Return Entropy Portfolio Optimization



 A Maximum Entropy Model for Largescale Portfolio Optimization

→ Publisher : IEEE

 Diversified portfolios with different entropy measures

→ Publisher : Applied Mathematics and Computation

Mean Variance Portfolio Optimization

Min: $w^T \Omega w$

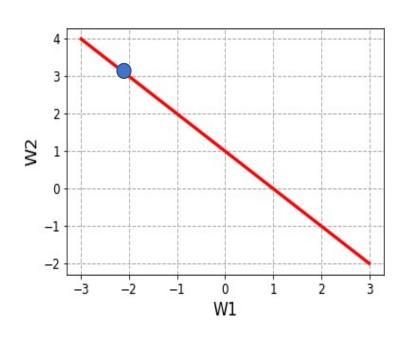
s.t
$$\sum_{i=1}^{n} r_i w_i = E \quad , i = 1, 2 \dots n$$

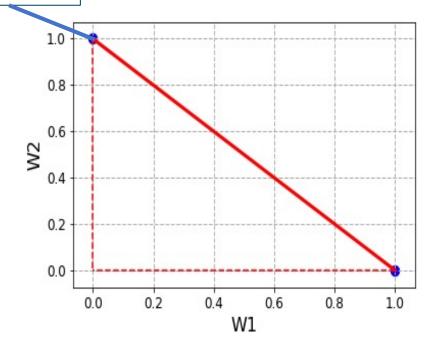
$$\sum_{i=1}^{n} w_i = 1 \quad , i = 1, 2 \dots n$$

Min: $w^T \Omega w$

s.t $\sum_{i=1}^{n} r_i w_i = E , i = 1, 2 \dots n$ $\sum_{i=1}^{n} w_i = 1 , i = 1, 2 \dots n$ $w_i \ge 0, i = 1, 2 \dots n$

Corner solution





Return Entropy Portfolio Optimization

Min:
$$w^T \Omega w$$

s.t
$$\begin{cases} \sum_{i=1}^{n} r_i w_i = E , i = 1, 2 \dots n \\ \sum_{i=1}^{n} w_i = 1 , i = 1, 2 \dots n \\ w_i \ge 0, i = 1, 2 \dots n \end{cases}$$

Min :
$$w^{T}\Omega w - [-\sum_{i=1}^{n} w_{i} * \ln(w_{i})]$$

s.t
$$\sum_{i=1}^{n} r_i w_i = E \quad , i = 1, 2 \dots n$$

$$\sum_{i=1}^{n} w_i = 1 \quad , i = 1, 2 \dots n$$
 Information Entropy

Example of Cost function in Machine Learning:

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h(x_i'\theta) - yi)^2 + \underbrace{Rgularization \ term}_{i=1}$$
Prevent
Overfitting

Maximum Entropy Proof

$$\mathsf{Max} : -\sum_{i=1}^n w_i \ln w_i$$

$$s. t. \qquad \sum_{i=1}^{n} w_i = 1$$

 $\mathsf{Min}: w^T \Omega w - [-\sum_{i=1}^n w_i * \ln(w_i)]$

Lagrange
$$L(w, \lambda) = -\sum_{i=1}^{n} w_i \ln w_i + (\lambda + 1)(\sum_{i=1}^{n} w_i - 1)$$

F.O.C
$$\begin{cases} \frac{\partial L}{\partial w_i} = -(1 + \ln w_i) + (\lambda + 1) = 0 & \ln w_i = \lambda \end{cases} \quad w_i = e^{\lambda}$$

$$\frac{\partial L}{\partial \lambda} = \sum_{i=1}^n w_i - 1 = 0 \qquad \sum_{i=1}^n e^{\lambda} - 1 = 0 \qquad ne^{\lambda} = 1$$

$$\begin{cases} w_i = e^{\lambda} \\ ne^{\lambda} = 1 \end{cases} \qquad w_i = e^{\lambda} = \frac{1}{n} \qquad \text{When Wi} = \frac{1}{n}, \\ \text{We can Maximize objective Function} \end{cases}$$

objective Function!

Mean Variance Portfolio Optimization

主要架構

```
def objective_function(w):
    w_tp=w.transpose()
    return np.dot(np.dot(w_tp,cov),w)

def equality_constraint_1(w):
    w_tp=w.transpose()
    return 1-np.dot(w_tp,ones)

def equality_constraint_2(w):
    w_tp=w.transpose()
    return u-np.dot(w_tp,returns)
```

```
Min: w^T \Omega w

s.t \sum_{i=1}^n r_i w_i = E , i = 1, 2 \dots n

\sum_{i=1}^n w_i = 1 , i = 1, 2 \dots n
```

 $w_i \ge 0, \quad i = 1, 2 \dots n$

```
ones=np.ones((cov.shape[0],1))
u=0.01
bounds=[(0,1000),(0,1000),(0,1000),(0,1000)]
w0=[1,1,1,1,1]
constraint_1={'type': 'eq','fun':equality_constraint_1}
constraint_2={'type': 'eq','fun':equality_constraint_2}
constraint=[constraint_1,constraint_2]
result=minimize(objective_function,w0,method='SLSQP',bounds=bounds,constraints=constraint)
w=result['x']
```

```
Data(2020/01~09)
```

```
    1. 0050
    2. 2330
    3. 3406
```

4. 1101

5. 2882

Mean Variance Portfolio Optimization modified by entropy

主要架構

```
def objective_function(w):
    w_tp=w.transpose()
    entropy_part=np.dot(w_tp,np.log(w))
    return np.dot(np.dot(w_tp,cov),w) + entropy_part

def equality_constraint_1(w):
    w_tp=w.transpose()
    return 1-np.dot(w_tp,ones)

def equality_constraint_2(w):
    w_tp=w.transpose()
    return u-np.dot(w_tp,returns)
```

```
Min: w^T \Omega w - [-\sum_{i=1}^n w_i * \ln(w_i)]

s.t \sum_{i=1}^n r_i w_i = E , i = 1, 2, ..., n

\sum_{i=1}^n w_i = 1 , i = 1, 2, ..., n
```

```
ones=np.ones((cov.shape[0],1))
u=0.01
bounds=[(0,1000),(0,1000),(0,1000),(0,1000)]
w0=[1,1,1,1,1]
constraint_1={'type': 'eq','fun':equality_constraint_1}
constraint_2={'type': 'eq','fun':equality_constraint_2}
constraint=[constraint_1,constraint_2]
result=minimize(objective_function,w0,method='SLSQP',bounds=bounds,constraints=constraint)
w=result['x']
```

```
-----use-entropy-modified-mean-weights1: 0.1682574722399195200
weights2: 0.0676868028906073005
weights3: 0.1400762290186602366
weights4: 0.2730539358447347520
weights5: 0.3509255600060781632
portfolio variance : 0.05950352128795654
```

Max Entropy with variance inequality constraint

主要架構

```
def objective_function(w):
    w_tp=w.transpose()
    entropy_part=np.dot(w_tp,np.log(w))
    return entropy_part

def equality_constraint_1(w):
    w_tp=w.transpose()
    return 1-np.dot(w_tp,ones)

def equality_constraint_2(w):
    w_tp=w.transpose()
    return u-np.dot(w_tp,returns)

def inequality_constraint(w):
    w_tp=w.transpose()
    return 0.05950352128795654-np.dot(np.dot(w_tp,cov),w)
```

```
ones=np.ones((cov.shape[0],1))
u=0.01
bounds=[(0,1000),(0,1000),(0,1000),(0,1000)]
w0=[1,1,1,1,1]
constraint_1={'type': 'eq','fun':equality_constraint_1}
constraint_2={'type': 'eq','fun':equality_constraint_2}
constraint_3={'type':'ineq','fun':inequality_constraint}
constraint=[constraint_1,constraint_2,constraint_3]
result=minimize(objective_function,w0,method='SLSQP',bounds=bounds,constraints=constraint)
w=result['x']
```

-----------------objective fnc 是 entropy partvariance 主觀設定不能大於 0.05950352128795654

weights1: 0.1683885095160338186 weights2: 0.0676402314816348382 weights3: 0.1400814831749573053 weights4: 0.2729565213797951473 weights5: 0.3509332544475788906

$$Min: w^T \Omega w - \left[-\sum_{i=1}^n w_i * \ln(w_i) \right]$$



Max:
$$-\sum_{i=1}^{n} w_i * \ln(w_i)$$

s.t $\sum_{i=1}^{n} r_i w_i = E$, $i = 1, 2, ..., n$
 $\sum_{i=1}^{n} w_i = 1$, $i = 1, 2, ..., n$
 $w^T \Omega w \le Var$

Max Entropy with variance inequality constraint

主要架構

```
def objective_function(w):
    w_tp=w.transpose()
    entropy_part=np.dot(w_tp,np.log(w))
    return entropy_part

def equality_constraint_1(w):
    w_tp=w.transpose()
    return 1-np.dot(w_tp,ones)

def equality_constraint_2(w):
    w_tp=w.transpose()
    return u-np.dot(w_tp,returns)

def inequality_constraint(w):
    w_tp=w.transpose()
    return 0.04288542001711603-np.dot(np.dot(w_tp,cov),w)
```

```
Max: -\sum_{i=1}^{n} w_i * \ln(w_i)

s.t \sum_{i=1}^{n} r_i w_i = E , i = 1, 2 \dots n

\sum_{i=1}^{n} w_i = 1 , i = 1, 2 \dots n

w^T \Omega w \le Var
```

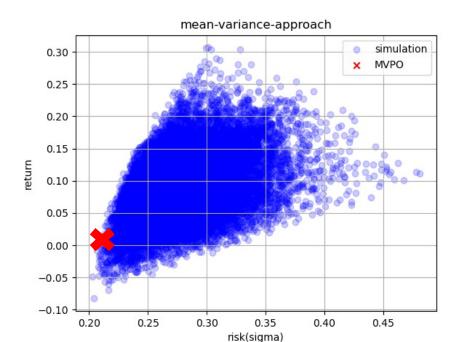
```
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constraint_3={'type':'ineq','fun':inequality_constraint}
constraint=[constraint_1,constraint_2,constraint_3]
result=minimize(objective_function,w0,method='SLSQP',bounds=bounds,constraints=constraint)
w=result['x']
```



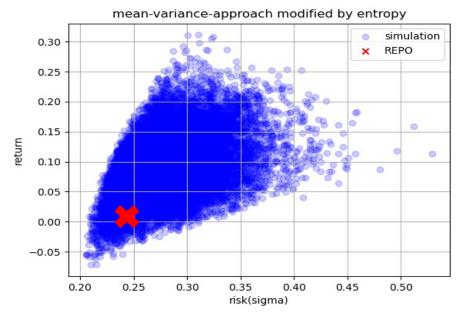
回到MVPO!

Comparison

Min : $w^T \Omega w$



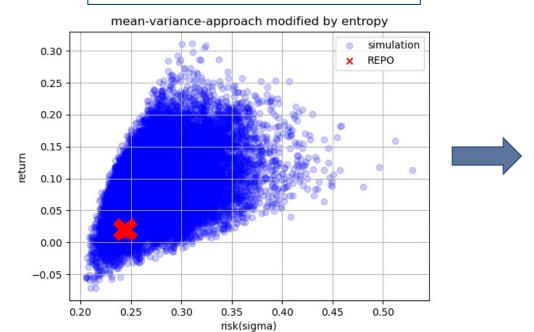
Min : $w^{T} \Omega w - [-\sum_{i=1}^{n} w_{i} * \ln(w_{i})]$



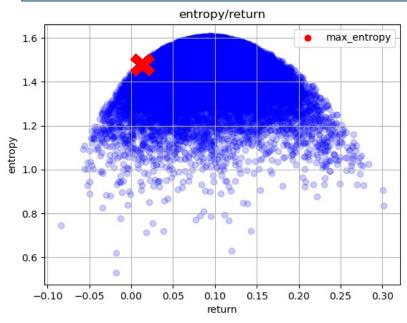
------objective fnc 是 entropy part-----variance 主觀設定不能大於 0.05950352128795654
weights1: 0.1683885095160338186
weights2: 0.0676402314816348382
weights3: 0.1400814831749573053
weights4: 0.2729565213797951473
weights5: 0.3509332544475788906
portfolio risk : 0.24393363076694946
portfolio return : 0.0099999999989635
portfolio entropy : 1.4794094170712746

Min: $w^T \Omega w - [-\sum_{i=1}^n w_i * \ln(w_i)]$

Portfolio risk and return



Portfolio entropy and return

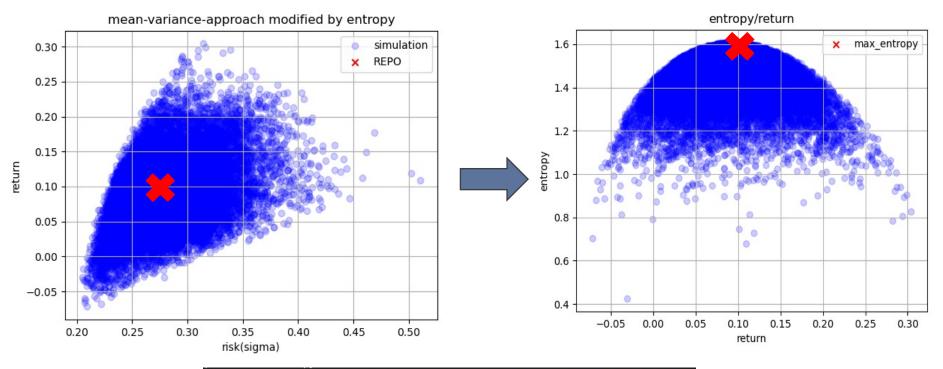


variance 主觀設定不能大於 0.05950352128795654

weights1: 0.1683885095160338186 weights2: 0.0676402314816348382 weights3: 0.1400814831749573053 weights4: 0.2729565213797951473 weights5: 0.3509332544475788906

portfolio risk : 0.24393363076694946
portfolio return : 0.009999999999989635
portfolio entropy : 1.4794094170712746

Without any Constraint



Thank you for your Listening~

報告人:清華大學計量財務金融學系,江晨立