

Implied Covariance Matrix Calculation

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Introduction

Suppose we have N_S stocks, N_F factors, with $N_S \gg N_F$.

The $N_S \times N_S$ **implied variance covariance matrix** Σ can be written as

$$\Sigma = B + \Psi,$$

where Ψ is a $N_S \times N_S$ diagonal **matrix of idiosyncratic returns** and B is the factor matrix,

$$B = F^{-1}AF,$$

where F is an $N_F \times N_S$ **matrix of factor-stock loadings** and A is an $N_F \times N_F$ **factor variance covariance matrix**.

Example

STOCKS:	GME	MSFT	NVDA	SBUX	TSLA
Date					
2021-01-04	4.3125	211.996597	130.851624	97.033089	243.256668
2021-01-05	4.3425	212.201141	133.757812	97.353081	245.036667
2021-01-06	4.5900	206.698914	125.872383	98.058937	251.993332
2021-01-07	4.5200	212.580917	133.151642	97.268364	272.013336
2021-01-08	4.4225	213.876144	132.480576	99.451843	293.339996

FACTORS:	QQQ	SPY
Date		
2021-01-04	304.244324	354.197357
2021-01-05	306.752563	356.636871
2021-01-06	302.503387	358.769043
2021-01-07	309.821533	364.099487
2021-01-08	313.805145	366.173981

Calculated F with shape (2, 5)
Calculated A with shape (2, 2)
Calculated F^{-1} with shape (5, 2)
Calculated B with shape (5, 5)

Calculated PSI with shape (5, 5)

Implied Variance-Covariance Matrix:

[[1.28411350e-01	2.21528468e-06	5.10564157e-06	8.84244400e-07	5.38855554e-06]
[1.12731732e-04	1.84688390e-02	2.42270650e-04	1.08987187e-04	2.05739261e-04]
[8.17390748e-05	9.73680229e-05	3.48392259e-02	7.67323950e-05	1.49727232e-04]
[1.80624187e-04	2.19347272e-04	3.88921784e-04	1.89742793e-02	3.29225943e-04]
[-3.77996246e-05	-4.81475066e-05	-8.29466915e-05	-4.05592148e-05	3.84230376e-02]]

Inverse of Implied Covariance Matrix

$$\Sigma = B + \Psi.$$

How do we compute Σ^{-1} ? If $N_S \gg 1$ this becomes very expensive.
Use a lemma from Miller 1981:

Knowing Ψ^{-1} (cheap: $\Psi_{ii} \rightarrow 1/\Psi_{ii}$), and if B_i is **rank 1**, we have:

$$(B_i + \Psi)^{-1} = \Psi^{-1} - \frac{1}{1 + g} \Psi^{-1} B_i \Psi^{-1} \quad \text{where} \quad g = \text{Tr}(B \Psi^{-1})$$

So, rewrite B as the **sum of matrices** B_i each of **rank 1**:

$$B = \sum_{i=1}^{N_S} B_i$$

Inverse of Implied Covariance Matrix

So, rewrite B as the **sum of matrices** B_i each of **rank 1**:

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And build up the inverse of Σ from these:

$$\Sigma^{-1} = (B + \Psi)^{-1} = C_{N_S}^{-1} \quad \text{where} \quad C_i^{-1} = C_{i-1}^{-1} - \frac{1}{1 + g_i} C_{i-1}^{-1} B_i C_{i-1}^{-1},$$

and $g_i = \text{Tr}(C_{i-1}^{-1} B_i)$, $C_0 = \Psi$.

Note: B will have rank of **at most** N_F , so it is possible to write B as a sum of N_F rank 1 matrices, further speeding up computation.

Example

```
print(np.linalg.inv(SIGMA))

>> [[ 7.78747575e+00 -9.23359207e-04 -1.13026653e-03 -3.52683837e-04 -1.07733194e-03]
      [-4.69478343e-02  5.41501739e+01 -3.73768708e-01 -3.10132223e-01 -2.85830195e-01]
      [-1.80107789e-02 -1.50253936e-01  2.87053449e+01 -1.15460760e-01 -1.10066649e-01]
      [-7.33496003e-02 -6.24058299e-01 -5.85104837e-01  5.27079334e+01 -4.45991405e-01]
      [ 7.48576611e-03  6.68696503e-02  6.08800699e-02  5.49990215e-02  2.60249841e+01]]

C = PSI.copy()
C_inv = np.diag(1/np.diagonal(C))
for i in range(0,N_S):
    B_i = np.zeros_like(B)
    B_i[i,:] = B[i,:]
    # They have a typo in the worksheet, the line below is false:
    #         vvvvv this is not just the trace
    # C_inv = C_inv - np.trace(B_i @ C_inv) * C_inv @ B_i @ C_inv
    C_inv = C_inv - 1/(1+np.trace(B_i @ C_inv)) * C_inv @ B_i @ C_inv

print(C_inv)

>> [[ 7.78747575e+00 -9.23359207e-04 -1.13026653e-03 -3.52683837e-04 -1.07733194e-03]
      [-4.69478343e-02  5.41501739e+01 -3.73768708e-01 -3.10132223e-01 -2.85830195e-01]
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      [ 7.48576611e-03  6.68696503e-02  6.08800699e-02  5.49990215e-02  2.60249841e+01]]
```

It's a match!