title: Modelling Results

nav_include: 7

Analysis Approach:

Since our model runs took a very long time, we saved all of our metrics into dataframes to be loaded for later analysis. Each metric has six different values for each metric, based on the mean of that metric for the results of that batch.

Initial Approach

Initially we planned on aggregating the results of the batches and then comaring the different model results. However we found that the way we created our metrics gave us results with very high variability. If we were able to run the models again, we would change the metrics to be proportions of change, i.e. %change in followers vs the current method of absolute change in followers. This would normalize our data and allow us to directly compare results on playlists with large differences in number of songs and number of followers.

Compromise Approach

In order to try and compare models with the metrics we already have, we combined the means of each batch along with the standard deviation of the means for each metric and compared those values. This led to some strange results, with the validation and test sets consistently outperforming the train set for each metric. However when you look at the $\pm 2\sigma$ bounds on the scores, you can see that there is significant overlap.

Results summary

- Our model generates playlists, even matches some of the original songs in playlist from which only 1 song is taken! I.e. it addresses both goals set out for the project
- Scoring and analysis shows that clustering and song similarity is a viable approach. Visual inspection shows that playlists seem to make sense (i.e. follow the "theme" of nucleus song)
- There's still variance in results which means there's room for improvement. A lot of variance come from estimated number of followers which is a metric that is subject to Spotify promotion and "hit" phenomena

Future work

Extension would be to test other metaparameters listed in "Modelling". Added song tags and experimenting with words (lyrics, playlist names) would be helpful. An interesting approach would be great to try - TF/IDF and collaborative filtering which were used in [https://ieatyanyans.github.io/music-recommender/ (https://ieatyanyans.github.io/music-recommender/)](https://ieatyanyans.github.io/music-recommender/)

```
Team Group 71:
```


- Brandon Joye
- Vladimir Yelizarov

In [1]:
```
import sys
import datetime
import numpy as np
import pandas as pd
import string
from sklearn.cluster import KMeans
from sklearn.linear_model import LinearRegression
import gzip
import csv
import matplotlib
import matplotlib.pyplot as plt

DATA_DIR="../../../data"
```

In [2]:
```
def add(r, names, df) :
    for m in names:
        r[m].append(df[m].mean())

def tonp (r, names):
    for m in names:
        r[m] = np.array(r[m])

def readResults(n, shortname, name):
    m_names = ['metric', 'match', 'distance', 'numf', 'diff']
    prefix = DATA_DIR + "/results/" + shortname + str(n) + "/result_" + n
ame
    suffix = "_" + str(n) + "_10.csv.gz"
    r = {'metric':[], 'match' : [], 'distance' : [], 'numf' : [], 'diff'
: [], 'metric2' : [] }
    for i in range(1, 7) :
        fullName = prefix + str(i) + suffix
        df = pd.read_csv(fullName, compression='gzip')#.drop(['Unnamed:
 0'],axis=1)
        add(r, m_names, df)
        r['metric2'].append(((1.0 / df['match']) + df['distance']).mean
())
    tonp(r, m_names)
    tonp(r, ['metric2'])
    return r

def readResults2(n, shortname, name):
    m_names = ['metric', 'match', 'distance', 'numf', 'diff']
    prefix = DATA_DIR + "/results/" + shortname + str(n) + "/result_" + n
ame
    suffix = "_" + str(n) + "_10.csv.gz"
    r = {'metric':[], 'match' : [], 'distance' : [], 'numf' : [], 'diff'
: [], 'metric2' : [] }
    df_full = pd.DataFrame()
    for i in range(1, 7) :
        fullName = prefix + str(i) + suffix
        df = pd.read_csv(fullName, compression='gzip')#.drop(['Unnamed:
 0'],axis=1)
        df_full = df_full.append(df)
        add(r, m_names, df)
        r['metric2'].append(((1.0 / df['match']) + df['distance']).mean
())
    tonp(r, m_names)
    tonp(r, ['metric2'])
    return df_full
```

In [3]:
```
t2 = readResults(2, "t", "train")
t10 = readResults(10, "t", "train")
t50 = readResults(50, "t", "train")
t100 = readResults(100, "t", "train")
```

In [4]:
```
v2 = readResults(2, "v", "validate")
v10 = readResults(10, "v", "validate")
v50 = readResults(50, "v", "validate")
v100 = readResults(100, "v", "validate")
```

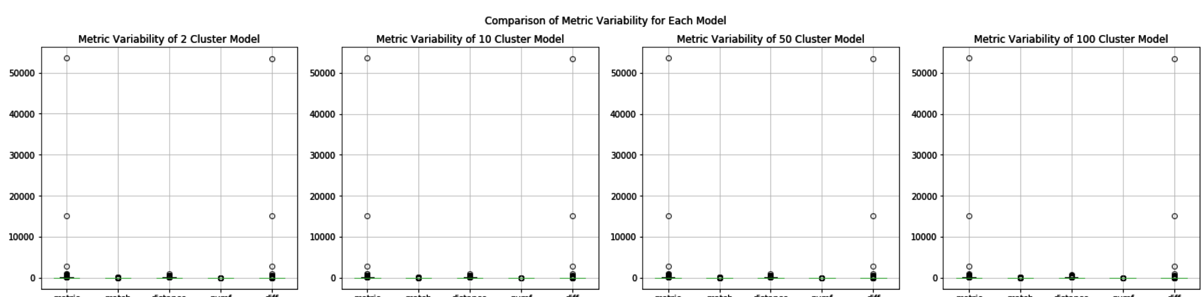
In [5]:
```
t2df = readResults2(2, "t", "train")
t10df = readResults2(10, "t", "train")
t50df = readResults2(50, "t", "train")
t100df = readResults2(100, "t", "train")
```

In [6]:
```
t2df.agg([np.mean, np.std])
```

Out[6]:

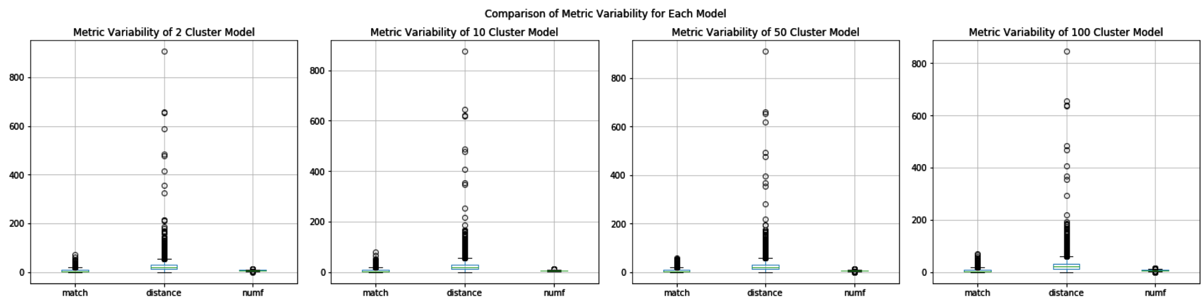
	playlist_id	n_clusters	start_num	metric	match	distance	numf	(
mean	492621.840113	2.0	10.0	41.498213	6.019840	23.742583	6.903134	17.3676
std	284337.026741	0.0	0.0	719.542719	5.571262	27.351196	1.296133	719.1216

In [7]:
```
fig, ax = plt.subplots(1,4,figsize=(20,5))
t2df.drop(['playlist_id', 'n_clusters', 'start_num'], axis=1).boxplot(ax=
ax[0])
ax[0].set_title('Metric Variability of 2 Cluster Model')
t10df.drop(['playlist_id', 'n_clusters', 'start_num'], axis=1).boxplot(ax
=ax[1])
ax[1].set_title('Metric Variability of 10 Cluster Model')
t50df.drop(['playlist_id', 'n_clusters', 'start_num'], axis=1).boxplot(ax
=ax[2])
ax[2].set_title('Metric Variability of 50 Cluster Model')
t100df.drop(['playlist_id', 'n_clusters', 'start_num'], axis=1).boxplot(a
x=ax[3])
ax[3].set_title('Metric Variability of 100 Cluster Model')
fig.suptitle('Comparison of Metric Variability for Each Model')
fig.tight_layout(rect=[0, 0, 1, .95])
plt.show()
```



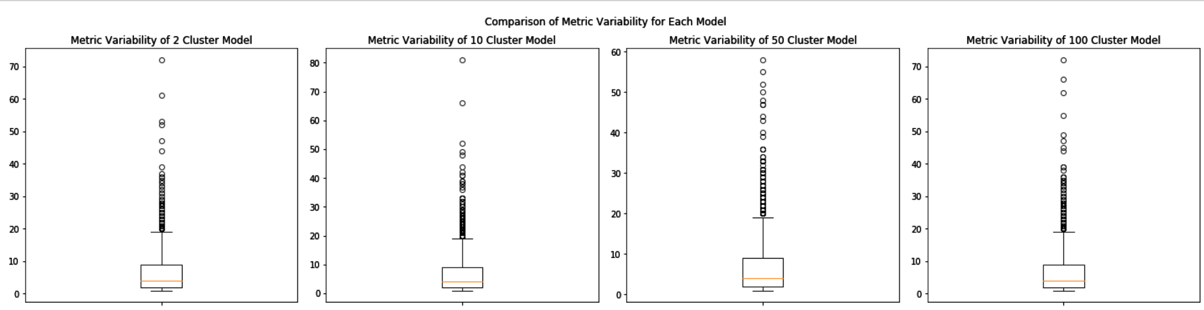
The above plots show that there is significant variability in each metric, this is most pronounced in the difference in predicted followers vs actual followers metric.

In [8]:
```
fig, ax = plt.subplots(1,4,figsize=(20,5))
t2df.drop(['playlist_id', 'n_clusters', 'start_num', 'metric', 'diff'], a
xis=1).boxplot(ax=ax[0])
ax[0].set_title('Metric Variability of 2 Cluster Model')
t10df.drop(['playlist_id', 'n_clusters', 'start_num', 'metric', 'diff'],
axis=1).boxplot(ax=ax[1])
ax[1].set_title('Metric Variability of 10 Cluster Model')
t50df.drop(['playlist_id', 'n_clusters', 'start_num', 'metric', 'diff'],
axis=1).boxplot(ax=ax[2])
ax[2].set_title('Metric Variability of 50 Cluster Model')
t100df.drop(['playlist_id', 'n_clusters', 'start_num', 'metric', 'diff'],
 axis=1).boxplot(ax=ax[3])
ax[3].set_title('Metric Variability of 100 Cluster Model')
fig.suptitle('Comparison of Metric Variability for Each Model')
fig.tight_layout(rect=[0, 0, 1, .95])
plt.show()
```

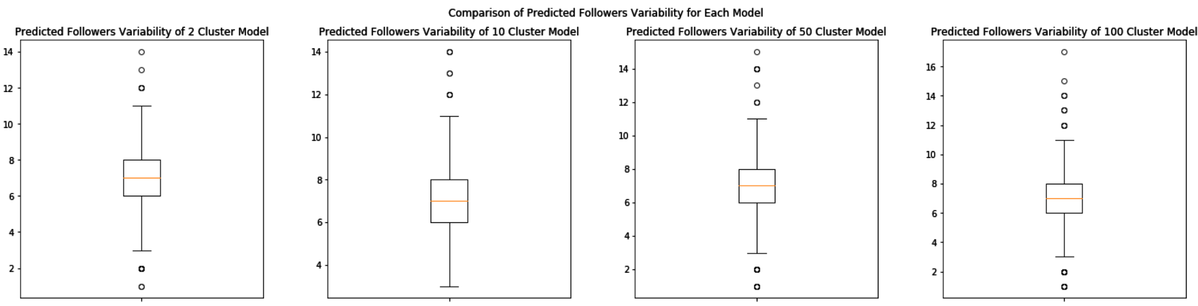


The distance between playlists also has significant variability, one way we could possibly reduce this is to normalize the distance variables so that distance is a number between 0 and 1.

In [8]:
```
fig, ax = plt.subplots(1,4,figsize=(20,5))
ax[0].boxplot(t2df.match)
ax[0].set_title('Metric Variability of 2 Cluster Model')
ax[1].boxplot(t10df.match)
ax[1].set_title('Metric Variability of 10 Cluster Model')
ax[2].boxplot(t50df.match)
ax[2].set_title('Metric Variability of 50 Cluster Model')
ax[3].boxplot(t100df.match)
ax[3].set_title('Metric Variability of 100 Cluster Model')
for axis in ax:
    axis.set_xticklabels('')
fig.suptitle('Comparison of Metric Variability for Each Model')
fig.tight_layout(rect=[0, 0, 1, .95])
plt.show()
```



In [9]:
```
fig, ax = plt.subplots(1,4,figsize=(20,5))
ax[0].boxplot(t2df.numf)
ax[0].set_title('Predicted Followers Variability of 2 Cluster Model')
ax[1].boxplot(t10df.numf)
ax[1].set_title('Predicted Followers Variability of 10 Cluster Model')
ax[2].boxplot(t50df.numf)
ax[2].set_title('Predicted Followers Variability of 50 Cluster Model')
ax[3].boxplot(t100df.numf)
ax[3].set_title('Predicted Followers Variability of 100 Cluster Model')
for axis in ax:
    axis.set_xticklabels('')
fig.suptitle('Comparison of Predicted Followers Variability for Each Mode
l')
fig.tight_layout(rect=[0, 0, 1, .95])
plt.show()
```



In [10]:
```
test2 = readResults(2, 'test', 'test')
test10 = readResults(10, 'test', 'test')
```

In [11]:
```
def make_mean_metrics(models, sn):
    results_dict = {}
    #models = [t2, t10, t50, t100]
    names = [2, 10, 50, 100]
    for model, name in zip(models, names):
        model_params = {}
        for key in model:
            model_params[key] = np.mean(model[key])
            model_params[key+'std'] = np.std(model[key])
        results_dict[sn+str(name)] = model_params
    return results_dict
```

In [12]:
```
models_train = [t2, t10, t50, t100]
train_dict = make_mean_metrics(models_train, 't')
results_train = pd.DataFrame.from_dict(train_dict).T
results_train
```

Out[12]:

	diff	diffstd	distance	distancestd	match	matchstd	metric	metric2	m
t2	17.366214	19.586043	23.742464	1.204582	6.019813	0.117456	41.496689	24.130509	
t10	17.447881	19.232502	24.761268	0.929312	6.129652	0.176668	42.599327	25.151356	
t50	17.313173	19.268623	25.829698	0.902331	6.151795	0.124508	43.530253	26.217108	
t100	17.419482	19.445556	25.663053	0.693858	6.215457	0.099706	43.468382	26.048898	

In [13]:
```
models_validate = [v2, v10, v50, v100]
validate_dict = make_mean_metrics(models_validate, 'v')
results_validate = pd.DataFrame.from_dict(validate_dict).T
results_validate
```

Out[13]:

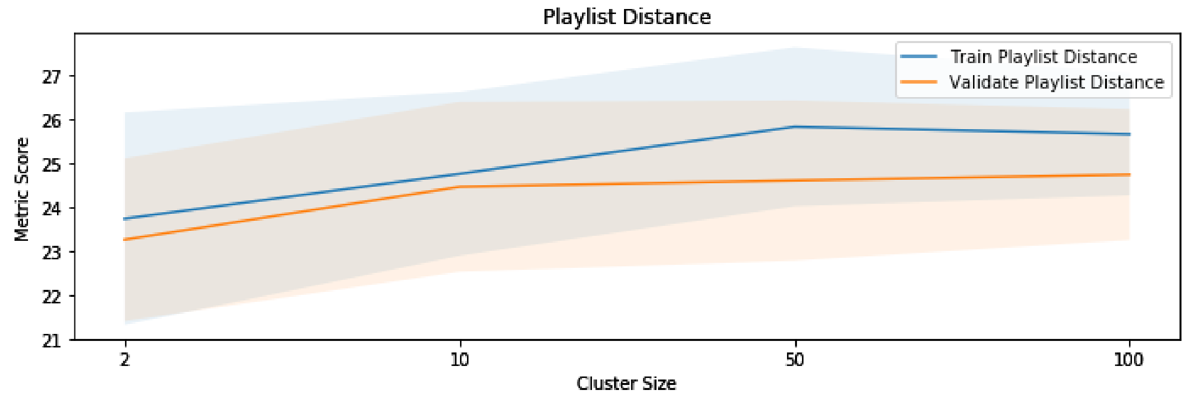
	diff	diffstd	distance	distancestd	match	matchstd	metric	metric2	met
v2	8.383877	3.004734	23.266120	0.923800	6.221482	0.087430	32.019275	23.635325	0.
v10	7.866056	2.634214	24.467220	0.964562	6.322889	0.081322	32.699332	24.833359	0.
v50	7.961983	2.822155	24.610007	0.909844	6.493108	0.070977	32.932138	24.970164	0.
v100	7.884393	2.696971	24.743925	0.742098	6.541668	0.095974	32.985807	25.101392	0.

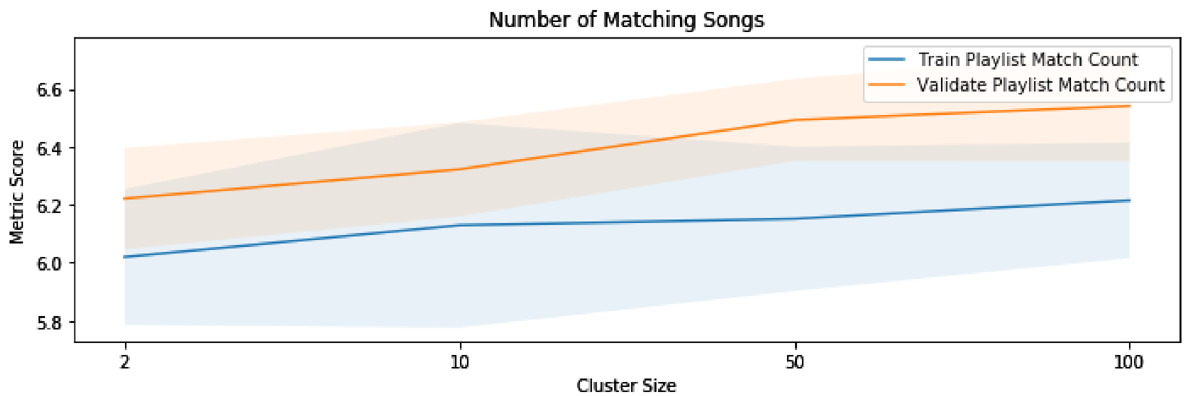
In [14]:
```
models_test = [test2, test10]
test_dict = make_mean_metrics(models_test, 'test')
results_test = pd.DataFrame.from_dict(test_dict).T
results_test
```

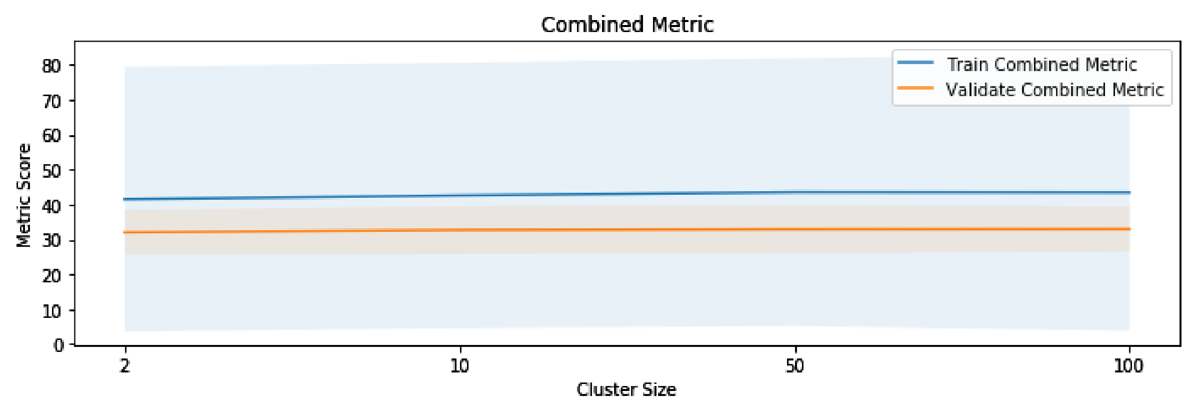
Out[14]:

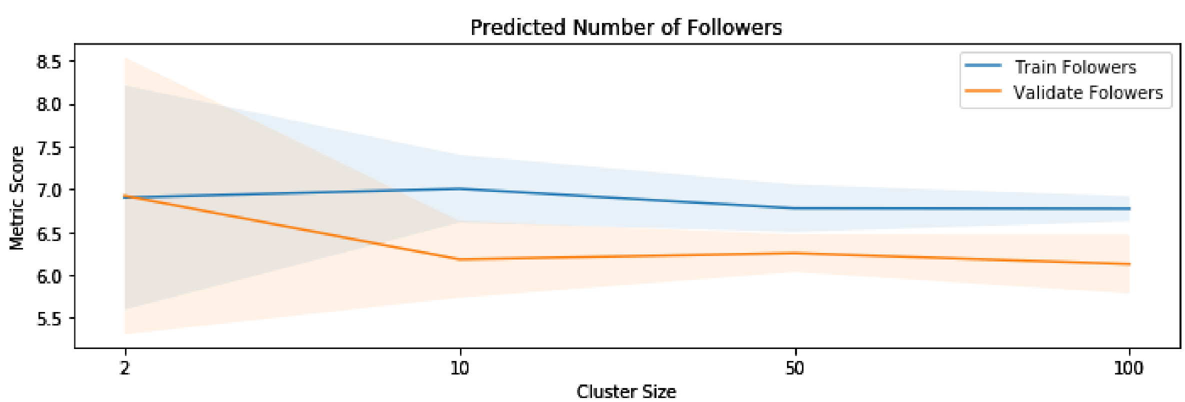
	diff	diffstd	distance	distancestd	match	matchstd	metric	metric2	m
test2	13.347084	7.996984	25.105574	1.956354	6.189874	0.139431	38.832057	25.48498	
test10	12.797532	8.089814	24.755806	0.846285	6.294219	0.155728	37.930501	25.13291	

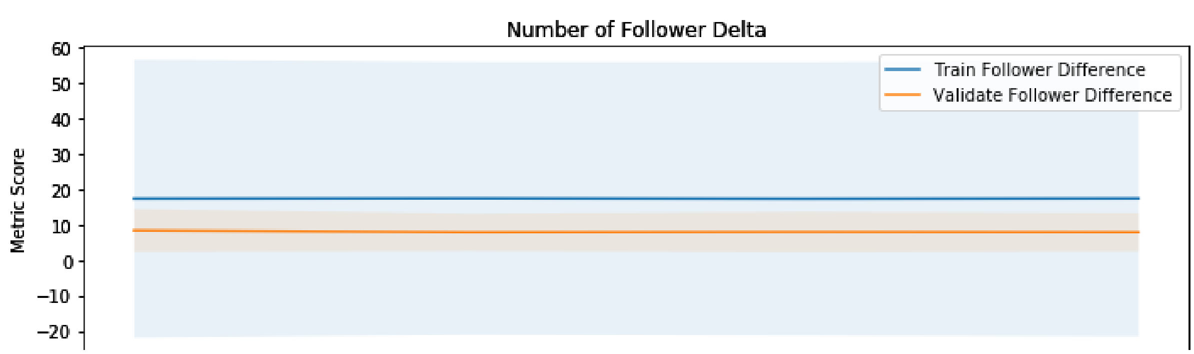
In [15]:
```
plot_alpha = .1
fig, ax = plt.subplots(6,1, figsize=(10,20))
labels_train = ['Train Playlist Distance', 'Train Playlist Match Count',
'Train Combined Metric', 'Train Folowers',
                'Train Follower Difference', 'Train Matching Songs plus D
istance']
labels_validate = ['Validate Playlist Distance', 'Validate Playlist Match
 Count', 'Validate Combined Metric',
                   'Validate Folowers', 'Validate Follower Difference',
'Validate Matching Songs plus Distance']
plot_order = ['distance', 'match', 'metric', 'numf', 'diff', 'metric2']
titles = ['Playlist Distance', 'Number of Matching Songs', 'Combined Metr
ic', 'Predicted Number of Followers',
          'Number of Follower Delta', 'Inverted Matching Songs plus Dista
nce']
names = [2, 10, 50, 100]
# results_train.plot(y='diff', ax=ax[0])
# results_train.plot(y='distance', ax=ax[1])
# results_train.plot(y='match', ax=ax[2])
# results_train.plot(y='metric', ax=ax[3])
for axis, po, labelt, labelv, title in \
zip(ax, plot_order, labels_train, labels_validate, titles):
    results_train.plot(y=po, ax=axis, label=labelt)
    axis.fill_between(np.arange(4), results_train[po] + 2*results_train[p
o+'std'],
                      results_train[po] - 2*results_train[po+'std'], alph
a=plot_alpha)
    results_validate.plot(y=po, ax=axis, label=labelv)
    axis.fill_between(np.arange(4), results_validate[po] + 2*results_vali
date[po+'std'],
                      results_validate[po] - 2*results_validate[po+'std'
], alpha=plot_alpha)
    axis.set_xlabel('Cluster Size')
    axis.set_ylabel('Metric Score')
    axis.set_xticks(np.arange(4))
    axis.set_xticklabels(names)
    axis.set_title(title)
fig.tight_layout()
plt.show()
```

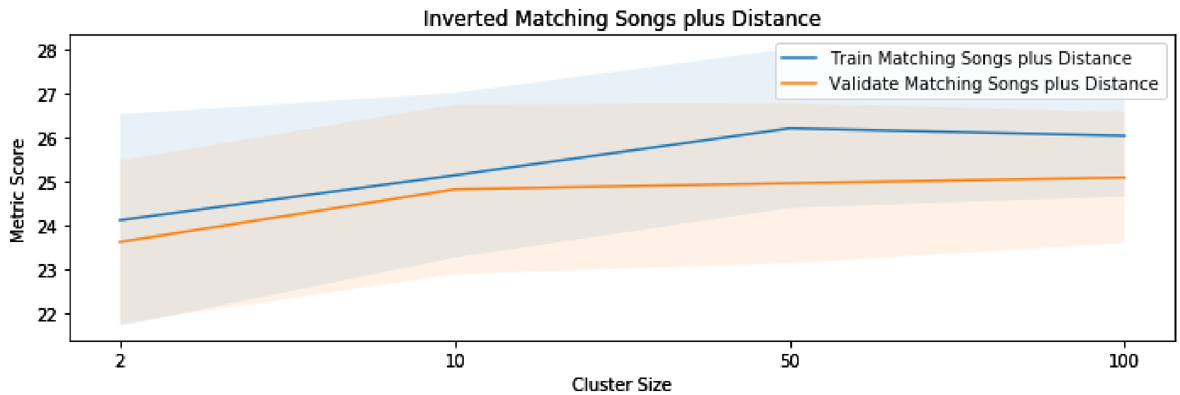

Playlist Distance
Train Playlist Distance
Validate Playlist Distance
Metric Score
21
22
23
24
25
26
27
2
10
50
100
Cluster Size


Number of Matching Songs
Train Playlist Match Count
Validate Playlist Match Count
Metric Score
5.8
6.0
6.2
6.4
6.6
2
10
50
100
Cluster Size


Combined Metric
Train Combined Metric
Validate Combined Metric
Metric Score
0
10
20
30
40
50
60
70
80
2
10
50
100
Cluster Size


Predicted Number of Followers
Train Folowers
Validate Folowers
Metric Score
5.5
6.0
6.5
7.0
7.5
8.0
8.5
2
10
50
100
Cluster Size


Number of Follower Delta
Train Follower Difference
Validate Follower Difference
Metric Score
−20
−10
0
10
20
30
40
50
60

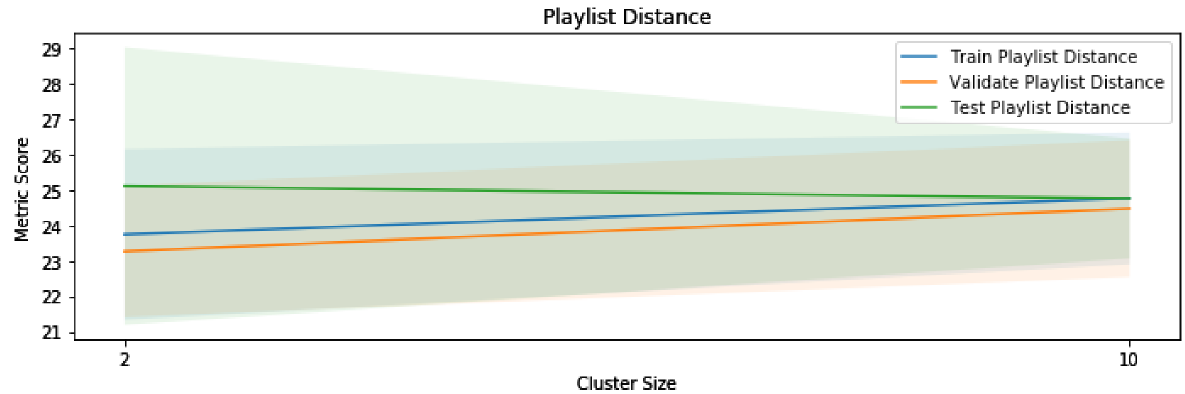


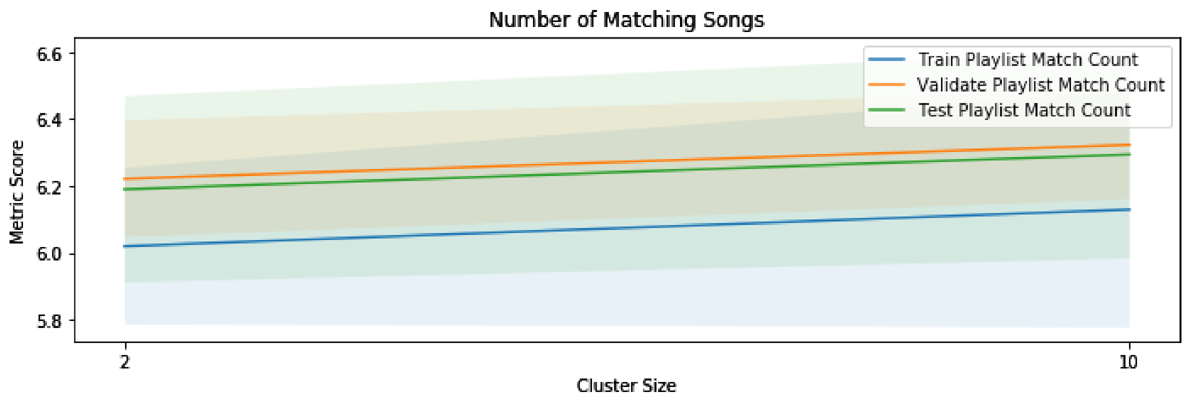
In [16]:
```
results_validate_test = results_validate.loc[['v2', 'v10'], :]
results_train_test = results_train.loc[['t2', 't10'], :]
```

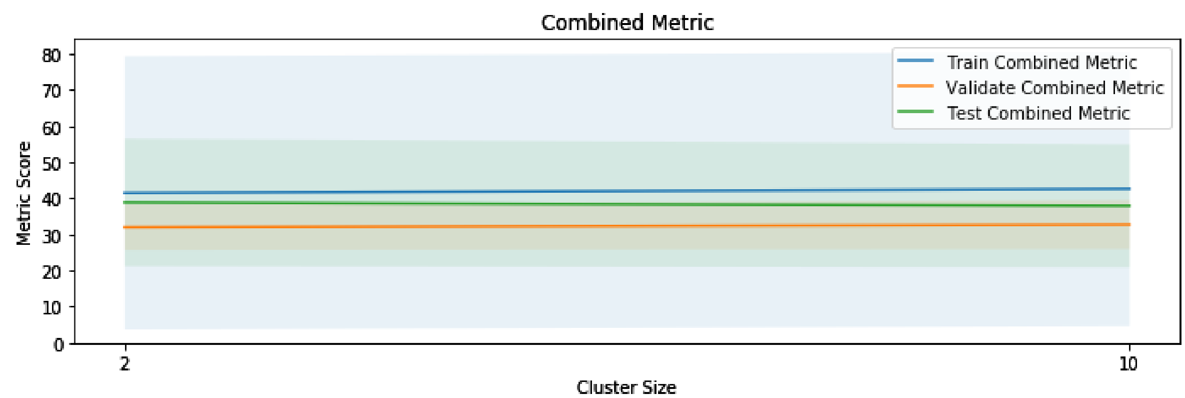
In [17]:
```
po, results_train[po+'std']
```

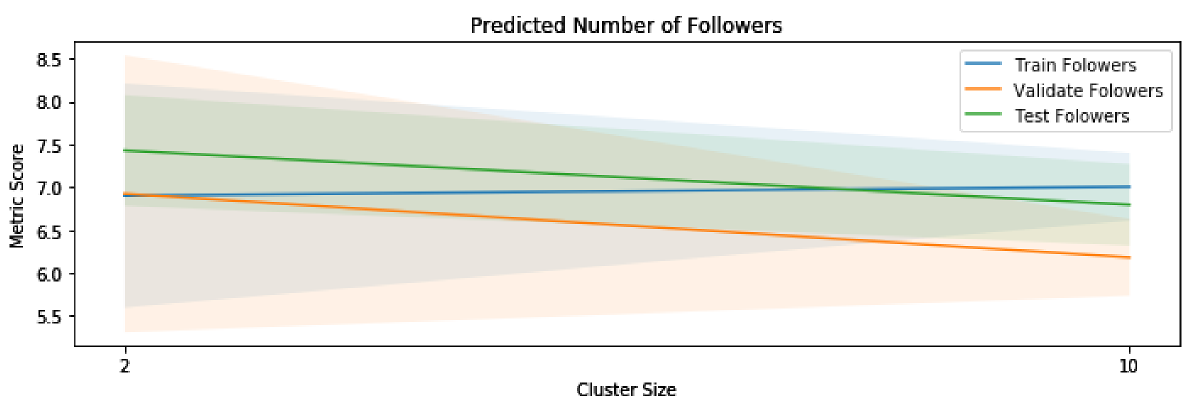
Out[17]:
```
('metric2', t2      1.202147
 t10     0.934653
 t50     0.903429
 t100    0.689577
 Name: metric2std, dtype: float64)
```

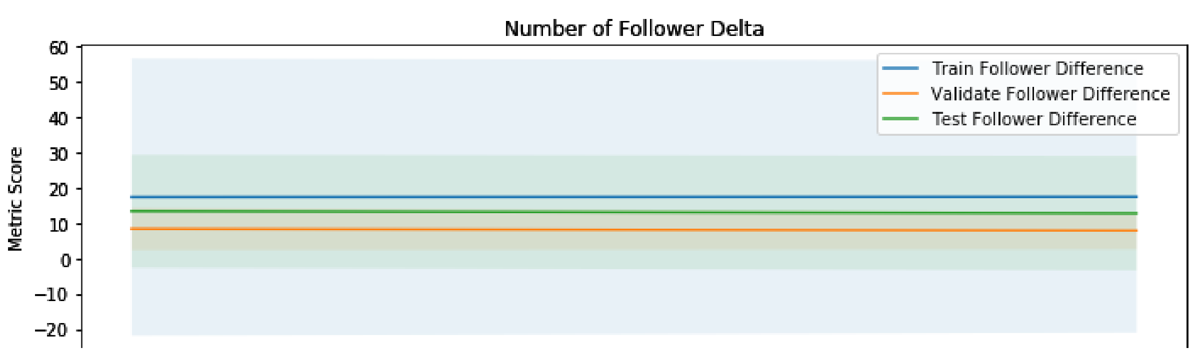
In [18]:
```
fig, ax = plt.subplots(6,1, figsize=(10,20))
labels_train = ['Train Playlist Distance', 'Train Playlist Match Count',
'Train Combined Metric', 'Train Folowers',
                'Train Follower Difference', 'Train Matching Songs plus D
istance']
labels_validate = ['Validate Playlist Distance', 'Validate Playlist Match
 Count', 'Validate Combined Metric',
                   'Validate Folowers', 'Validate Follower Difference',
'Validate Matching Songs plus Distance']
labels_test = ['Test Playlist Distance', 'Test Playlist Match Count', 'Te
st Combined Metric', 'Test Folowers',
               'Test Follower Difference', 'Test Matching Songs plus Dist
ance']
plot_order = ['distance', 'match', 'metric', 'numf', 'diff', 'metric2']
titles = ['Playlist Distance', 'Number of Matching Songs', 'Combined Metr
ic', 'Predicted Number of Followers',
          'Number of Follower Delta', 'Inverted Matching Songs plus Dista
nce']
names = [2, 10]
# results_train.plot(y='diff', ax=ax[0])
# results_train.plot(y='distance', ax=ax[1])
# results_train.plot(y='match', ax=ax[2])
# results_train.plot(y='metric', ax=ax[3])
for axis, po, labelt, labelv, title, labeltest in \
zip(ax, plot_order, labels_train, labels_validate, titles, labels_test):
    results_train_test.plot(y=po, ax=axis, label=labelt)
    axis.fill_between(np.arange(2), results_train_test[po] + 2*results_tr
ain_test[po+'std'],
                      results_train_test[po] - 2*results_train_test[po+'s
td'], alpha=plot_alpha)
    results_validate_test.plot(y=po, ax=axis, label=labelv)
    axis.fill_between(np.arange(2), results_validate_test[po] + 2*results
_validate_test[po+'std'],
                      results_validate_test[po] - 2*results_validate_test
[po+'std'], alpha=plot_alpha)
    results_test.plot(y=po, ax=axis, label=labeltest)
    axis.fill_between(np.arange(2), results_test[po] + 2*results_test[po+
'std'],
                      results_test[po] - 2*results_test[po+'std'], alpha=
plot_alpha)
    axis.set_xlabel('Cluster Size')
    axis.set_ylabel('Metric Score')
    axis.set_xticks(np.arange(2))
    axis.set_xticklabels(names)
    axis.set_title(title)
fig.tight_layout()
plt.show()
```

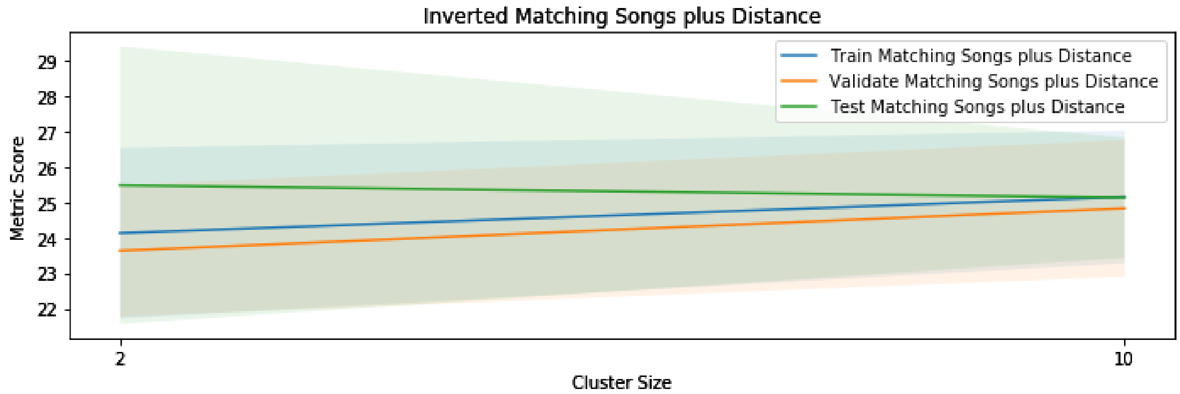

Playlist Distance
Train Playlist Distance
Validate Playlist Distance
Test Playlist Distance
Metric Score
Cluster Size
29
28
27
26
25
24
23
22
21
2
10


Number of Matching Songs
Train Playlist Match Count
Validate Playlist Match Count
Test Playlist Match Count
Metric Score
Cluster Size
6.6
6.4
6.2
6.0
5.8
2
10

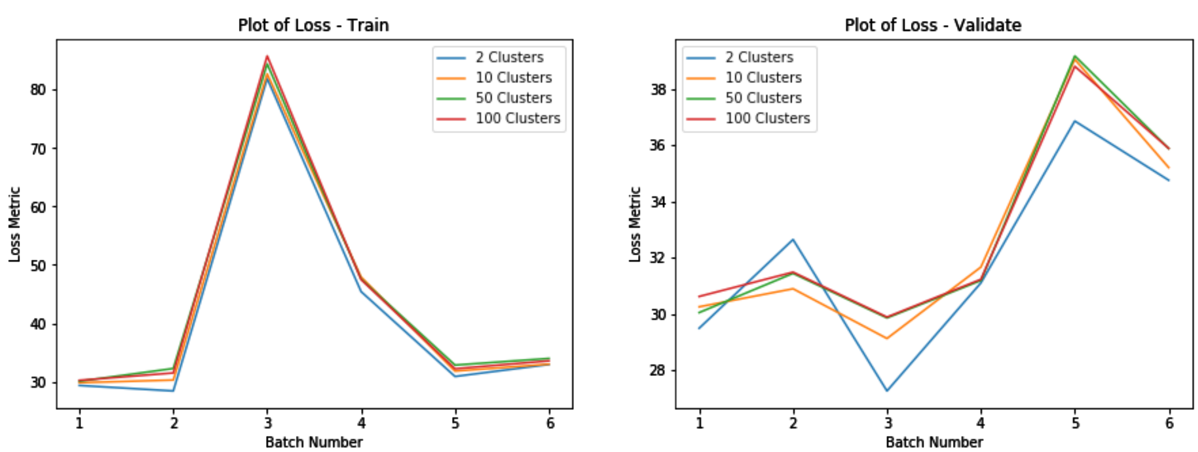

Combined Metric
Train Combined Metric
Validate Combined Metric
Test Combined Metric
Metric Score
Cluster Size
80
70
60
50
40
30
20
10
0
2
10


Predicted Number of Followers
Train Folowers
Validate Folowers
Test Folowers
Metric Score
Cluster Size
8.5
8.0
7.5
7.0
6.5
6.0
5.5
2
10


Number of Follower Delta
Train Follower Difference
Validate Follower Difference
Test Follower Difference
Metric Score
60
50
40
30
20
10
0
−10
−20

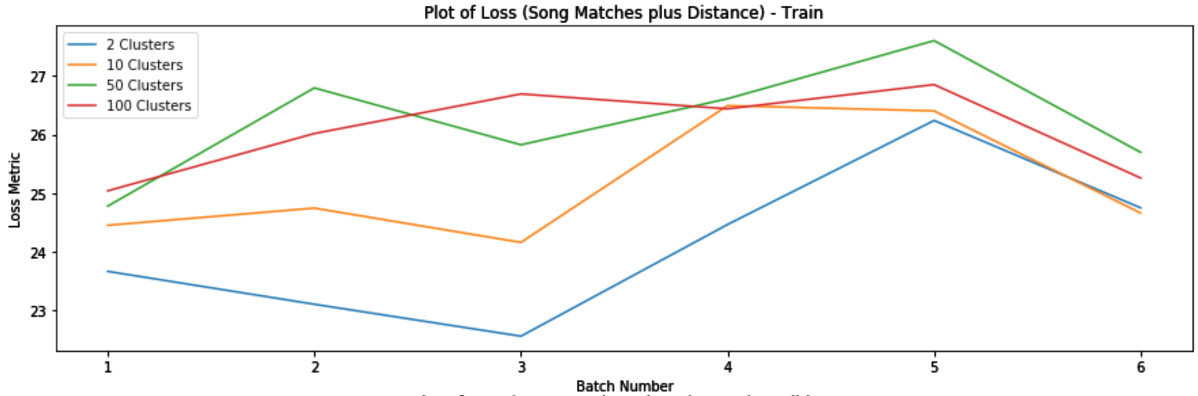


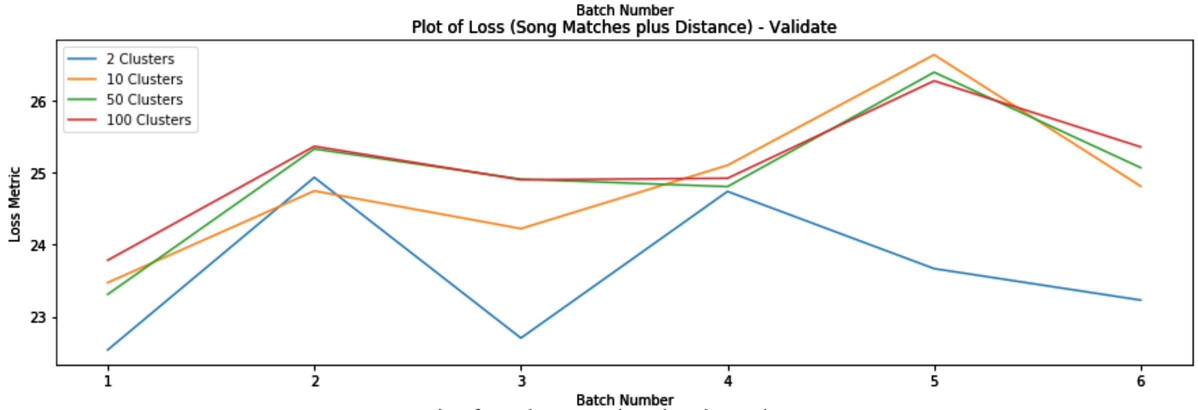
In [19]:
```
x = range(1, 7)
fig, axes = plt.subplots(1,2,figsize=(15,5))
axes[0].set_title('Plot of Loss - Train')
axes[0].plot(x, t2['metric'], label='2 Clusters')
axes[0].plot(x, t10['metric'], label='10 Clusters')
axes[0].plot(x, t50['metric'], label='50 Clusters')
axes[0].plot(x, t100['metric'], label='100 Clusters')
axes[0].set_xlabel('Batch Number')
axes[0].set_ylabel('Loss Metric')
axes[0].legend()
axes[1].set_title('Plot of Loss - Validate')
axes[1].plot(x, v2['metric'], label='2 Clusters')
axes[1].plot(x, v10['metric'], label='10 Clusters')
axes[1].plot(x, v50['metric'], label='50 Clusters')
axes[1].plot(x, v100['metric'], label='100 Clusters')
axes[1].set_xlabel('Batch Number')
axes[1].set_ylabel('Loss Metric')
axes[1].legend()
plt.show()
```

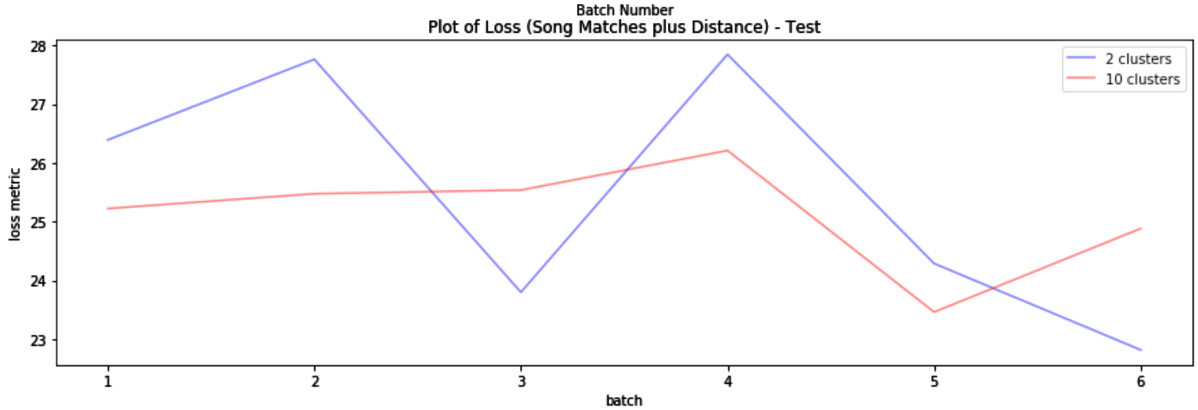


Looking at the combined metric by batch shows that each model reacted to the individual batches in a fairly consistent manner. This is slightly less true for the validation set, but the relationship is still there for at least the 10, 50 and 100 cluster models.

In [20]:
```
x = range(1, 7)
fig, axes = plt.subplots(3,1,figsize=(15,15))
axes = axes.ravel()
axes[0].set_title('Plot of Loss (Song Matches plus Distance) - Train')
axes[0].plot(x, t2['metric2'], label='2 Clusters')
axes[0].plot(x, t10['metric2'], label='10 Clusters')
axes[0].plot(x, t50['metric2'], label='50 Clusters')
axes[0].plot(x, t100['metric2'], label='100 Clusters')
axes[0].set_xlabel('Batch Number')
axes[0].set_ylabel('Loss Metric')
axes[0].legend()
axes[1].set_title('Plot of Loss (Song Matches plus Distance) - Validate')
axes[1].plot(x, v2['metric2'], label='2 Clusters')
axes[1].plot(x, v10['metric2'], label='10 Clusters')
axes[1].plot(x, v50['metric2'], label='50 Clusters')
axes[1].plot(x, v100['metric2'], label='100 Clusters')
axes[1].set_xlabel('Batch Number')
axes[1].set_ylabel('Loss Metric')
axes[1].legend()
axes[2].set_title('Plot of Loss (Song Matches plus Distance) - Test')
axes[2].plot(x, test2['metric2'], alpha=0.5, color='b', label='2 cluster
s')
axes[2].plot(x, test10['metric2'], alpha=0.5, color='r', label='10 cluste
rs')
axes[2].set_xlabel('batch')
axes[2].set_ylabel('loss metric')
axes[2].legend()
plt.show()
```







We created a second combined metric aimed at reducing the variability, this metric has results that are more in line with expectations with the model performing slightly better on the train set than the other sets.