04_factor_evaluation

September 29, 2021

1 Alpha Factor Evaluation

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[43]:
```
%matplotlib inline

import os, sys
from time import time

from pathlib import Path
import numpy as np
import pandas as pd
import pandas_datareader.data as web

import statsmodels.api as sm
from sklearn.feature_selection import mutual_info_regression
from sklearn.preprocessing import scale
import lightgbm as lgb
from scipy.stats import spearmanr
from tqdm import tqdm
import shap

import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
sys.path.insert(1, os.path.join(sys.path[0], '..'))
from utils import MultipleTimeSeriesCV
```

[4]:
```
sns.set_style('whitegrid')
idx = pd.IndexSlice
deciles = np.arange(.1, 1, .1).round(1)
```

[19]:
```
results_path = Path('results')
if not results_path.exists():
    results_path.mkdir()
```

1.1 Load Data

[5]:
```python
factors = (pd.concat([pd.read_hdf('data.h5', 'factors/common'),
                      pd.read_hdf('data.h5', 'factors/formulaic')
                      .rename(columns=lambda x: f'alpha_{int(x):03}')],
                     axis=1)
           .dropna(axis=1, thresh=100000)
           .sort_index())
```

[6]:
```python
factors.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 1255093 entries, ('A', Timestamp('2007-01-04 00:00:00')) to ('ZION',
Timestamp('2016-12-29 00:00:00'))
Columns: 135 entries, sector to alpha_101
dtypes: float64(123), int64(12)
memory usage: 1.3+ GB
```

[7]:
```python
fwd_returns = factors.filter(like='fwd').columns
features = factors.columns.difference(fwd_returns).tolist()
alphas = pd.Index([f for f in features if f.startswith('alpha')])
```

[8]:
```python
features
```

[8]:
```
['AARONOSC',
 'AD',
 'ADOSC',
 'ADX',
 'ADXR',
 'ALPHA_21',
 'ALPHA_252',
 'ALPHA_63',
 'ATR',
 'BB_LOW',
 'BB_SQUEEZE',
 'BB_UP',
 'BOP',
 'CCI',
 'CMA_21',
 'CMA_252',
 'CMA_63',
 'HML_21',
 'HML_252',
 'HML_63',
 'HT',
 'MACD',
 'MACD_HIST',
 'MACD_SIGNAL',
```

```
'MARKET_21',
'MARKET_252',
'MARKET_63',
'MFI',
'OBV',
'PPO',
'RMW_21',
'RMW_252',
'RMW_63',
'RSI',
'SAR',
'SMB_21',
'SMB_252',
'SMB_63',
'STOCH',
'STOCHRSI',
'ULTOSC',
'WILLR',
'alpha_001',
'alpha_002',
'alpha_003',
'alpha_004',
'alpha_005',
'alpha_006',
'alpha_007',
'alpha_008',
'alpha_009',
'alpha_010',
'alpha_011',
'alpha_012',
'alpha_013',
'alpha_014',
'alpha_015',
'alpha_016',
'alpha_017',
'alpha_018',
'alpha_019',
'alpha_020',
'alpha_021',
'alpha_022',
'alpha_023',
'alpha_024',
'alpha_025',
'alpha_026',
'alpha_027',
'alpha_028',
'alpha_029',
```

```
'alpha_030',
'alpha_032',
'alpha_033',
'alpha_034',
'alpha_035',
'alpha_036',
'alpha_037',
'alpha_038',
'alpha_039',
'alpha_040',
'alpha_041',
'alpha_042',
'alpha_043',
'alpha_044',
'alpha_045',
'alpha_046',
'alpha_047',
'alpha_049',
'alpha_050',
'alpha_051',
'alpha_052',
'alpha_053',
'alpha_054',
'alpha_055',
'alpha_057',
'alpha_060',
'alpha_061',
'alpha_062',
'alpha_064',
'alpha_065',
'alpha_066',
'alpha_068',
'alpha_071',
'alpha_073',
'alpha_074',
'alpha_075',
'alpha_077',
'alpha_078',
'alpha_081',
'alpha_083',
'alpha_084',
'alpha_085',
'alpha_086',
'alpha_092',
'alpha_094',
'alpha_095',
'alpha_098',
```

```
 'alpha_099',
 'alpha_101',
 'ret_01',
 'ret_02',
 'ret_03',
 'ret_04',
 'ret_05',
 'ret_10',
 'ret_126',
 'ret_21',
 'ret_252',
 'ret_42',
 'ret_63',
 'sector',
 'size_factor',
 'size_proxy']
```

[9]:
```
len(alphas)
```

[9]:
```
78
```

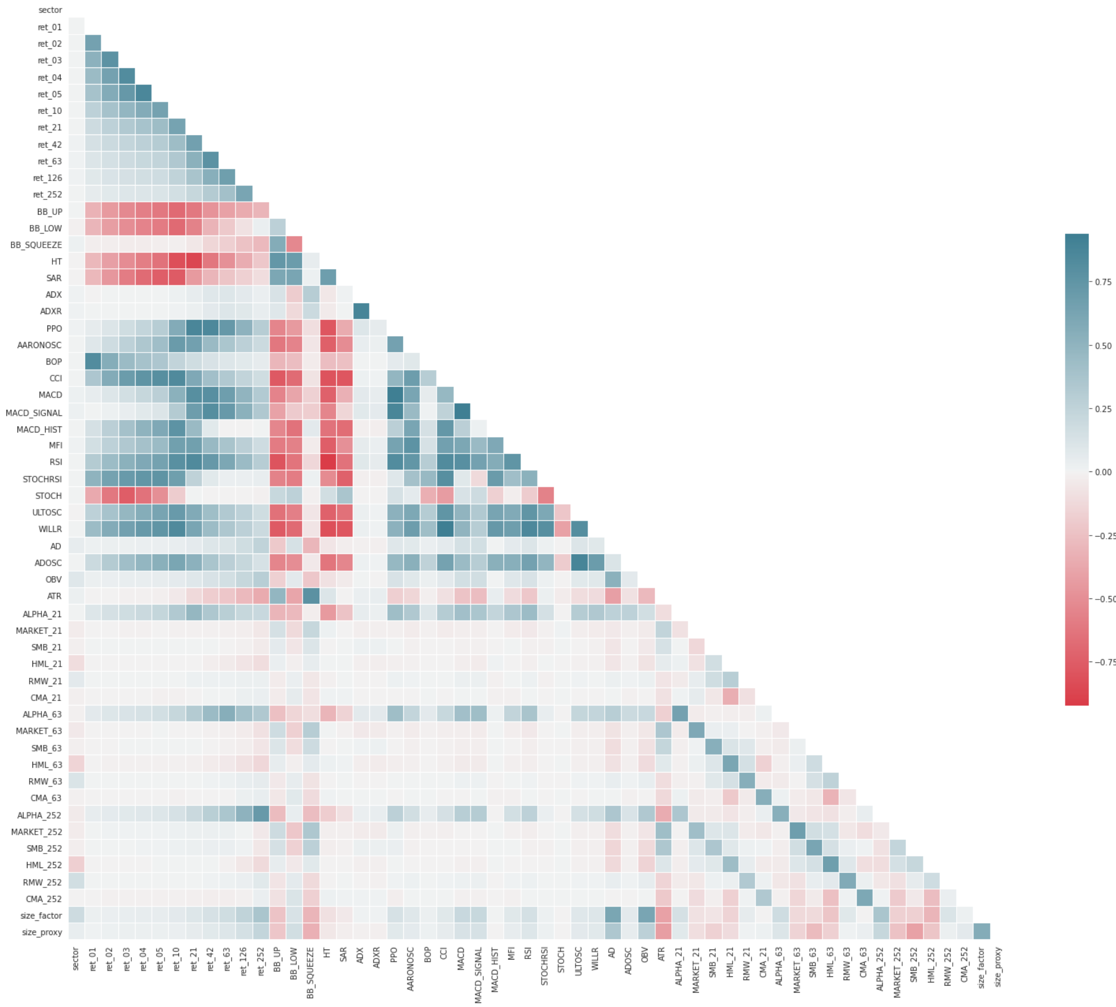
1.2 Factor Correlation

1.2.1 'Classic' Factors

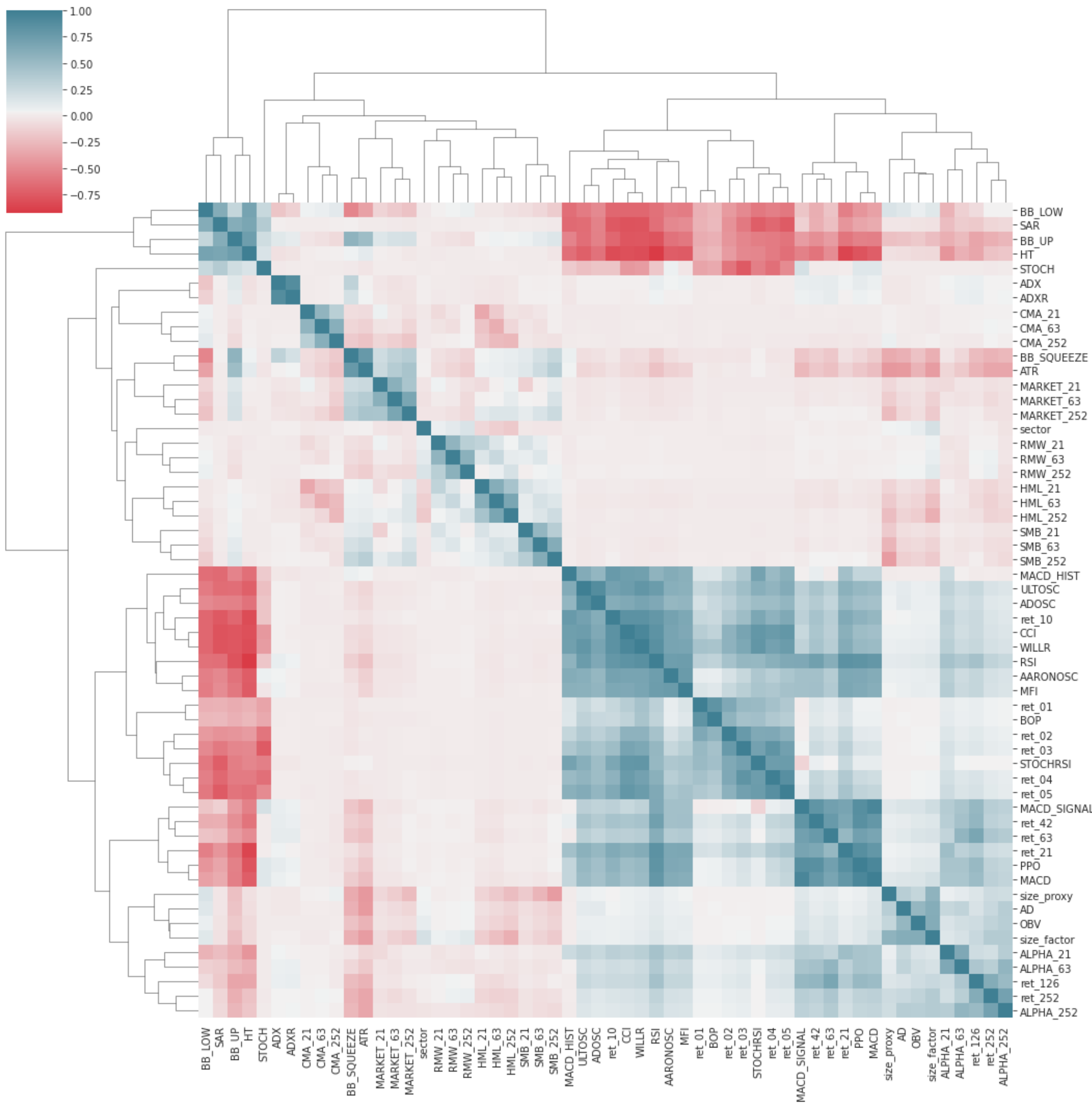
[10]:
```
corr_common = factors.drop(fwd_returns.union(alphas), axis=1).
 ↪corr(method='spearman')
```

[11]:
```
corr_common.to_hdf('data.h5', 'correlation/common')
```

[20]:
```
mask = np.triu(np.ones_like(corr_common, dtype=np.bool))
fig, ax = plt.subplots(figsize=(22, 18))
cmap = sns.diverging_palette(10, 220, as_cmap=True)

sns.heatmap(corr_common, mask=mask, cmap=cmap, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
fig.tight_layout()
fig.savefig(results_path / 'factor_corr_common', dpi=300);
```



```
[21]: g = sns.clustermap(corr_common, cmap=cmap, figsize=(15, 15))
      g.savefig(results_path / 'factor_corr_common_cluster', dpi=300);
```



[16]:
```
corr_ = corr_common.stack().reset_index()
corr_.columns = ['x1', 'x2', 'rho']
corr_ = corr_[corr_.x1!=corr_.x2].drop_duplicates('rho')
```

[17]:
```
corr_.nlargest(5, columns='rho').append(corr_.nsmallest(5, columns='rho'))
```

[17]:

	x1	x2	rho
1312	MACD	MACD_SIGNAL	0.936793
1263	CCI	WILLR	0.925544
1087	PPO	MACD	0.925282
970	ADX	ADXR	0.885147
1713	ULTOSC	ADOSC	0.881911
867	HT	RSI	-0.923566

```
407   ret_21          HT -0.866342
351   ret_10          HT -0.828103
871       HT       WILLR -0.825403
862       HT         CCI -0.806064
```

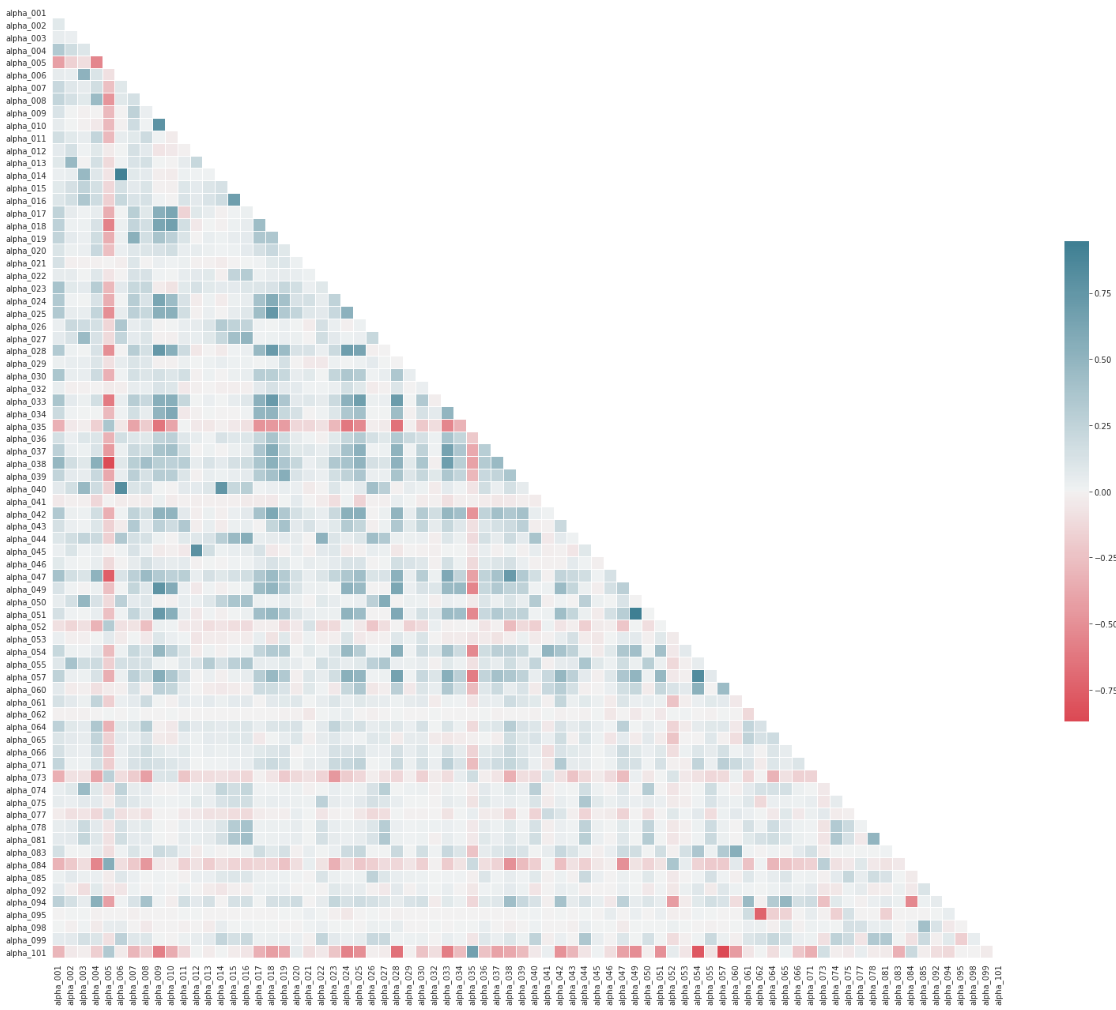
1.2.2 Formulaic Alphas

[22]:
```
%%time
corr_formula = factors[alphas].sort_index().corr(method='spearman').
 ↪dropna(how='all', axis=1)
corr_formula.to_hdf('data.h5', 'correlation/formula')
```

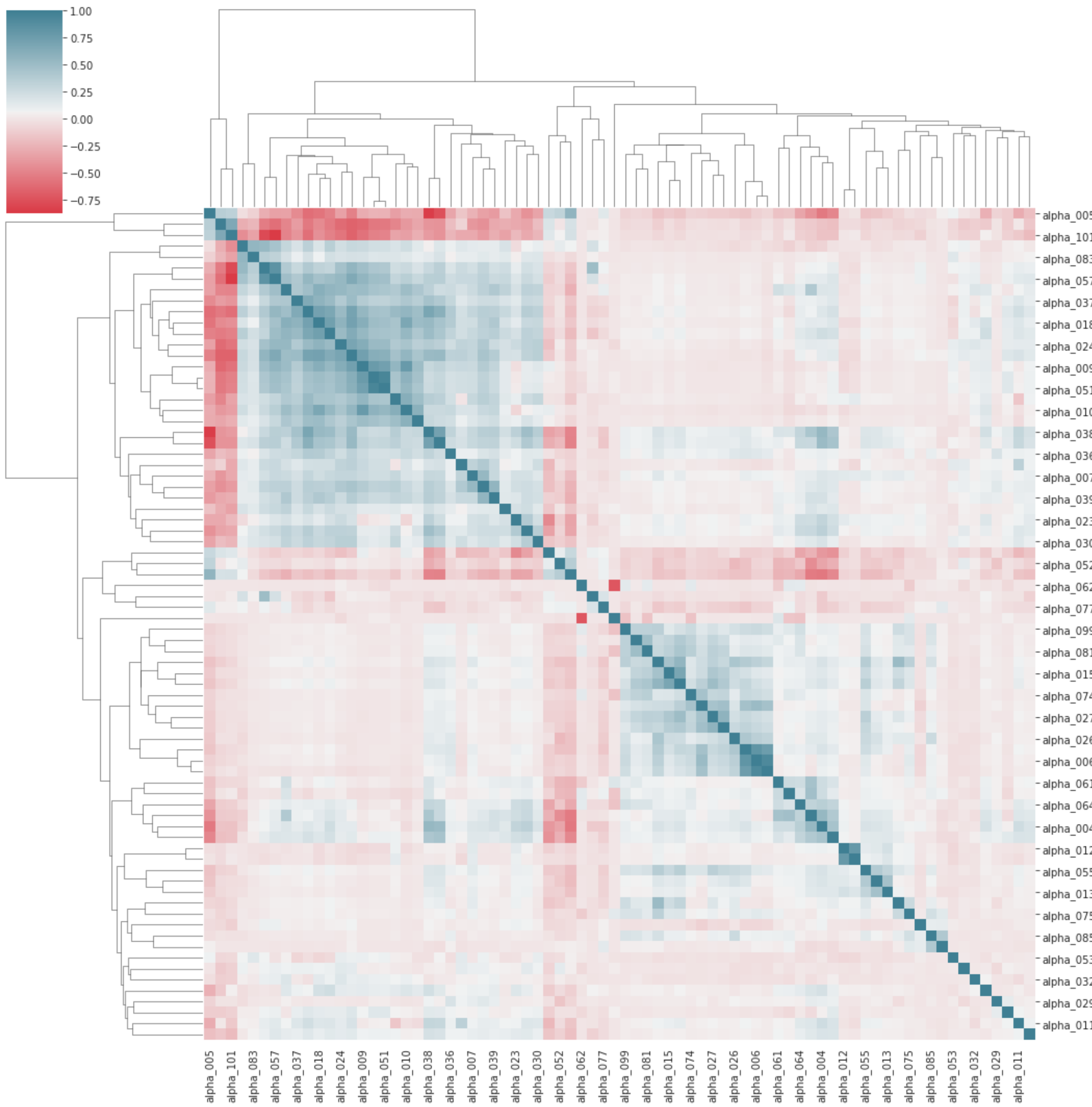
```
CPU times: user 11min 33s, sys: 6.96 s, total: 11min 40s
Wall time: 11min 41s
```

[23]:
```
corr_formula = corr_formula.dropna(how='all').dropna(how='all', axis=1)
```

[24]:
```
mask = np.triu(np.ones_like(corr_formula, dtype=np.bool))
fig, ax = plt.subplots(figsize=(22, 18))
cmap = sns.diverging_palette(10, 220, as_cmap=True)

sns.heatmap(corr_formula, mask=mask, cmap=cmap, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
fig.tight_layout()
fig.savefig(results_path / 'factor_correlation_formula', dpi=300);
```



[25]:
```
g = sns.clustermap(corr_formula.replace((np.inf, -np.inf), np.nan), cmap=cmap,␣
↪figsize=(15, 15))
g.savefig(results_path / 'factor_correlation_formula_cluster', dpi=300);
```



[26]:
```
corr_formula_ = corr_formula.stack().reset_index()
corr_formula_.columns = ['x1', 'x2', 'rho']
corr_formula_ = corr_formula_[corr_formula_.x1!=corr_formula_.x2].
↪drop_duplicates('rho')
```

[27]:
```
corr_formula_.nlargest(5, columns='rho').append(corr_formula_.nsmallest(5,␣
↪columns='rho'))
```

[27]:

	x1	x2	rho
3544	alpha_049	alpha_051	0.945057
393	alpha_006	alpha_014	0.919212
3929	alpha_054	alpha_057	0.835764
418	alpha_006	alpha_040	0.818868

```
879   alpha_012  alpha_045  0.790135
4103  alpha_057  alpha_101 -0.869973
340   alpha_005  alpha_038 -0.855128
3951  alpha_054  alpha_101 -0.789516
349   alpha_005  alpha_047 -0.753111
4328  alpha_062  alpha_095 -0.730927
```

1.2.3 All Factors

[28]:
```
corr = factors.drop(['ret_fwd', 'alpha_051'], axis=1).corr()
```

[29]:
```
corr = corr.dropna(how='all').dropna(how='all', axis=1)
```

[30]:
```
corr.to_hdf('data.h5', 'correlation/all')
```

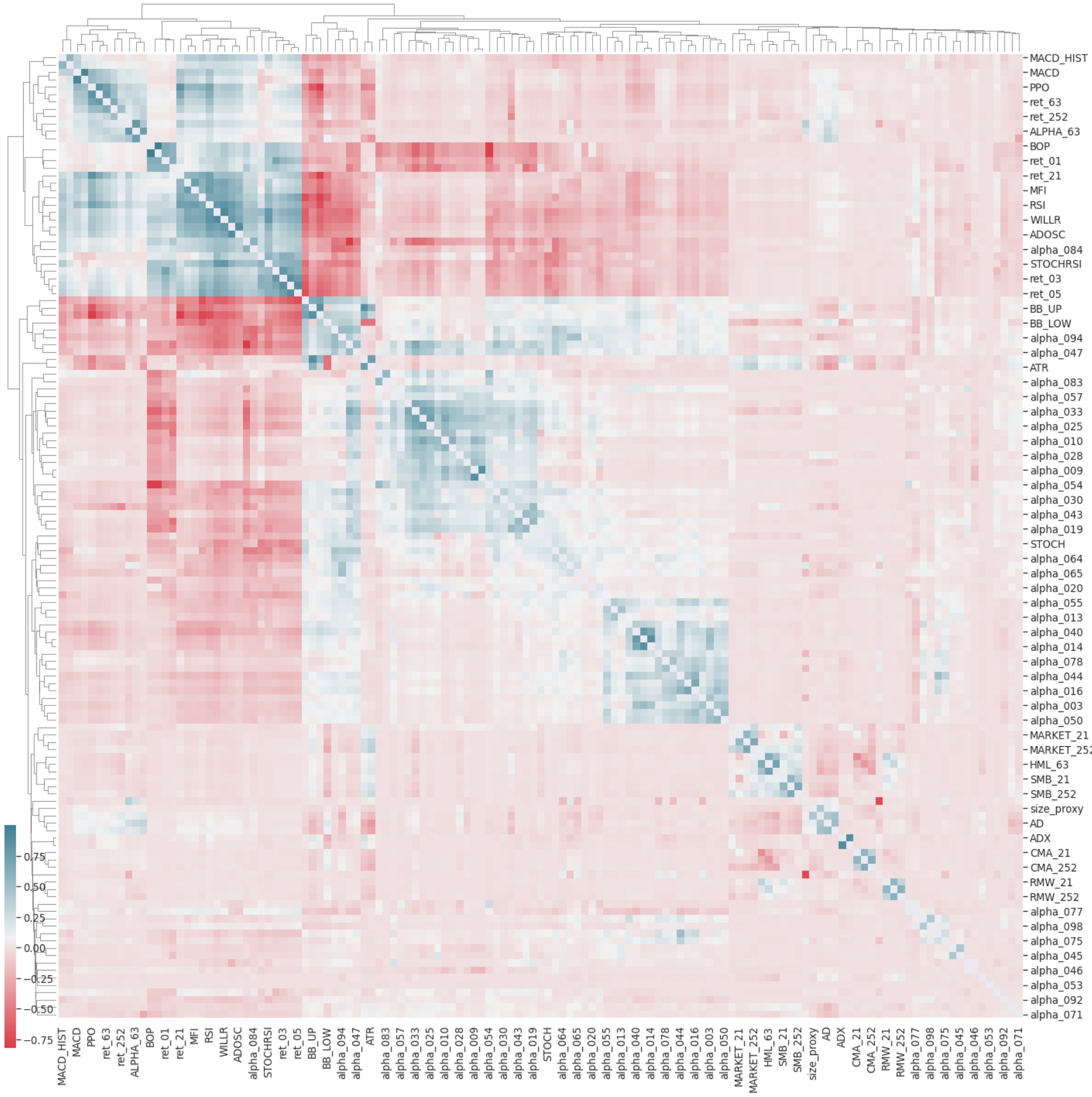
[31]:
```
corr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 131 entries, sector to alpha_101
Columns: 131 entries, sector to alpha_101
dtypes: float64(131)
memory usage: 135.1+ KB
```

[32]:
```
corr.shape
```

[32]:
```
(131, 131)
```

[33]:
```
sns.set(font_scale=1.2)

mask = np.zeros_like(corr)
np.fill_diagonal(mask, 1)

g = sns.clustermap(corr,
                   cmap=cmap,
                   figsize=(20, 20),
                   dendrogram_ratio=.05,
                   mask=mask,
                   cbar_pos=(0.01, 0.05, 0.01, 0.2));

g.savefig(results_path / 'factor_correlation_all', dpi=300);
```



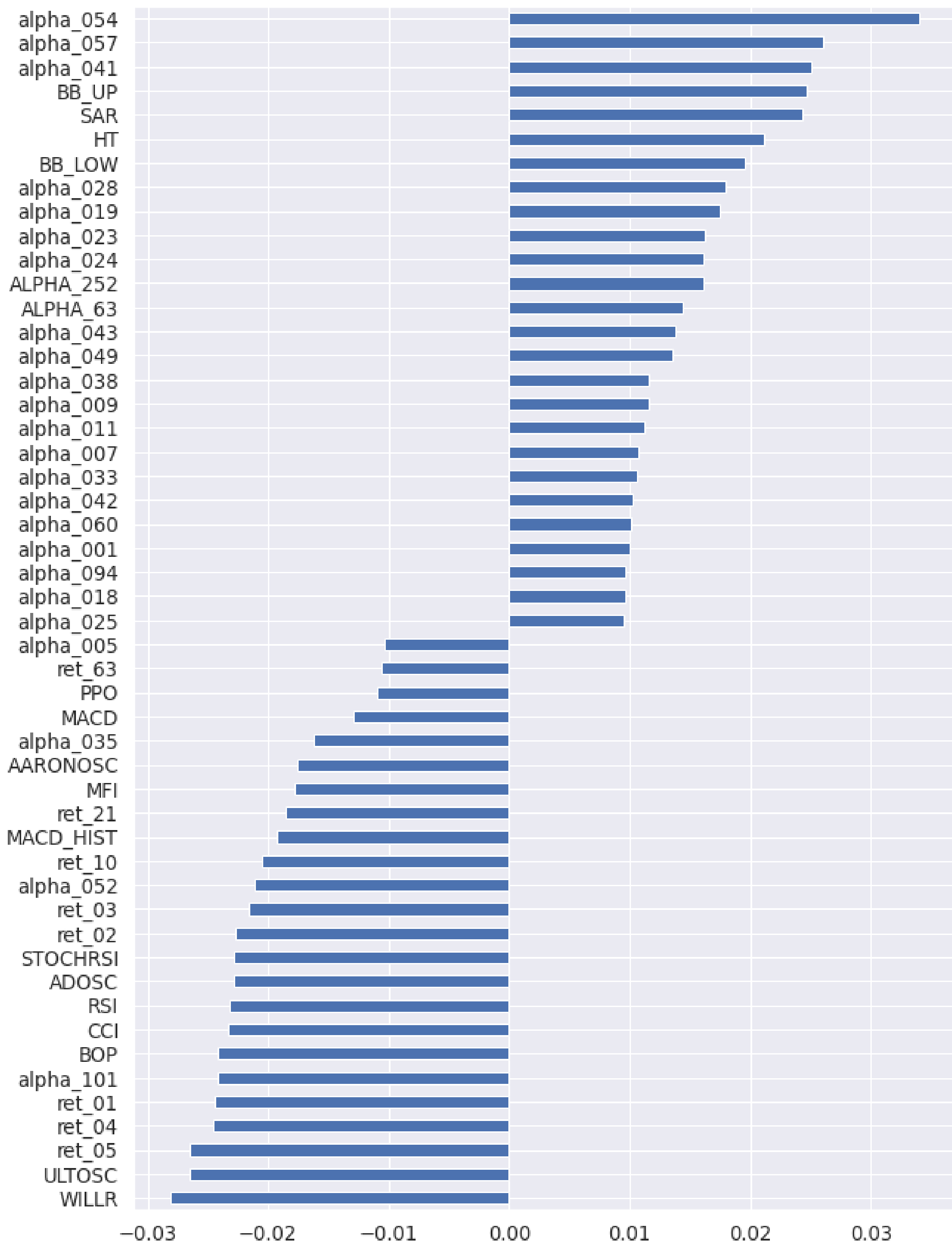
1.3 Forward return correlation

[34]:
```
fwd_corr = factors.drop(['ret_fwd', 'alpha_051'], axis=1).corrwith(factors.
 ↪ret_fwd, method='spearman')
```

[35]:
```
fwd_corr = fwd_corr.dropna()
```

[36]:
```
fwd_corr.to_hdf('data.h5', 'correlation/fwd_ret')
```

[37]:
```
top50 = fwd_corr.abs().nlargest(50).index
fwd_corr.loc[top50].sort_values().plot.barh(figsize=(10, 15),
                                             legend=False);
```

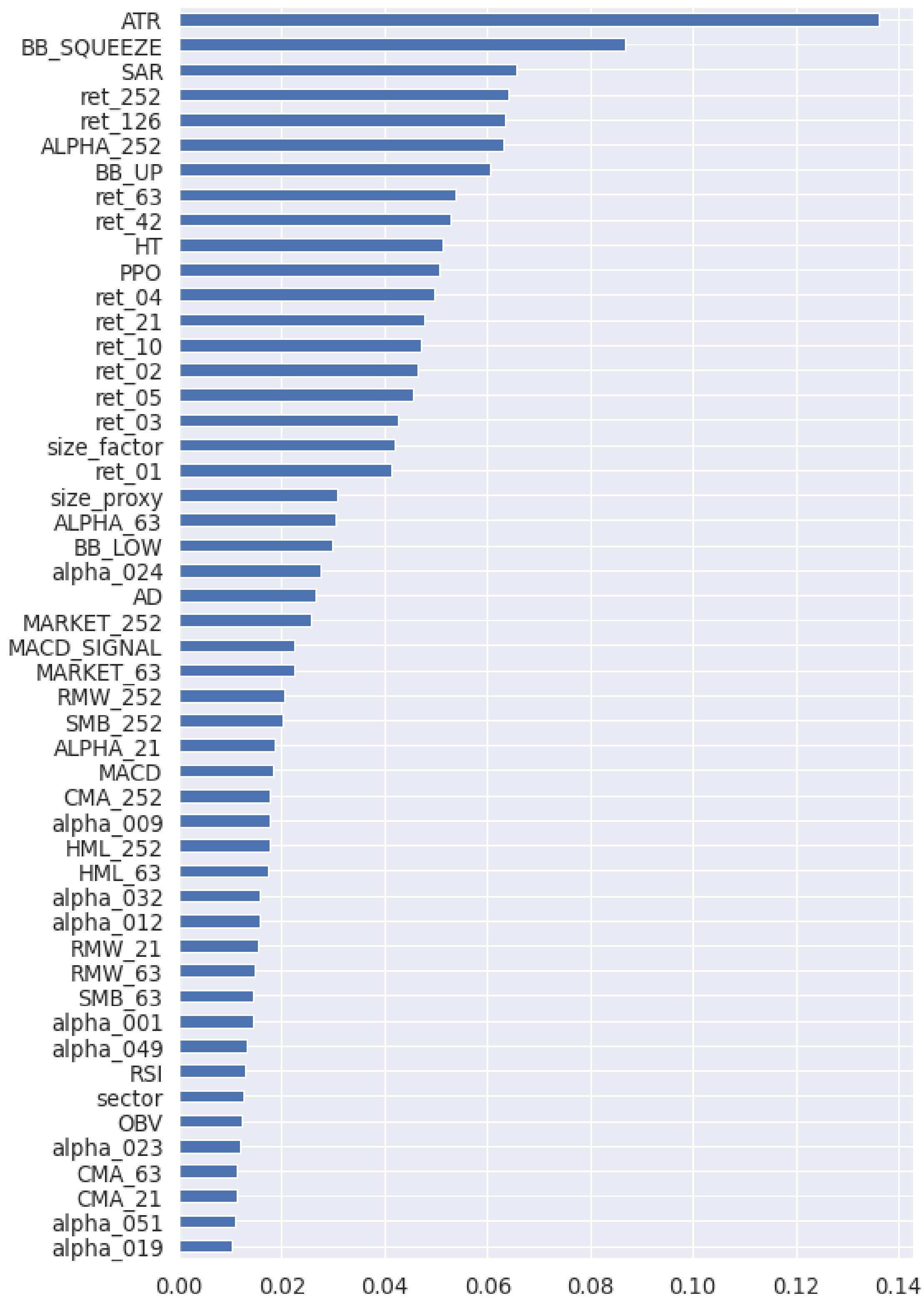

alpha_054
alpha_057
alpha_041
BB_UP
SAR
HT
BB_LOW
alpha_028
alpha_019
alpha_023
alpha_024
ALPHA_252
ALPHA_63
alpha_043
alpha_049
alpha_038
alpha_009
alpha_011
alpha_007
alpha_033
alpha_042
alpha_060
alpha_001
alpha_094
alpha_018
alpha_025
alpha_005
ret_63
PPO
MACD
alpha_035
AARONOSC
MFI
ret_21
MACD_HIST
ret_10
alpha_052
ret_03
ret_02
STOCHRSI
ADOSC
RSI
CCI
BOP
alpha_101
ret_01
ret_04
ret_05
ULTOSC
WILLR
−0.03
−0.02
−0.01
0.00
0.01
0.02
0.03

1.4 Mutual Information

[45]:
```
mi = {}
for feature in tqdm(features):
    df = (factors
          .loc[:, ['ret_fwd', feature]]
          .dropna().sample(n=100000))
    discrete_features = df[feature].nunique() < 10
    mi[feature] = mutual_info_regression(X=df[[feature]],
                                         y=df.ret_fwd,
                                         discrete_features=discrete_features)[0]
mi = pd.Series(mi)
```

```
100%|      | 134/134 [01:28<00:00,  1.51it/s]
```

[55]:
```
mi.nlargest(50).sort_values().plot.barh(figsize=(8, 14));
```


ATR
BB_SQUEEZE
SAR
ret_252
ret_126
ALPHA_252
BB_UP
ret_63
ret_42
HT
PPO
ret_04
ret_21
ret_10
ret_02
ret_05
ret_03
size_factor
ret_01
size_proxy
ALPHA_63
BB_LOW
alpha_024
AD
MARKET_252
MACD_SIGNAL
MARKET_63
RMW_252
SMB_252
ALPHA_21
MACD
CMA_252
alpha_009
HML_252
HML_63
alpha_032
alpha_012
RMW_21
RMW_63
SMB_63
alpha_001
alpha_049
RSI
sector
OBV
alpha_023
CMA_63
CMA_21
alpha_051
alpha_019
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14

[49]:
```
mi.to_hdf('data.h5', 'mutual_information')
```

1.5 LightGBM Feature Importance

[56]:
```
def get_fi(model):
    fi = model.feature_importance(importance_type='gain')
    return (pd.Series(fi / fi.sum(),
                      index=model.feature_name()))
```

[57]:
```
def ic_lgbm(preds, train_data):
    """Custom IC eval metric for lightgbm"""
    is_higher_better = True
    return 'ic', spearmanr(preds, train_data.get_label())[0], is_higher_better
```

[58]:
```
uniques = factors.nunique()
```

[59]:
```
categoricals = uniques[uniques < 20].index.tolist()
```

[60]:
```
categoricals
```

[60]:
```
['sector',
 'alpha_004',
 'alpha_021',
 'alpha_027',
 'alpha_061',
 'alpha_062',
 'alpha_064',
 'alpha_065',
 'alpha_068',
 'alpha_073',
 'alpha_074',
 'alpha_075',
 'alpha_081',
 'alpha_086',
 'alpha_092',
 'alpha_095',
 'alpha_099']
```

[61]:
```
features = factors.columns.difference(fwd_returns).tolist()
```

[62]:
```
label = 'ret_fwd'
```

[63]:
```
train_length = int(8.5 * 252)
test_length = 252
n_splits = 1
```

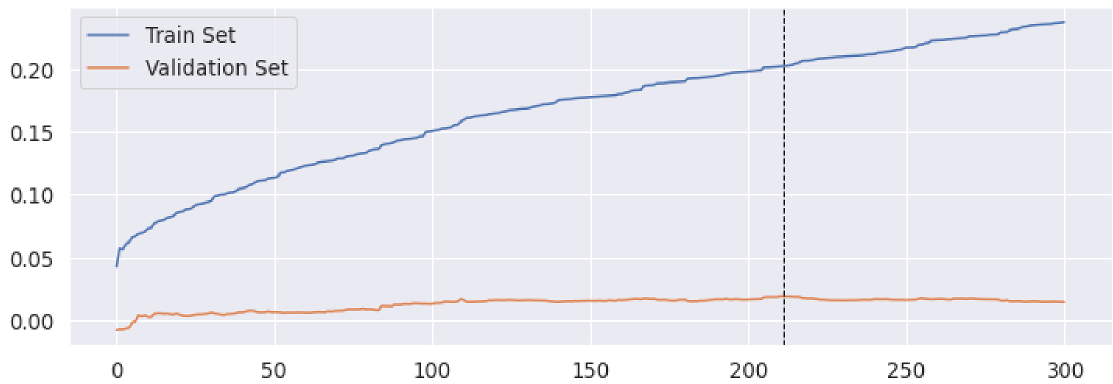
[66]:
```
params = dict(boosting='gbdt',
              objective='regression',
              verbose=-1,
              metric='None')
num_boost_round = 5000
```

[67]:
```
lgb_data = lgb.Dataset(data=factors.loc[:, features],
                       label=factors.loc[:, label],
                       categorical_feature=categoricals,
                       free_raw_data=False)

cv = MultipleTimeSeriesCV(n_splits=n_splits,
                          lookahead=1,
                          test_period_length=test_length,
                          train_period_length=train_length)

feature_importance, ic, daily_ic = [], [], []

for i, (train_idx, test_idx) in enumerate(cv.split(X=factors)):
    start = time()
    lgb_train = lgb_data.subset(used_indices=train_idx.tolist(),
                               params=params).construct()
    lgb_test = lgb_data.subset(used_indices=test_idx.tolist(),
                               params=params).construct()
    evals_result = {}
    model = lgb.train(params=params,
                      train_set=lgb_train,
                      num_boost_round=num_boost_round,
                      valid_sets=[lgb_train, lgb_test],
                      valid_names=['train', 'valid'],
                      feval=ic_lgbm,
                      evals_result=evals_result,
                      early_stopping_rounds=500,
                      verbose_eval=100)
    model.save_model(f'models/lgb_model.txt')
    fi = get_fi(model)
    fi.to_hdf('data.h5', f'fi/{i:02}')
    test_set = factors.iloc[test_idx, :]
    X_test = test_set.loc[:, model.feature_name()]
    y_test = test_set.loc[:, label]
    y_pred = model.predict(X_test)
    cv_preds = y_test.to_frame('y_test').assign(y_pred=y_pred)
    cv_preds.to_hdf('preds.h5', f'preds/{i:02}')

    by_day = cv_preds.groupby(level='date')
    ic_by_day = by_day.apply(lambda x: spearmanr(x.y_test, x.y_pred)[0])
    daily_ic_mean = ic_by_day.mean()
```

```
    daily_ic_median = ic_by_day.median()
    ic = spearmanr(cv_preds.y_test, cv_preds.y_pred)[0]
    print(f'\n{time()-start:6.1f} | {ic:6.2%} | {daily_ic_mean: 6.2%} |␣
↪{daily_ic_median: 6.2%}')
```

```
Training until validation scores don't improve for 500 rounds
[100]   train's ic: 0.150317    valid's ic: 0.0129224
[200]   train's ic: 0.198109    valid's ic: 0.0163492
[300]   train's ic: 0.237158    valid's ic: 0.0146011
[400]   train's ic: 0.265874    valid's ic: 0.0153144
[500]   train's ic: 0.290307    valid's ic: 0.0127802
[600]   train's ic: 0.30687     valid's ic: 0.0139538
[700]   train's ic: 0.324543    valid's ic: 0.0116832
Early stopping, best iteration is:
[212]   train's ic: 0.202416    valid's ic: 0.0191778

 271.4 |  1.92% |  0.85% |  1.57%
```

[68]:
```
cv_result = pd.DataFrame({'Train Set': evals_result['train']['ic'],
                          'Validation Set': evals_result['valid']['ic']})

ax = cv_result.loc[:300].plot(figsize=(12, 4))
ax.axvline(cv_result['Validation Set'].idxmax(), c='k', ls='--', lw=1);
```



1.6 SHAP Values

[69]:
```
shap.initjs()
```

<IPython.core.display.HTML object>

[70]:
```
# model = lgb.Booster(model_file='models/lgb_model.txt')
```

[71]:
```
explainer = shap.TreeExplainer(model)
```

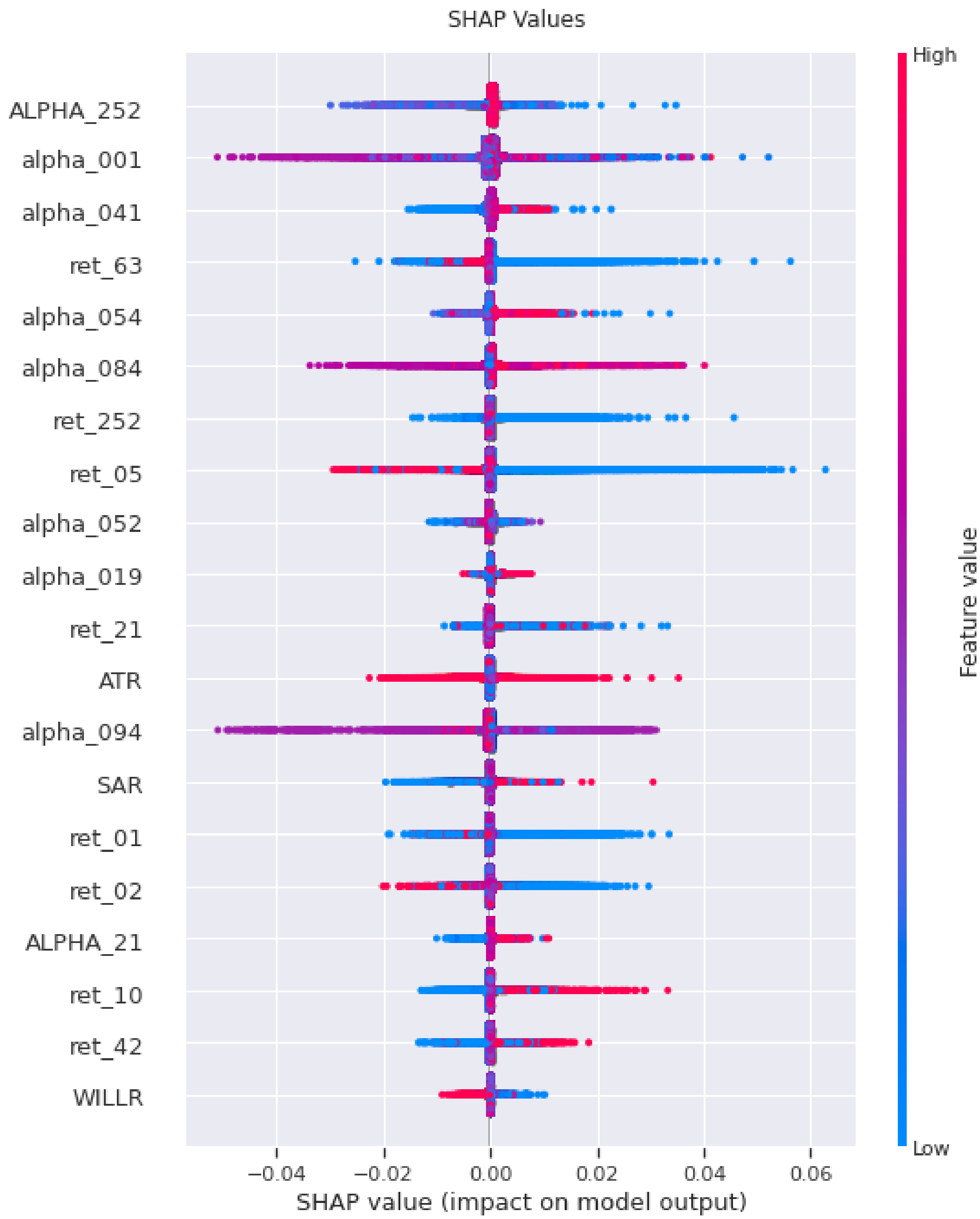
[72]:
```
# workaround for SHAP version 0.30: https://github.com/slundberg/shap/issues/794
model.params['objective'] = 'regression'
```

[73]:
```
shap_values = explainer.shap_values(factors.iloc[train_idx, :].loc[:, model.
↪feature_name()])
```

[74]:
```
np.save(models / 'shap_values.npy', shap_values)
```

[75]:
```
shap_values = np.load(models / 'shap_values.npy')
```

[76]:
```
shap.summary_plot(shap_values,
                  factors
                  .iloc[train_idx, :]
                  .loc[:, model.feature_name()],
                  show=False)
plt.gcf().suptitle('SHAP Values')
plt.gcf().tight_layout()
plt.gcf().savefig(results_path / 'shap_summary_dot', dpi=300)
```



[77]:
```
shap_values = pd.DataFrame(shap_values, columns = features)
```

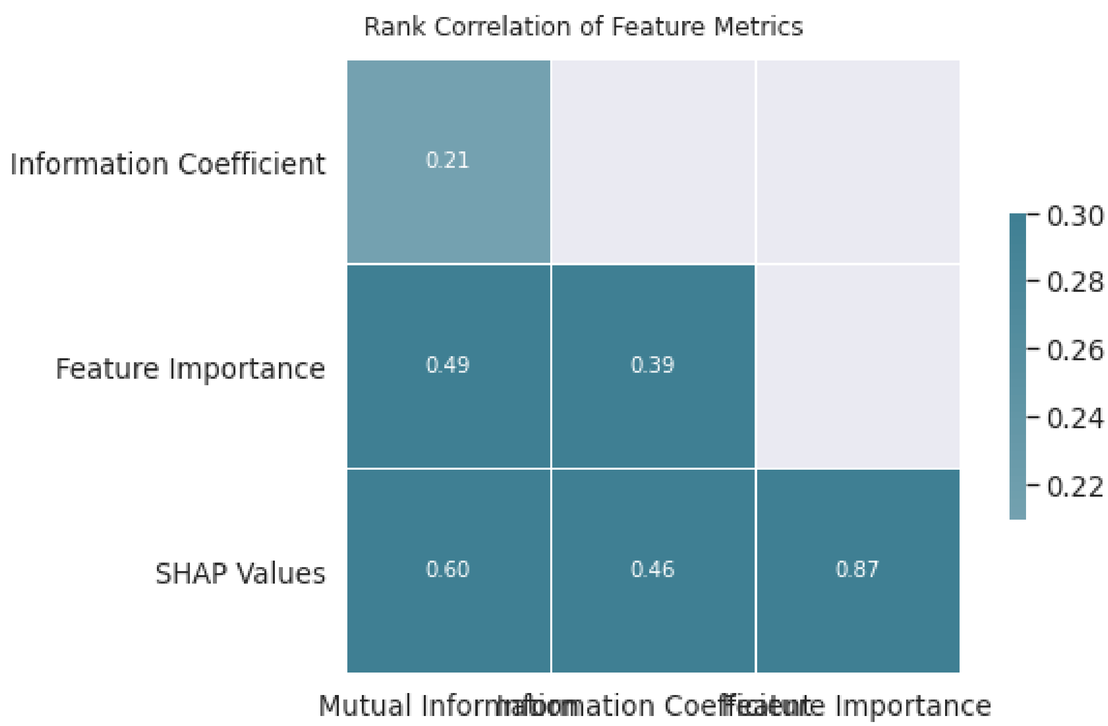
1.7 Summary

[78]:
```
mi = pd.read_hdf('data.h5', 'mutual_information')
fwd_corr = pd.read_hdf('data.h5', 'correlation/fwd_ret')
```

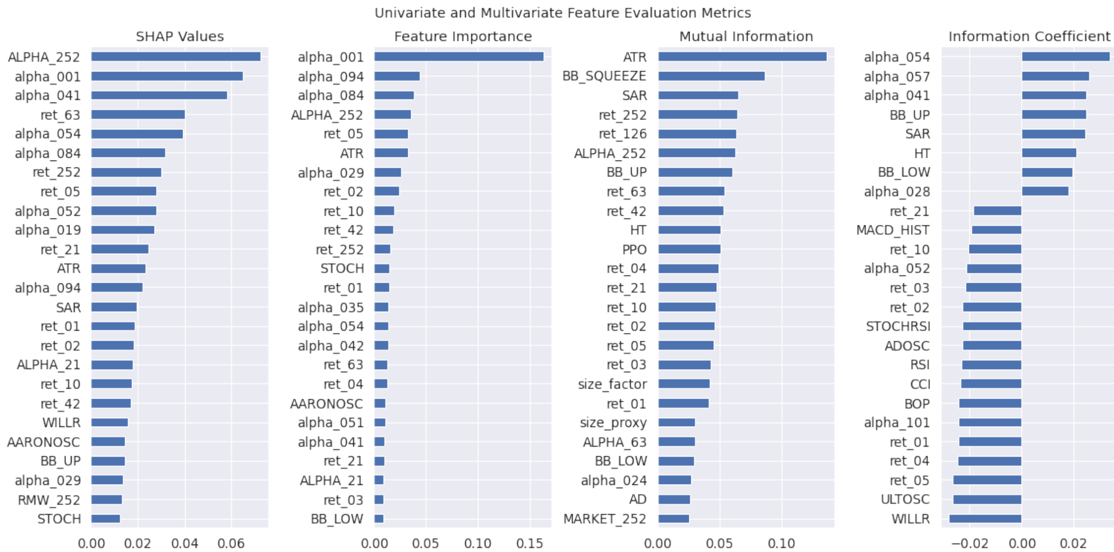
[79]:
```
shap_summary = shap_values.abs().mean()
shap_summary /= shap_summary.sum()
```

[80]:
```
stats = (mi.to_frame('Mutual Information')
         .join(fwd_corr.to_frame('Information Coefficient'))
         .join(fi.to_frame('Feature Importance'))
         .join(shap_summary.to_frame('SHAP Values')))
```

[81]:
```
cols = {'Information Coefficient': stats['Information Coefficient'].abs()}
corr = stats.assign(**cols).corr('spearman')
mask = np.triu(np.ones_like(corr, dtype=np.bool))
corr = corr.iloc[1:, :-1]
mask = mask[1:, :-1]

fig, ax = plt.subplots(figsize=(8, 5))

cmap = sns.diverging_palette(10, 220, as_cmap=True)

sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True,␣
 ↪fmt='.2f')
plt.xticks(rotation=0)
fig.suptitle('Rank Correlation of Feature Metrics', fontsize=12)
fig.tight_layout()
fig.subplots_adjust(top=.92)
fig.savefig(results_path / 'metrics_correlation', dpi=300);
```



[82]:
```
top_n = 25
fig, axes = plt.subplots(ncols=4, figsize=(16, 8))

shap_summary.nlargest(top_n).sort_values().plot.barh(ax=axes[0], title='SHAP␣
↪Values')

fi.nlargest(top_n).sort_values().plot.barh(ax=axes[1], title='Feature␣
↪Importance')

mi.nlargest(top_n).sort_values().plot.barh(ax=axes[2], title='Mutual␣
↪Information')

top_corr = fwd_corr.abs().nlargest(top_n).index
fwd_corr.loc[top_corr].sort_values().plot.barh(ax=axes[3], title='Information␣
↪Coefficient')

fig.suptitle('Univariate and Multivariate Feature Evaluation Metrics',␣
↪fontsize=14)
fig.tight_layout()
fig.subplots_adjust(top=.91)
fig.savefig(results_path / 'all_feature_metrics');
```


Univariate and Multivariate Feature Evaluation Metrics
SHAP Values
Feature Importance
Mutual Information
Information Coefficient
ALPHA_252
alpha_001
alpha_041
ret_63
alpha_054
alpha_084
ret_252
ret_05
alpha_052
alpha_019
ret_21
ATR
alpha_094
SAR
ret_01
ret_02
ALPHA_21
ret_10
ret_42
WILLR
AARONOSC
BB_UP
alpha_029
RMW_252
STOCH
alpha_001
alpha_094
alpha_084
ALPHA_252
ret_05
ATR
alpha_029
ret_02
ret_10
ret_42
ret_252
STOCH
ret_01
alpha_035
alpha_054
alpha_042
ret_63
ret_04
AARONOSC
alpha_051
alpha_041
ret_21
ALPHA_21
ret_03
BB_LOW
ATR
BB_SQUEEZE
SAR
ret_252
ret_126
ALPHA_252
BB_UP
ret_63
ret_42
HT
PPO
ret_04
ret_21
ret_10
ret_02
ret_05
ret_03
size_factor
ret_01
size_proxy
ALPHA_63
BB_LOW
alpha_024
AD
MARKET_252
alpha_054
alpha_057
alpha_041
BB_UP
SAR
HT
BB_LOW
alpha_028
ret_21
MACD_HIST
ret_10
alpha_052
ret_03
ret_02
STOCHRSI
ADOSC
RSI
CCI
BOP
alpha_101
ret_01
ret_04
ret_05
ULTOSC
WILLR
0.00 0.02 0.04 0.06
0.00 0.05 0.10 0.15
0.00 0.05 0.10
−0.02 0.00 0.02