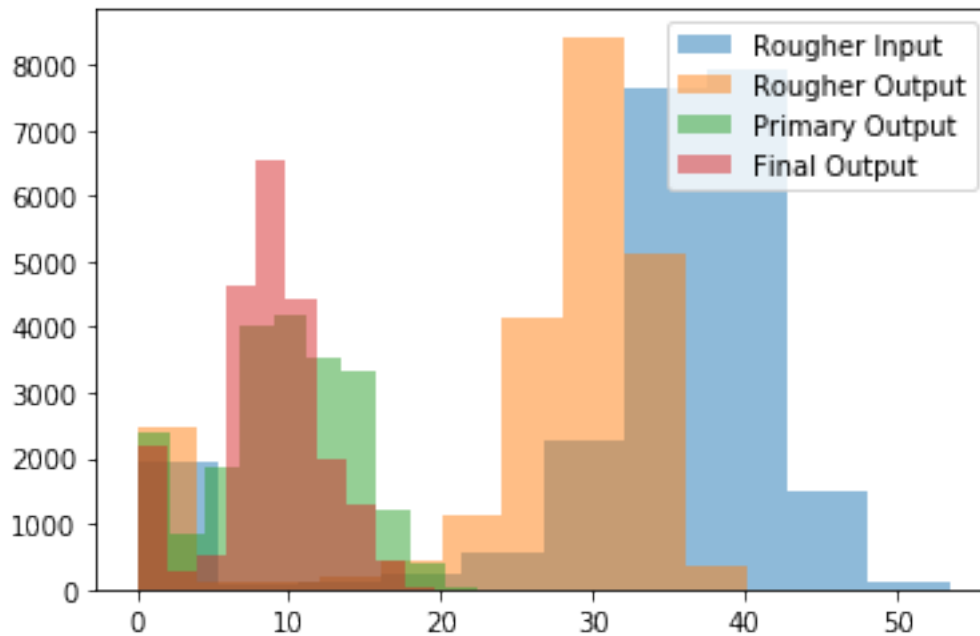
the stages. Which makes sense, because we would want the model to learn to predict outcomes from what goes in to each stage. The test dataset would only need the inputs, while we use the calculations, and actual outputs, to verify the accuracy of the model.

```
[ ]: au_conc = gold_full.filter(['rougher.input.feed_au', 'rougher.output.
    ↪concentrate_au', 'primary_cleaner.output.concentrate_au', 'final.output.
    ↪concentrate_au'])
sol_conc = gold_full.filter(['rougher.input.feed_sol', 'rougher.output.
    ↪concentrate_sol', 'primary_cleaner.output.concentrate_sol', 'final.output.
    ↪concentrate_sol'])
pb_conc = gold_full.filter(['rougher.input.feed_pb', 'rougher.output.
    ↪concentrate_pb', 'primary_cleaner.output.concentrate_pb', 'final.output.
    ↪concentrate_pb'])
ag_conc = gold_full.filter(['rougher.input.feed_ag', 'rougher.output.
    ↪concentrate_ag', 'primary_cleaner.output.concentrate_ag', 'final.output.
    ↪concentrate_ag'])

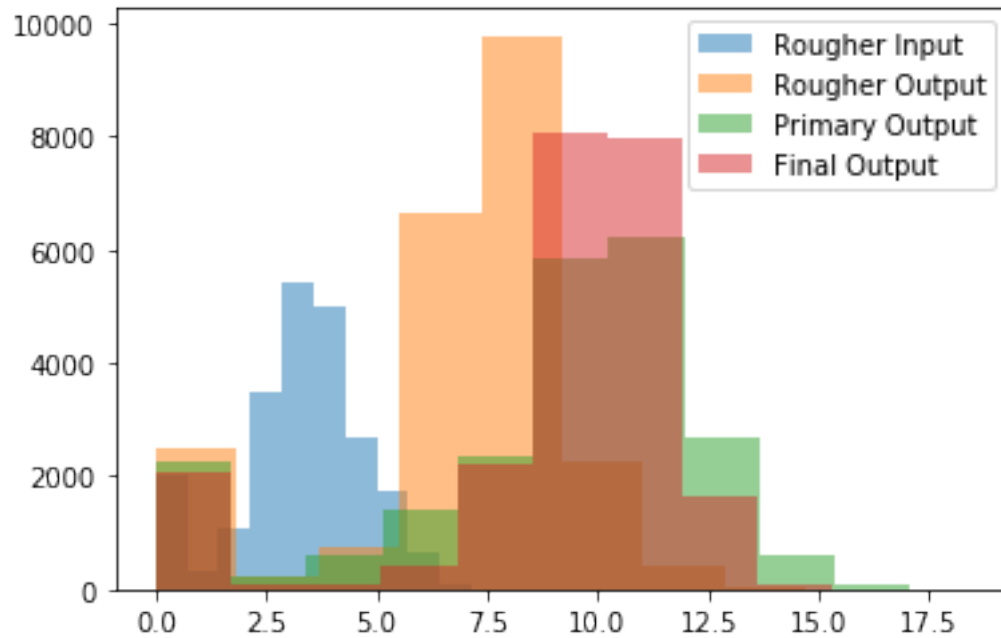
[ ]: plt.hist(au_conc['rougher.input.feed_au'], alpha=0.5, label='Rougher Input')
plt.hist(au_conc['rougher.output.concentrate_au'], alpha=0.5, label='Rougher_
    ↪Output')
plt.hist(au_conc['primary_cleaner.output.concentrate_au'], alpha=0.5,
    ↪label='Primary Output')
plt.hist(au_conc['final.output.concentrate_au'], alpha=0.5, label='Final_
    ↪Output')
plt.legend(loc='upper left')
plt.show()
```



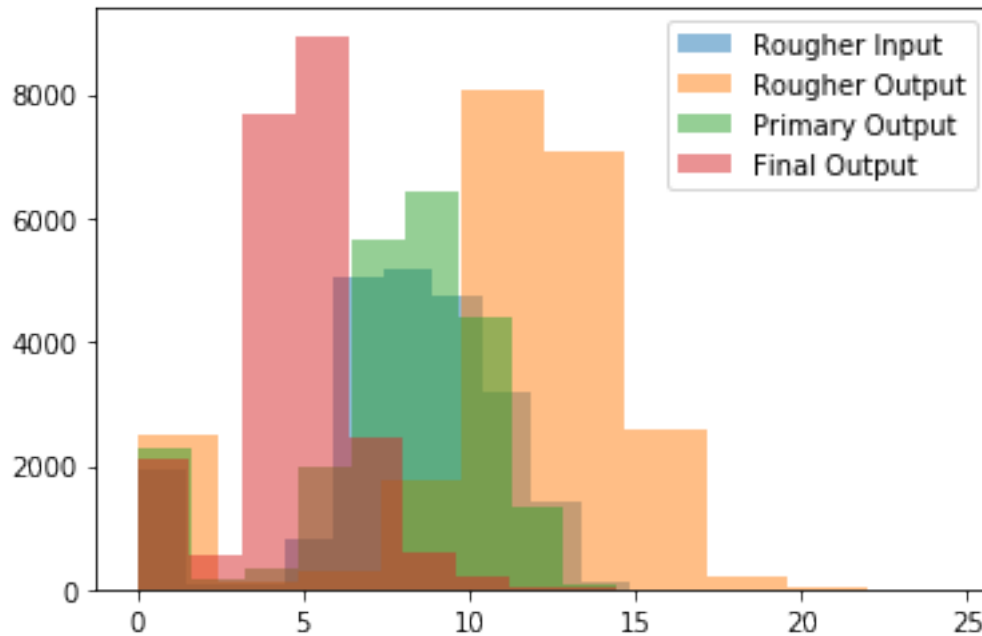
```
[ ]: plt.hist(sol_conc['rougher.input.feed_sol'], alpha=0.5, label='Rougher Input')
plt.hist(sol_conc['rougher.output.concentrate_sol'], alpha=0.5, label='Rougher_
↳Output')
plt.hist(sol_conc['primary_cleaner.output.concentrate_sol'], alpha=0.5,
↳label='Primary Output')
plt.hist(sol_conc['final.output.concentrate_sol'], alpha=0.5, label='Final_
↳Output')
plt.legend(loc='upper right')
plt.show()
```



```
[ ]: plt.hist(pb_conc['rougher.input.feed_pb'], alpha=0.5, label='Rougher Input')
plt.hist(pb_conc['rougher.output.concentrate_pb'], alpha=0.5, label='Rougher_
↳Output')
plt.hist(pb_conc['primary_cleaner.output.concentrate_pb'], alpha=0.5,
↳label='Primary Output')
plt.hist(pb_conc['final.output.concentrate_pb'], alpha=0.5, label='Final_
↳Output')
plt.legend(loc='upper right')
plt.show()
```

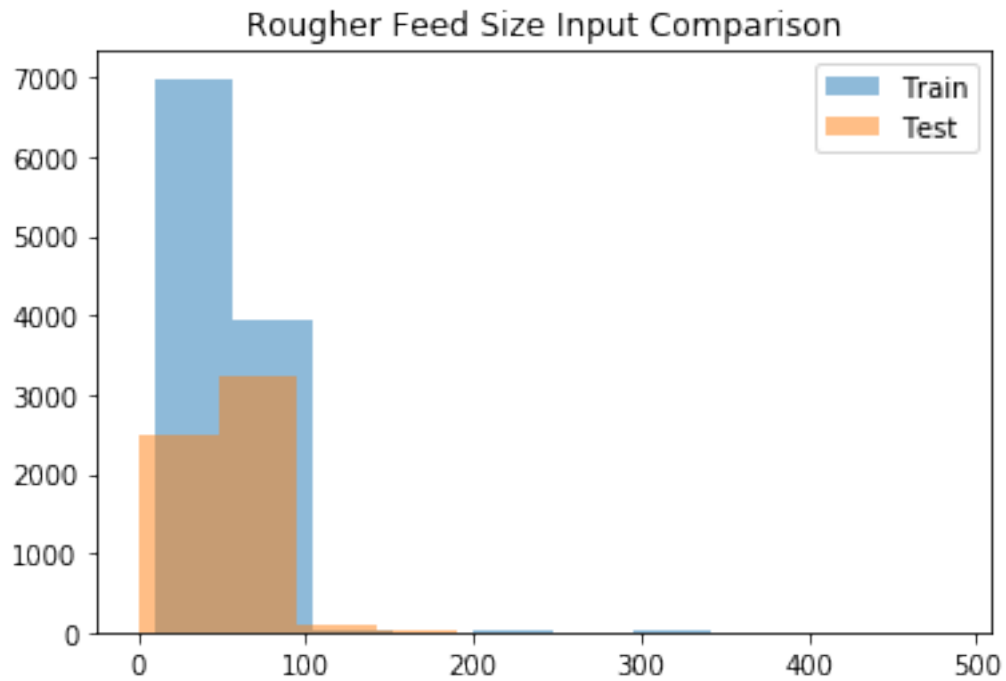


```
[ ]: plt.hist(ag_conc['rougher.input.feed_ag'], alpha=0.5, label='Rougher Input')
plt.hist(ag_conc['rougher.output.concentrate_ag'], alpha=0.5, label='Rougher_
    ↳Output')
plt.hist(ag_conc['primary_cleaner.output.concentrate_ag'], alpha=0.5,
    ↳label='Primary Output')
plt.hist(ag_conc['final.output.concentrate_ag'], alpha=0.5, label='Final_
    ↳Output')
plt.legend(loc='upper right')
plt.show()
```

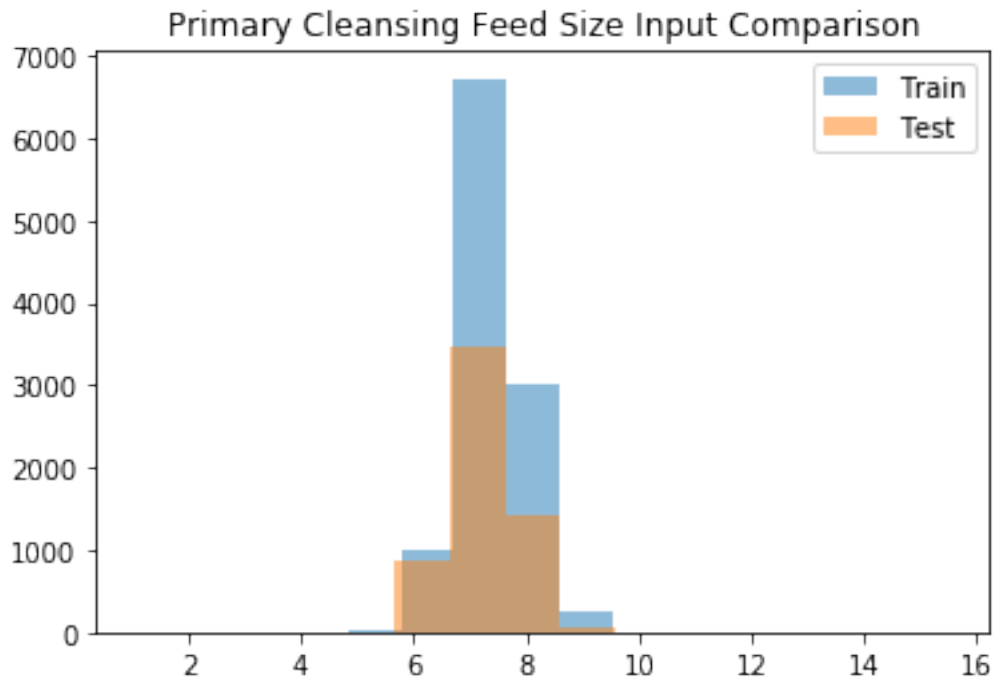


When we look at how concentrations change throughout the process, the most important to observe is the Au (gold) concentration. We can see that the concentration grows as the ore moves through the process, which aligns with the goal to purify and improve the concentration of gold with each step. The other minerals do not show as clear a progress, but they do not mimic the Au process. This tells us that the process is prioritizing the purification of Au, and that each different step assists with reducing a different contaminant.

```
[ ]: plt.hist(gold_train['rougher.input.feed_size'], alpha=0.5, label='Train')
plt.hist(gold_test['rougher.input.feed_size'], alpha=0.5, label='Test')
plt.title('Rougher Feed Size Input Comparison')
plt.legend(loc='upper right')
plt.show()
```

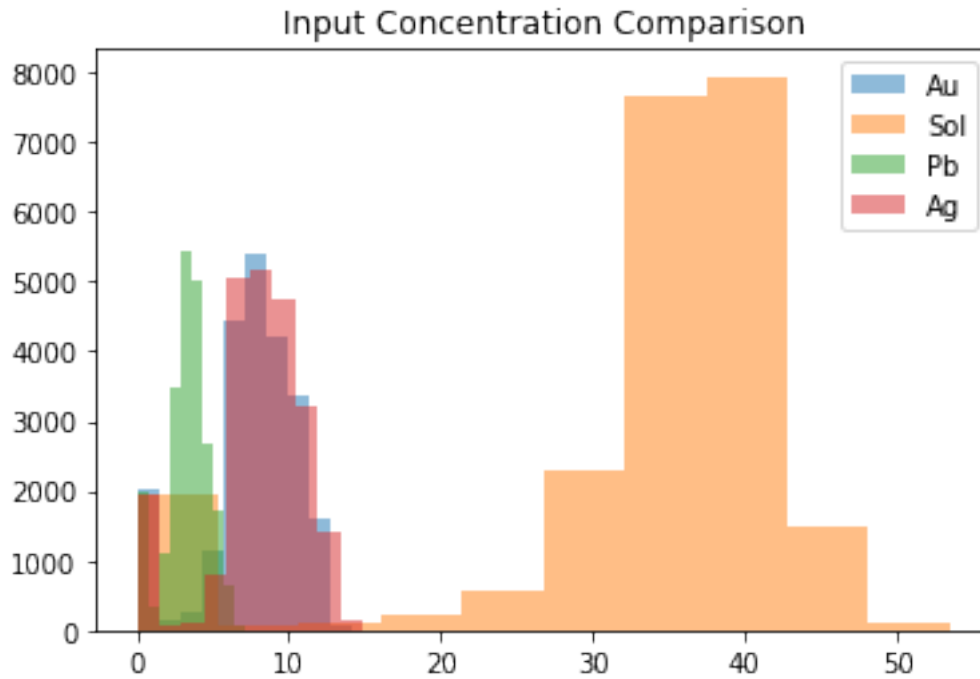


```
[ ]: plt.hist(gold_train['primary_cleaner.input.feed_size'], alpha=0.5, label='Train')
plt.hist(gold_test['primary_cleaner.input.feed_size'], alpha=0.5, label='Test')
plt.title('Primary Cleansing Feed Size Input Comparison')
plt.legend(loc='upper right')
plt.show()
```



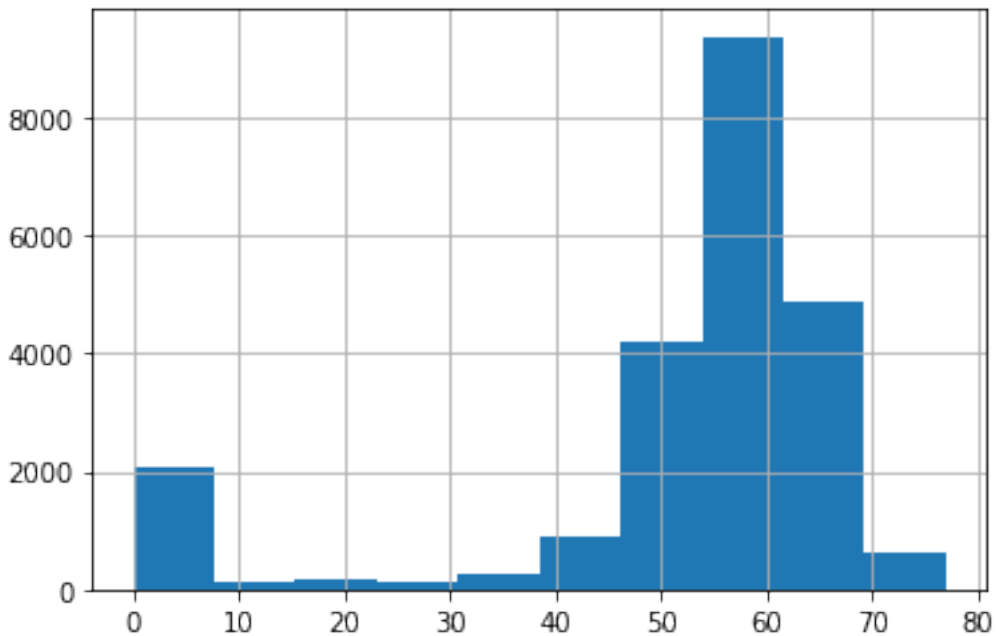
Feed size has approximately similar distributions between train and test sets, so models should be accurate.

```
[ ]: plt.hist(gold_full['rougher.input.feed_au'], alpha=0.5, label='Au')
plt.hist(gold_full['rougher.input.feed_sol'], alpha=0.5, label='Sol')
plt.hist(gold_full['rougher.input.feed_pb'], alpha=0.5, label='Pb')
plt.hist(gold_full['rougher.input.feed_ag'], alpha=0.5, label='Ag')
plt.title('Input Concentration Comparison')
plt.legend(loc='upper right')
plt.show()
```

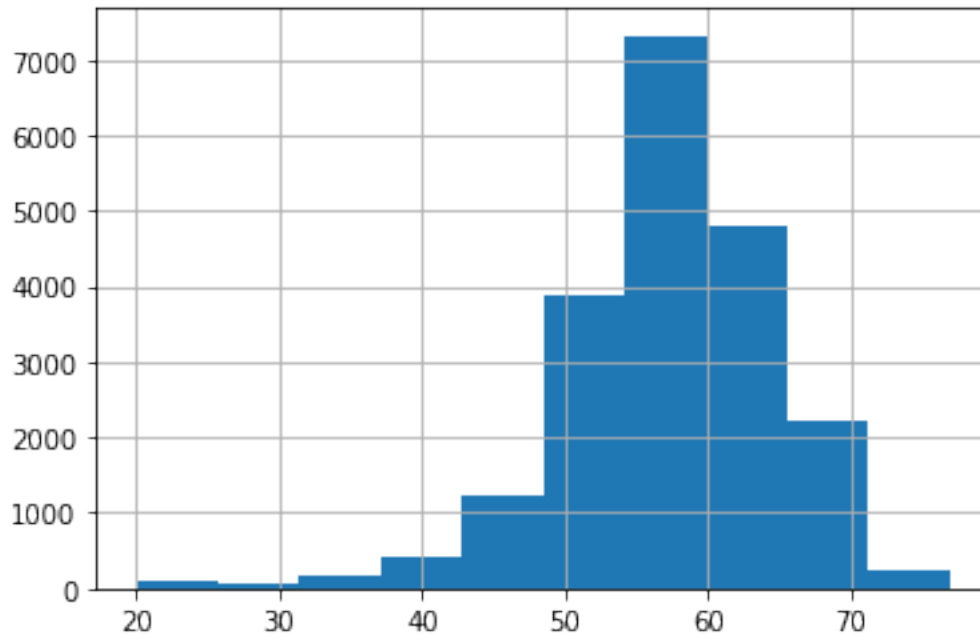
```
[ ]: rougher_input = ['rougher.input.feed_au', 'rougher.input.feed_sol', 'rougher.
    ↪input.feed_pb', 'rougher.input.feed_ag']
gold_full[rougher_input].sum(1).hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443d4d6410>
```



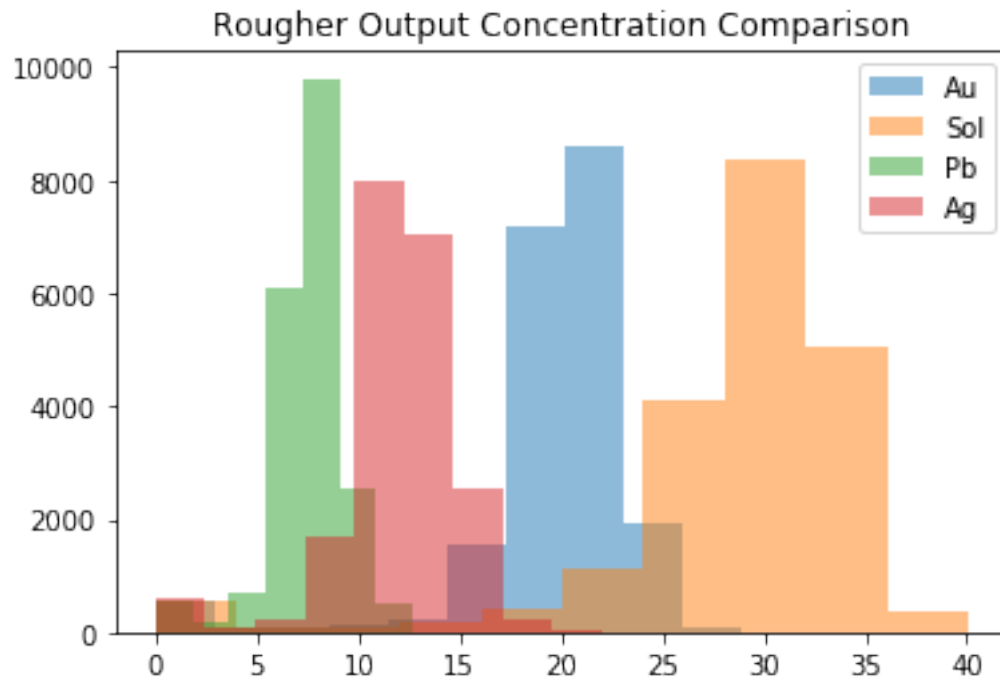
```
[ ]: gold_full['rougher_input'] = gold_full[rougher_input].sum(1)
gold_full.drop(gold_full[gold_full['rougher_input'] <= 20].index, inplace=True)
gold_full['rougher_input'].hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443d54f2d0>
```



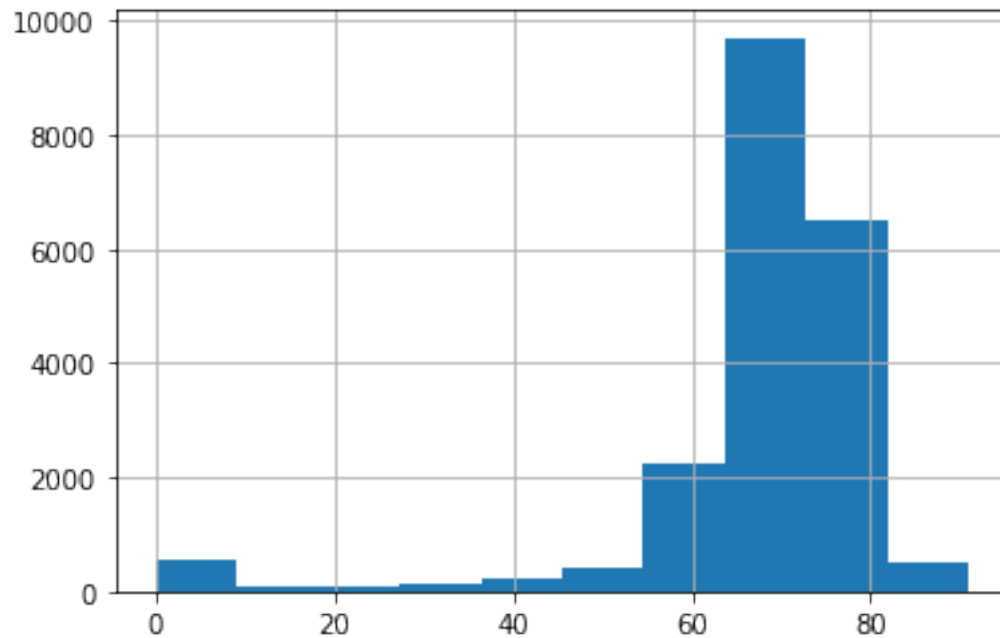
```
[ ]: gold_train['rougher_input'] = gold_train[rougher_input].sum(1)
gold_train.drop(gold_train[gold_train['rougher_input'] <= 20].index,
↳inplace=True)
```

```
[ ]: plt.hist(gold_full['rougher.output.concentrate_au'], alpha=0.5, label='Au')
plt.hist(gold_full['rougher.output.concentrate_sol'], alpha=0.5, label='Sol')
plt.hist(gold_full['rougher.output.concentrate_pb'], alpha=0.5, label='Pb')
plt.hist(gold_full['rougher.output.concentrate_ag'], alpha=0.5, label='Ag')
plt.title('Rougher Output Concentration Comparison')
plt.legend(loc='upper right')
plt.show()
```



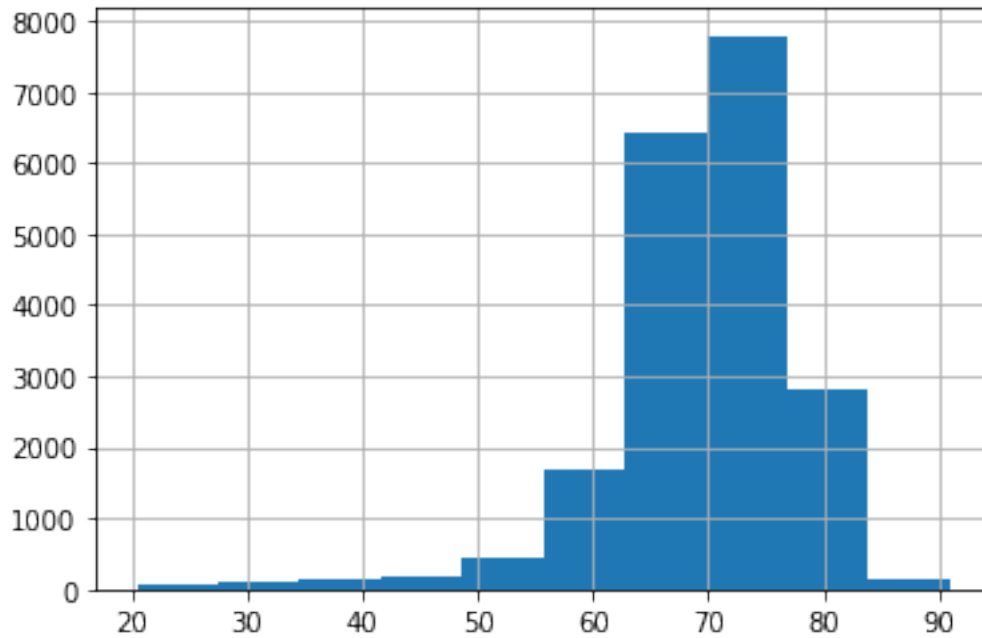
```
[ ]: rougher_output = ['rougher.output.concentrate_au', 'rougher.output.
    ↳concentrate_sol', 'rougher.output.concentrate_pb', 'rougher.output.
    ↳concentrate_ag']
gold_full[rougher_output].sum(1).hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443db39850>
```

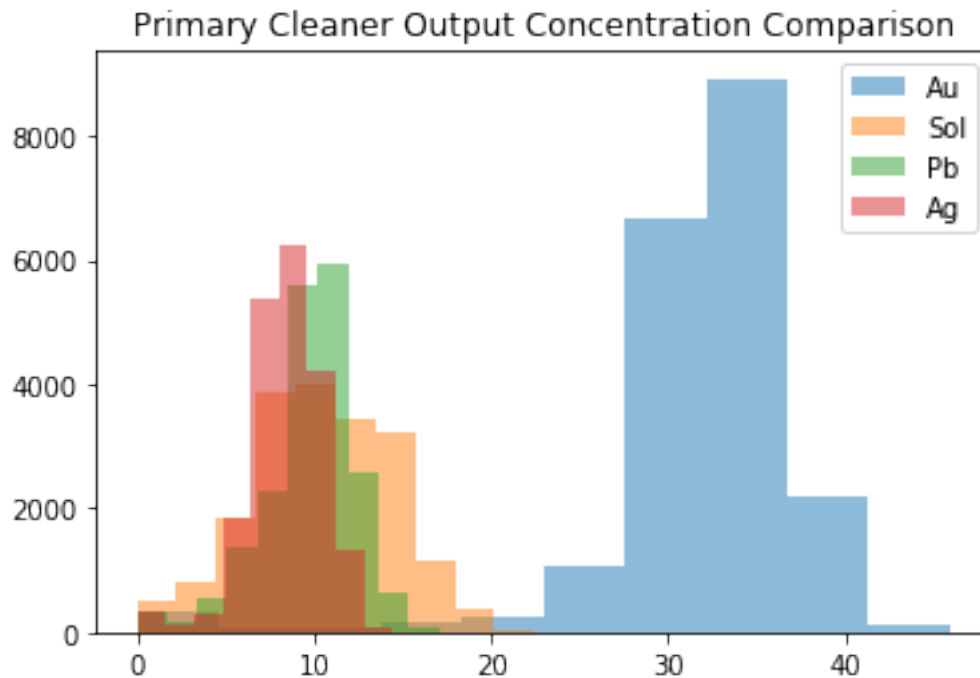


```
[ ]: gold_full['rougner_output'] = gold_full[rougner_output].sum(1)
gold_full.drop(gold_full[gold_full['rougner_output'] <= 20].index, inplace=True)
gold_train['rougner_output'] = gold_train[rougner_output].sum(1)
gold_train.drop(gold_train[gold_train['rougner_output'] <= 20].index,
               ↪inplace=True)
gold_full['rougner_output'].hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443e1da4d0>
```

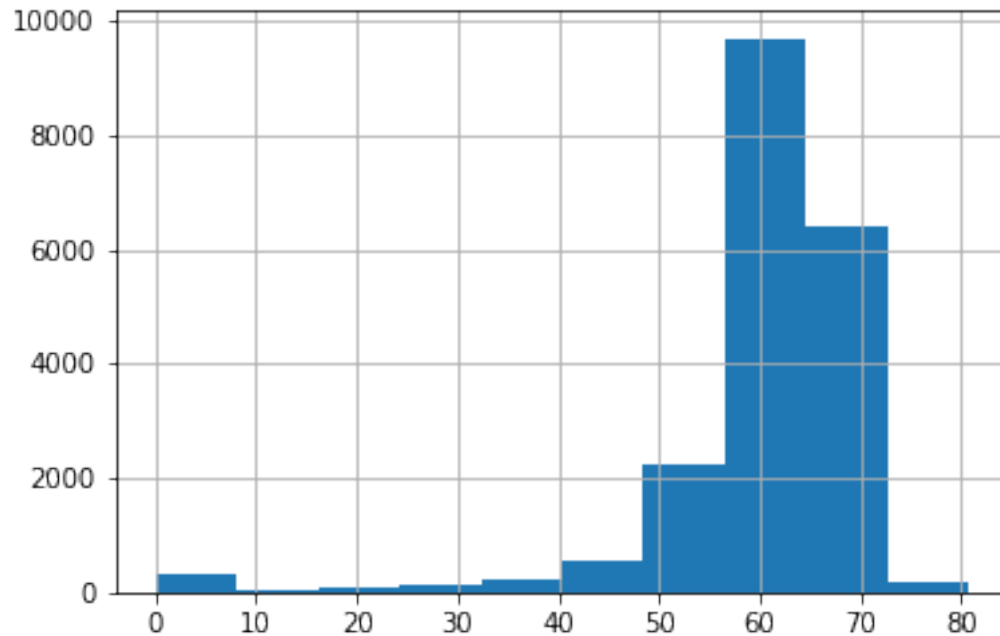


```
[ ]: plt.hist(gold_full['primary_cleaner.output.concentrate_au'], alpha=0.5,
             ↪label='Au')
plt.hist(gold_full['primary_cleaner.output.concentrate_sol'], alpha=0.5,
         ↪label='Sol')
plt.hist(gold_full['primary_cleaner.output.concentrate_pb'], alpha=0.5,
         ↪label='Pb')
plt.hist(gold_full['primary_cleaner.output.concentrate_ag'], alpha=0.5,
         ↪label='Ag')
plt.title('Primary Cleaner Output Concentration Comparison')
plt.legend(loc='upper right')
plt.show()
```



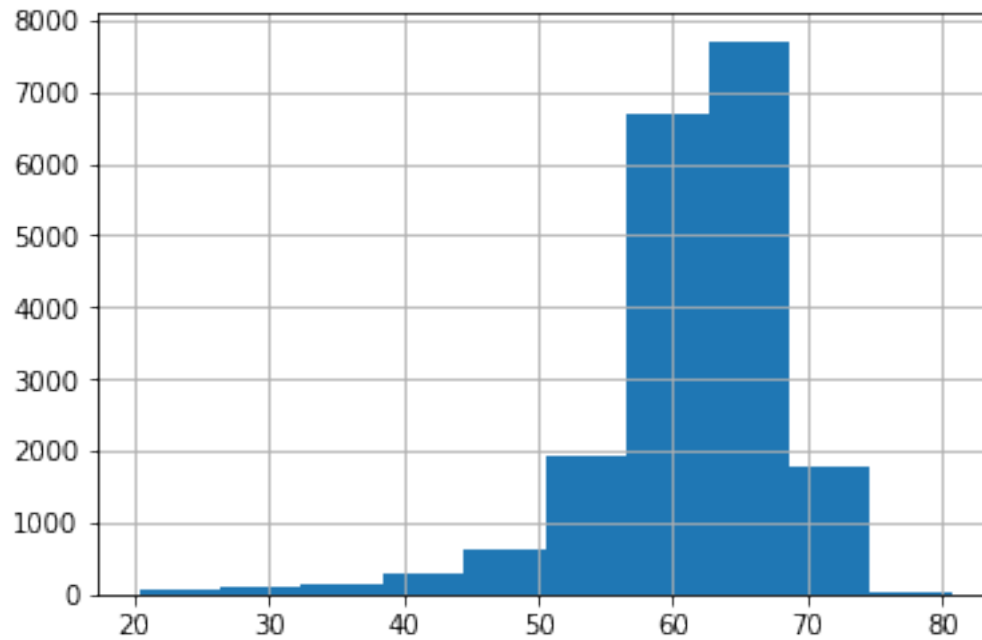
```
[ ]: primary_cleaner_output = ['primary_cleaner.output.concentrate_au',  
    ↪ 'primary_cleaner.output.concentrate_sol', 'primary_cleaner.output.  
    ↪ concentrate_pb', 'primary_cleaner.output.concentrate_ag']  
gold_full[primary_cleaner_output].sum(1).hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443e004ed0>
```

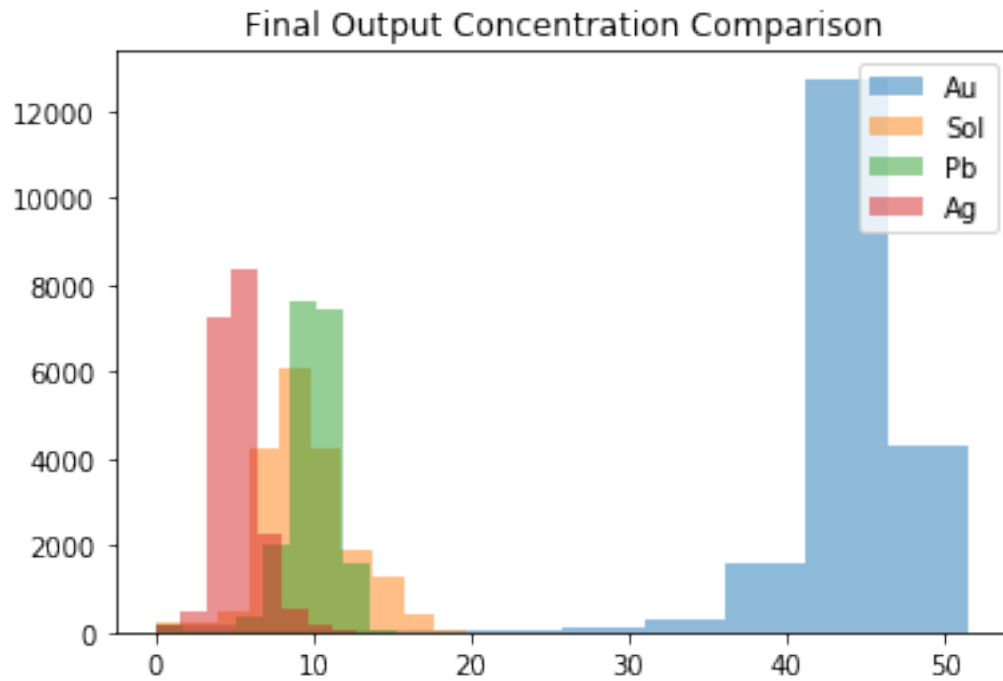


```
[ ]: gold_full['primary_cleaner_output'] = gold_full[primary_cleaner_output].sum(1)
gold_full.drop(gold_full[gold_full['primary_cleaner_output'] <= 20].index,
               inplace=True)
gold_train['primary_cleaner_output'] = gold_train[primary_cleaner_output].sum(1)
gold_train.drop(gold_train[gold_train['primary_cleaner_output'] <= 20].index,
                inplace=True)
gold_full['primary_cleaner_output'].hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443d49c5d0>
```

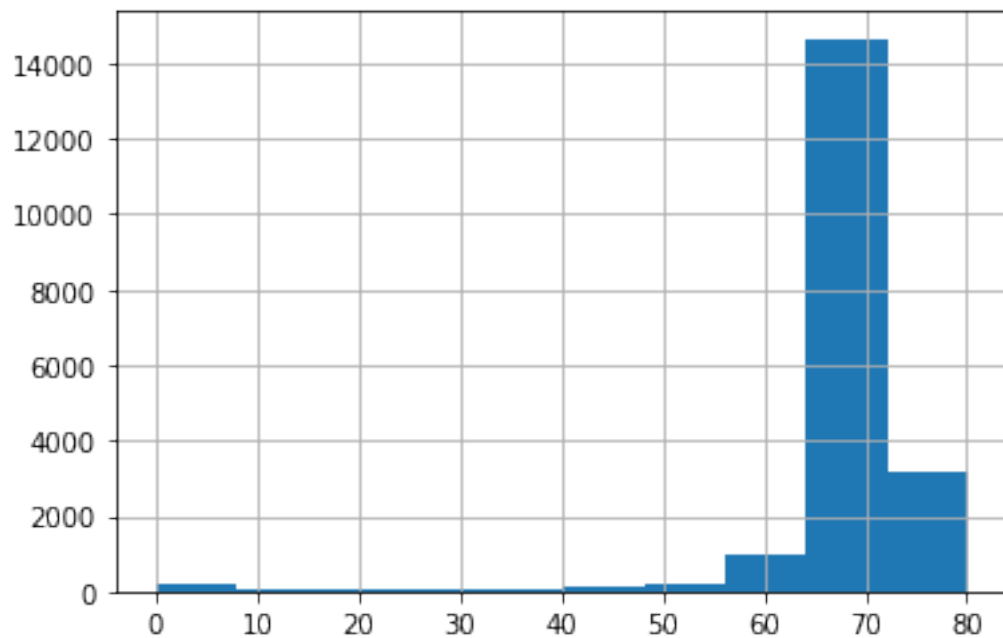


```
[ ]: plt.hist(gold_full['final.output.concentrate_au'], alpha=0.5, label='Au')
plt.hist(gold_full['final.output.concentrate_sol'], alpha=0.5, label='Sol')
plt.hist(gold_full['final.output.concentrate_pb'], alpha=0.5, label='Pb')
plt.hist(gold_full['final.output.concentrate_ag'], alpha=0.5, label='Ag')
plt.title('Final Output Concentration Comparison')
plt.legend(loc='upper right')
plt.show()
```

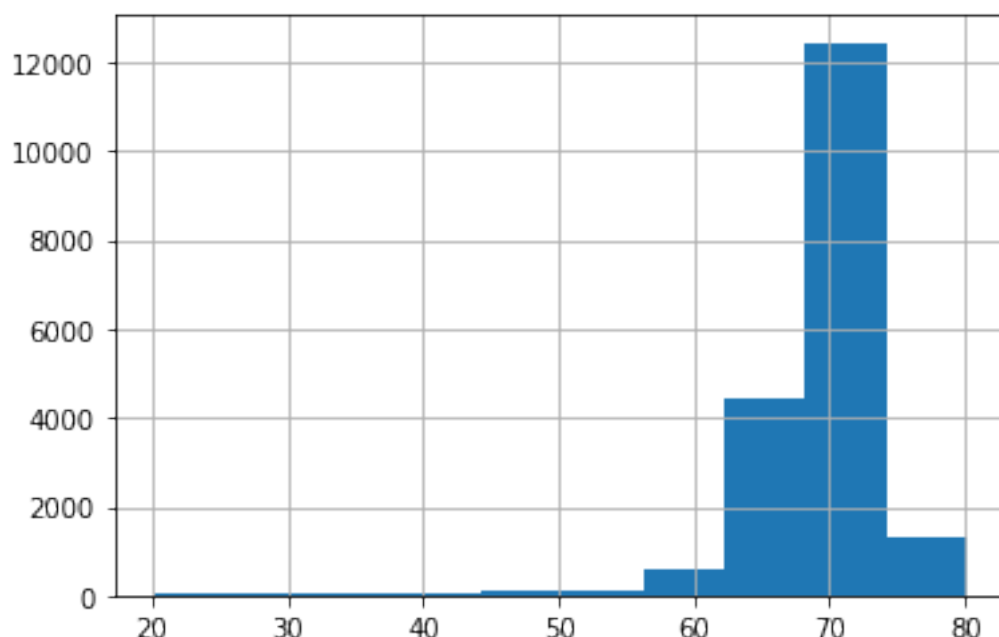
```
[ ]: final_output = ['final.output.concentrate_au', 'final.output.concentrate_sol', 'final.output.concentrate_pb', 'final.output.concentrate_ag']
gold_full[final_output].sum(1).hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443db5ffd0>
```



```
[ ]: gold_full['final_output'] = gold_full[final_output].sum(1)
gold_full.drop(gold_full[gold_full['final_output'] <= 20].index, inplace=True)
gold_full['final_output'].hist()
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f443e558110>
```



It does appear that there are some outliers of 0 in all of our concentrations, these may just be missing values or erroneous values. They have been dropped from the full dataset, and also from the train dataset to avoid mistraining the model.

```
[ ]: def smape(y_true, y_pred):
    return (1/(len(y_true)))*np.sum((np.abs(y_true-y_pred))/(np.abs(y_true)+np.
    ↪abs(y_pred))/2)*100
```

```
[ ]: def finalsmape(smape_rough, smape_final):
    return .25* smape_rough + .75* smape_final
```

```
[ ]: smape_rough = smape(gold_train['rougher.output.recovery'], recovery)
```

```
[ ]: c = gold_train['final.output.concentrate_au']
f = gold_train['rougher.output.concentrate_au']
t = gold_train['final.output.tail_au']
recovery = ((c*(f-t))/(f*(c-t))) *100
smape_final = smape(gold_train['final.output.recovery'], recovery)
```

```
[ ]: finalsmape(smape_rough, smape_final)
```

```
[ ]: 5.856398012142628
```

```
[ ]: from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

features = gold_train[gold_test.columns].drop(['date'], axis=1)
target = gold_train[['rougher.output.recovery', 'final.output.recovery']]
features_train, features_test, target_train, target_test = \
    train_test_split(features, target, test_size=.25, random_state=42)
gold_test_target = gold_test.merge(gold_full, on='date', how='inner')[['date', \
    'rougher.output.recovery', 'final.output.recovery']]
gold_test = gold_test.merge(gold_test_target, on='date', how='inner')
gold_test_target = gold_test_target.drop(['date'], axis=1)
gold_test = gold_test.drop(['date', 'rougher.output.recovery', 'final.output.
    recovery'], axis=1)
```

```
[ ]: gold_test_target
```

```
[ ]:      rougher.output.recovery  final.output.recovery
0          89.993421          70.273583
1          88.089657          68.910432
2          88.412756          68.143213
3          87.360133          67.776393
4          83.236367          61.467078
...          ...          ...
5154         95.172585          68.919891
5155         94.575036          68.440582
5156         93.018138          67.092759
5157         92.599042          68.061186
5158         91.177695          71.699976
```

```
[5159 rows x 2 columns]
```

```
[ ]: gold_test
```

```
[ ]:      primary_cleaner.input.sulfate  primary_cleaner.input.depressant \
0          210.800909          14.993118
1          215.392455          14.987471
2          215.259946          12.884934
3          215.336236          12.006805
4          199.099327          10.682530
...          ...          ...
```

5154	173.957757	15.963399
5155	172.910270	16.002605
5156	171.135718	15.993669
5157	179.697158	15.438979
5158	181.556856	14.995850

	primary_cleaner.input.feed_size	primary_cleaner.input.xanthate \
0	8.080000	1.005021
1	8.080000	0.990469
2	7.786667	0.996043
3	7.640000	0.863514
4	7.530000	0.805575
...
5154	8.070000	0.896701
5155	8.070000	0.896519
5156	8.070000	1.165996
5157	8.070000	1.501068
5158	8.070000	1.623454

	primary_cleaner.state.floatbank8_a_air \
0	1398.981301
1	1398.777912
2	1398.493666
3	1399.618111
4	1401.268123
...	...
5154	1401.930554
5155	1447.075722
5156	1498.836182
5157	1498.466243
5158	1498.096303

	primary_cleaner.state.floatbank8_a_level \
0	-500.225577
1	-500.057435
2	-500.868360
3	-498.863574
4	-500.808305
...	...
5154	-499.728848
5155	-494.716823
5156	-501.770403
5157	-500.483984
5158	-499.796922

	primary_cleaner.state.floatbank8_b_air \
0	1399.144926

1	1398.055362
2	1398.860436
3	1397.440120
4	1398.128818
...	...
5154	1401.441445
5155	1448.851892
5156	1499.572353
5157	1497.986986
5158	1501.743791

	primary_cleaner.state.floatbank8_b_level \
0	-499.919735
1	-499.778182
2	-499.764529
3	-499.211024
4	-499.504543
...	...
5154	-499.193423
5155	-465.963026
5156	-495.516347
5157	-519.200340
5158	-505.146931

	primary_cleaner.state.floatbank8_c_air \
0	1400.102998
1	1396.151033
2	1398.075709
3	1400.129303
4	1402.172226
...	...
5154	1399.810313
5155	1443.890424
5156	1502.749213
5157	1496.569047
5158	1499.535978

	primary_cleaner.state.floatbank8_c_level ... \
0	-500.704369 ...
1	-499.240168 ...
2	-502.151509 ...
3	-498.355873 ...
4	-500.810606 ...
...
5154	-499.599127 ...
5155	-503.587739 ...
5156	-520.667442 ...

5157	-487.479567	...
5158	-492.428226	...

	secondary_cleaner.state.floatbank4_a_air \	
0	12.023554	
1	12.058140	
2	11.962366	
3	12.033091	
4	12.025367	
...	...	
5154	13.995957	
5155	16.749781	
5156	19.994130	
5157	19.958760	
5158	20.034715	

	secondary_cleaner.state.floatbank4_a_level \	
0	-497.795834	
1	-498.695773	
2	-498.767484	
3	-498.350935	
4	-500.786497	
...	...	
5154	-500.157454	
5155	-496.031539	
5156	-499.791312	
5157	-499.958750	
5158	-500.728588	

	secondary_cleaner.state.floatbank4_b_air \	
0	8.016656	
1	8.130979	
2	8.096893	
3	8.074946	
4	8.054678	
...	...	
5154	12.069155	
5155	13.365371	
5156	15.101425	
5157	15.026853	
5158	14.914199	

	secondary_cleaner.state.floatbank4_b_level \	
0	-501.289139	
1	-499.634209	
2	-500.827423	
3	-499.474407	

4	-500.397500
...	...
5154	-499.673279
5155	-499.122723
5156	-499.936252
5157	-499.723143
5158	-499.948518

	secondary_cleaner.state.floatbank5_a_air \
0	7.946562
1	7.958270
2	8.071056
3	7.897085
4	8.107890
...	...
5154	7.977259
5155	9.288553
5156	10.989181
5157	11.011607
5158	10.986607

	secondary_cleaner.state.floatbank5_a_level \
0	-432.317850
1	-525.839648
2	-500.801673
3	-500.868509
4	-509.526725
...	...
5154	-499.516126
5155	-496.892967
5156	-498.347898
5157	-499.985046
5158	-500.658027

	secondary_cleaner.state.floatbank5_b_air \
0	4.872511
1	4.878850
2	4.905125
3	4.931400
4	4.957674
...	...
5154	5.933319
5155	7.372897
5156	9.020944
5157	9.009783
5158	8.989497

```

secondary_cleaner.state.floatbank5_b_level \
0 -500.037437
1 -500.162375
2 -499.828510
3 -499.963623
4 -500.360026
...
5154 -499.965973
5155 -499.942956
5156 -500.040448
5157 -499.937902
5158 -500.337588

```

```

secondary_cleaner.state.floatbank6_a_air \
0 26.705889
1 25.019940
2 24.994862
3 24.948919
4 25.003331
...
5154 8.987171
5155 8.986832
5156 8.982038
5157 9.012660
5158 8.988632

```

```

secondary_cleaner.state.floatbank6_a_level
0 -499.709414
1 -499.819438
2 -500.622559
3 -498.709987
4 -500.856333
...
5154 -499.755909
5155 -499.903761
5156 -497.789882
5157 -500.154284
5158 -500.764937

```

[5159 rows x 52 columns]

```

[ ]: LinReg = LinearRegression()
LinReg.fit(features_train, target_train)
LinRegPredict=pd.DataFrame(LinReg.predict(features_test))
smape_rough = smape(target_test['rougher.output.recovery'], LinRegPredict[0])
smape_final = smape(target_test['final.output.recovery'], LinRegPredict[1])
finalsmape(smape_rough, smape_final)

```



```
[ ]: 0.45784446552154245
```

```
[ ]: for estim in range(5, 51, 5):  
    for depth in range(5, 20, 5):  
        RanFor = RandomForestRegressor(n_estimators=estim, max_depth=depth,  
↪random_state=12345)  
        RanFor.fit(features_train, target_train)  
        RanForPredict = RanFor.predict(features_test)  
        smape_rough = smape(target_test['rougher.output.recovery'],  
↪RanForPredict[:,0])  
        smape_final = smape(target_test['final.output.recovery'],  
↪RanForPredict[:,1])  
        total_smape = final_smape(smape_rough, smape_final)  
        print('N-estimator:', estim, ' | Depth:', depth, ' | sMAPE:',  
↪total_smape)
```

```
N-estimator: 5 | Depth: 5 | sMAPE: 1.5571076204997591  
N-estimator: 5 | Depth: 10 | sMAPE: 1.3897854182543772  
N-estimator: 5 | Depth: 15 | sMAPE: 1.3426019169488914  
N-estimator: 10 | Depth: 5 | sMAPE: 1.5629710859071269  
N-estimator: 10 | Depth: 10 | sMAPE: 1.3481799513693564  
N-estimator: 10 | Depth: 15 | sMAPE: 1.2718503085106792  
N-estimator: 15 | Depth: 5 | sMAPE: 1.5604005124628415  
N-estimator: 15 | Depth: 10 | sMAPE: 1.3357094442175526  
N-estimator: 15 | Depth: 15 | sMAPE: 1.249945280817667  
N-estimator: 20 | Depth: 5 | sMAPE: 1.5558131352357407  
N-estimator: 20 | Depth: 10 | sMAPE: 1.3267885572538463  
N-estimator: 20 | Depth: 15 | sMAPE: 1.2380285277364578  
N-estimator: 25 | Depth: 5 | sMAPE: 1.557714292473178  
N-estimator: 25 | Depth: 10 | sMAPE: 1.3207788988866975  
N-estimator: 25 | Depth: 15 | sMAPE: 1.231689094585287  
N-estimator: 30 | Depth: 5 | sMAPE: 1.5550407275282083  
N-estimator: 30 | Depth: 10 | sMAPE: 1.319476847625792  
N-estimator: 30 | Depth: 15 | sMAPE: 1.2261083665833772  
N-estimator: 35 | Depth: 5 | sMAPE: 1.5552075683746347  
N-estimator: 35 | Depth: 10 | sMAPE: 1.3158867301953852  
N-estimator: 35 | Depth: 15 | sMAPE: 1.2195801835854312  
N-estimator: 40 | Depth: 5 | sMAPE: 1.5545822464269303  
N-estimator: 40 | Depth: 10 | sMAPE: 1.3123101134919433  
N-estimator: 40 | Depth: 15 | sMAPE: 1.2141682166341456  
N-estimator: 45 | Depth: 5 | sMAPE: 1.5522834570870234  
N-estimator: 45 | Depth: 10 | sMAPE: 1.3081021581822214  
N-estimator: 45 | Depth: 15 | sMAPE: 1.2085760211054908  
N-estimator: 50 | Depth: 5 | sMAPE: 1.5537979650960074  
N-estimator: 50 | Depth: 10 | sMAPE: 1.3062765161898446  
N-estimator: 50 | Depth: 15 | sMAPE: 1.2050041919216232
```

```
[ ]: for depth in range(1, 41):
    DecTree = DecisionTreeRegressor(max_depth=depth, random_state=12345)
    DecTree.fit(features_train, target_train)
    DecTreePredict = DecTree.predict(features_test)
    smape_rough = smape(target_test['rougher.output.recovery'], DecTreePredict[:
↪,0])
    smape_final = smape(target_test['final.output.recovery'], DecTreePredict[:
↪,1])
    total_smape = final_smape(smape_rough, smape_final)
    print('Depth:', depth, ' | sMAPE:', total_smape)
```

```
Depth: 1 | sMAPE: 1.8904854399935058
Depth: 2 | sMAPE: 1.8007765642156657
Depth: 3 | sMAPE: 1.7316619050914737
Depth: 4 | sMAPE: 1.655258829244849
Depth: 5 | sMAPE: 1.6214803590320255
Depth: 6 | sMAPE: 1.6341874432713217
Depth: 7 | sMAPE: 1.5934930915221932
Depth: 8 | sMAPE: 1.6114083163084576
Depth: 9 | sMAPE: 1.5856983317329798
Depth: 10 | sMAPE: 1.5492788264586281
Depth: 11 | sMAPE: 1.5828456042477665
Depth: 12 | sMAPE: 1.5423959809095495
Depth: 13 | sMAPE: 1.5581503908115497
Depth: 14 | sMAPE: 1.5890104319485339
Depth: 15 | sMAPE: 1.5866599430750707
Depth: 16 | sMAPE: 1.6389366497653821
Depth: 17 | sMAPE: 1.650925478624972
Depth: 18 | sMAPE: 1.6623329328419585
Depth: 19 | sMAPE: 1.732813872177719
Depth: 20 | sMAPE: 1.699985476513528
Depth: 21 | sMAPE: 1.6744488210163637
Depth: 22 | sMAPE: 1.7137702353462976
Depth: 23 | sMAPE: 1.732146692691994
Depth: 24 | sMAPE: 1.7144717037420194
Depth: 25 | sMAPE: 1.6658849011075436
Depth: 26 | sMAPE: 1.72046869054606
Depth: 27 | sMAPE: 1.7129876439659473
Depth: 28 | sMAPE: 1.6876205312917438
Depth: 29 | sMAPE: 1.7046304481807646
Depth: 30 | sMAPE: 1.6822253034790204
Depth: 31 | sMAPE: 1.702510290888545
Depth: 32 | sMAPE: 1.7166626469323076
Depth: 33 | sMAPE: 1.6733371055703437
Depth: 34 | sMAPE: 1.692050236901453
Depth: 35 | sMAPE: 1.7371661831129872
Depth: 36 | sMAPE: 1.7264300080688697
Depth: 37 | sMAPE: 1.7264300080688697
```

```
Depth: 38 | sMAPE: 1.7264300080688697
Depth: 39 | sMAPE: 1.7264300080688697
Depth: 40 | sMAPE: 1.7264300080688697
```

```
[ ]: mean_absolute_error(target_test, LinReg.predict(features_test))
```

```
[ ]: 3.924412492800389
```

```
[ ]: predictions0 = pd.Series(target_test.iloc[:,0].mean(), index=target_test.index)
      predictions1 = pd.Series(target_test.iloc[:,1].mean(), index=target_test.index)
      predictions = pd.concat([predictions0, predictions1], axis=1)
      predictions
```

```
[ ]:
      0      1
1888  84.257823  66.75486
2913  84.257823  66.75486
2862  84.257823  66.75486
9329  84.257823  66.75486
324   84.257823  66.75486
...
7592  84.257823  66.75486
3981  84.257823  66.75486
5625  84.257823  66.75486
12172 84.257823  66.75486
1454  84.257823  66.75486
```

```
[2663 rows x 2 columns]
```

```
[ ]: mean_absolute_error(target_test, predictions)
```

```
[ ]: 5.790588358203398
```

```
[ ]: smape_rough = smape(target_test['rougher.output.recovery'], predictions.iloc[
      ↪,0])
      smape_final = smape(target_test['final.output.recovery'], predictions.iloc[:,1])
      finalsmape(smape_rough, smape_final)
```

```
[ ]: 2.1674310014318103
```

When we compare sMAPE values across various methods of determining recovery, we can see that LinearRegressor gives us the best predictions, with the lowest sMAPE score. With the provided equation to determine recovery as a baseline, our sMAPE score was 5.85, much higher than the score of 0.45 that LinearRegressor got. Estimating with the mean recoveries as a baseline, the MAE is 5.79, so we can see that LinearRegressor is more effective than the baseline prediction. sMAPE with the baseline predictions is also 2.1, which is still higher than LinearRegressor.

```
[ ]: linreg_valid = LinReg.predict(gold_test)
```

```
[ ]: smape_rough = smape(gold_test_target['rougher.output.recovery'], linreg_valid[:  
    ↪,0])  
    smape_final = smape(gold_test_target['final.output.recovery'], linreg_valid[:  
    ↪,1])  
    finalsmape(smape_rough, smape_final)
```

```
[ ]: 1.793065917135099
```

Final sMAPE value with the chosen model is 1.79, which is still a very good score, and lower than many of the trained models.