

# Machine Learning and Financial Applications

## Lecture 3 Modern Portfolio Management

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Liu Peng

liupeng@smu.edu.sg

# Learning outcomes



Get to know modern  
portfolio theory



Able to implement  
common portfolios



Know the pros and  
cons of common  
portfolio strategies

$w_1 + w_2 + w_3 = 1$  (budget constraint)

optional (  $w_i \geq 0$  (no-short constraint) )

objective

# What is Portfolio Management?

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# Portfolio Risk and Return

Q: Do we have access to asset risk and return parameters?

## Portfolio Return:

n assets

$$\underline{R_p} = \sum_{i=1}^n w_i R_i$$

$w^T R$

- $R_p$ : Expected return of the portfolio
- $w_i$ : Weight of asset  $i$  in the portfolio
- $R_i$ : Expected return of asset  $i$

## Portfolio Variance (Risk):

$w^T \sigma (w = [w_1, w_2, w_3])$

$\rho_{ij} < 1$

$$\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \underline{\sigma_{ij}}$$

- $\sigma_p^2$ : Variance of portfolio returns
- $\sigma_{ij}$ : Covariance between returns of asset  $i$  and asset  $j$

## Portfolio Standard Deviation (Volatility):

$$\sigma_p = \sqrt{\sigma_p^2}$$

- $\sigma_p$ : Standard deviation (volatility) of the portfolio

# Mean-Variance Optimization

$$\max R_p \text{ s.t. } \sigma_p^2 \leq \sigma_0^2$$

$$\left( \text{Minimize } \sigma_p^2 \text{ subject to } R_p \geq R_t, \sum_{i=1}^n w_i = 1 \right)$$

$w^*$

- $R_t$ : Target return
- Optimization problem balances risk ( $\sigma_p^2$ ) and return ( $R_p$ ).

Q:

- What is an alternative formulation?
- How does the risk aversion parameter come into the picture?

# Risk-Adjusted Return

## Efficient Frontier:

- Set of portfolios offering the maximum expected return for a given level of risk (or minimum risk for a given return).

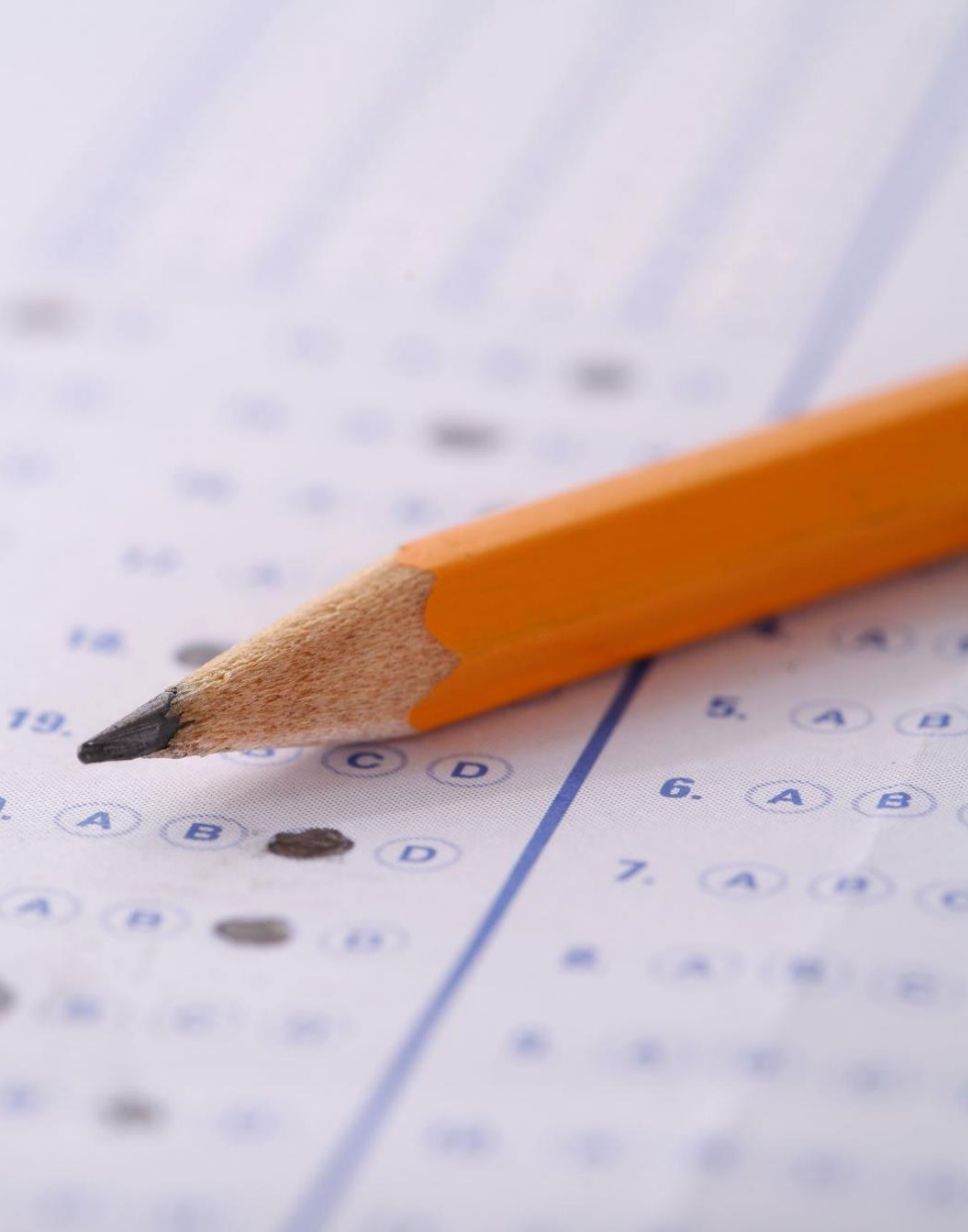
## Sharpe Ratio:

$$S_p = \frac{R_p - R_f}{\sigma_p}$$

Rf (benchmark)  
excess return =  $R_p - R_f$

- $S_p$ : Sharpe ratio of the portfolio
- $R_f$ : Risk-free rate
- Measures risk-adjusted return; higher values indicate better performance.

- Risk and return constitute two objectives
- Often there is a tradeoff in these two
- To analyze both metrics together, we can use:
  - Efficient frontier
  - Sharpe ratio
  - Etc...



# In-class quiz

- Q1-3

# Common Portfolio Strategies

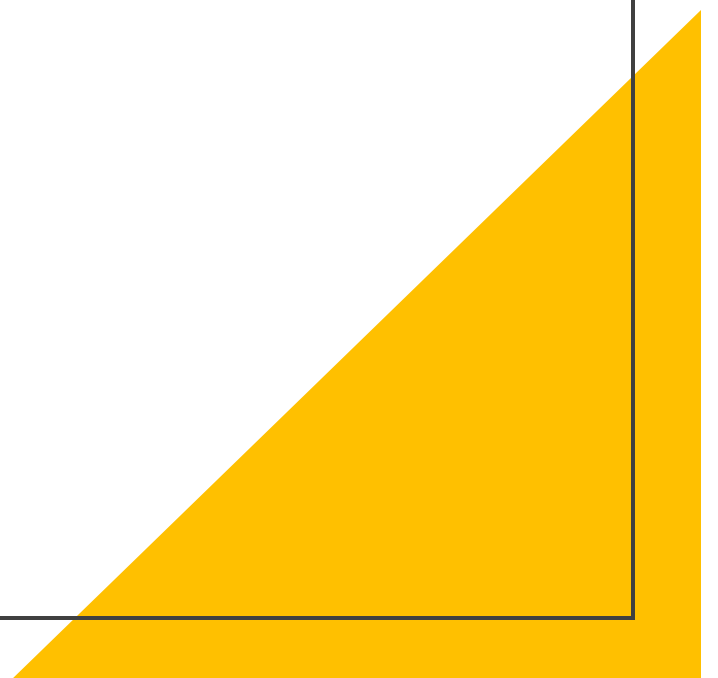
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- Maximum return portfolio
- Minimum variance portfolio
- Mean-variance portfolio
- Maximum Sharpe ratio portfolio
- Etc...



# Group Discussion

How to properly evaluate and assess different portfolio strategies?



# Maximum Return Portfolio (MRP)

Example:

$\mu_1 = 10\%$ ,  $\mu_2 = 20\%$ ,  $\mu_3 = 15\%$

$$w = [0 \quad 1 \quad 0]$$

**Objective:** Maximize the expected portfolio return

$$\text{maximize}_w \mathbf{w}^T \mu$$

- $\mathbf{w}$ : Weight vector of assets in the portfolio
- $\mu$ : Expected return vector of the assets

**Constraint:**

$$\mathbf{w}^T \mathbf{1} = 1$$

- Ensures the sum of the portfolio weights equals 1 (full investment).

**Optimal Strategy:**

- Allocate entire investment to the asset with the highest expected return.

**Optimal Weight Vector ( $\mathbf{w}_{MRP}$ ):**

$$w_{MRP,j} = \begin{cases} 1 & \text{if } j = i^* \\ 0 & \text{otherwise} \end{cases}$$

- $i^* = \arg \max_j \{\mu_j\}$
- $\mu_j$ : Expected return of asset  $j$
- Asset  $i^*$  has the highest expected return, so  $w_{i^*} = 1$  and  $w_j = 0$  for all  $j \neq i^*$ .

**Implications:**

- The MRP is risk-indifferent; it maximizes return without considering variance.
- It typically resides on one end of the efficient frontier, representing the highest potential return but also the highest risk.

# Global Minimum Variance Portfolio (GMVP)

Q: Do we need to predict asset returns?

**Objective:** Minimize Portfolio Variance

$$\min_{\mathbf{w}} \mathbf{w}^T \Sigma \mathbf{w}$$

**Constraint:**

$$\mathbf{w}^T \mathbf{1} = 1$$

- Ensures the portfolio is fully invested.

**Lagrangian Formulation:**

$$\mathcal{L}(\mathbf{w}, \gamma) = \mathbf{w}^T \Sigma \mathbf{w} + \gamma(1 - \mathbf{w}^T \mathbf{1})$$

- $\gamma$ : Lagrange multiplier for the constraint.

**First-Order Condition:**

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = 2\Sigma \mathbf{w} - \gamma \mathbf{1} = 0$$

**Solving for  $\mathbf{w}$ :**

$$\mathbf{w} = \frac{\gamma}{2} \Sigma^{-1} \mathbf{1}$$

**Determine  $\gamma$  Using Full Investment Constraint:**

$$\frac{\gamma}{2} \mathbf{1}^T \Sigma^{-1} \mathbf{1} = 1 \implies \gamma = \frac{2}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}}$$

**GMVP Weight Vector:**

$$\mathbf{w}_{GMVP} = \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}}$$

# Expected Return and Variance of GMVP

Expected Return of GMVP:

$$\mu_{GMVP} = \mathbf{w}_{GMVP}^T \boldsymbol{\mu}$$

- $\boldsymbol{\mu}$ : Vector of expected returns for the assets.

Substitute GMVP Weights:

$$\mu_{GMVP} = \left( \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} \right)^T \boldsymbol{\mu} = \frac{\mathbf{1}^T \Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}}$$

Variance of GMVP:

$$\sigma_{GMVP}^2 = \mathbf{w}_{GMVP}^T \Sigma \mathbf{w}_{GMVP}$$

Substitute GMVP Weights into Variance Expression:

$$\sigma_{GMVP}^2 = \left( \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} \right)^T \Sigma \left( \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} \right)$$

Simplify Variance Formula:

$$\sigma_{GMVP}^2 = \frac{1}{(\mathbf{1}^T \Sigma^{-1} \mathbf{1})^2} (\mathbf{1}^T \Sigma^{-1} \Sigma \Sigma^{-1} \mathbf{1})$$

Final Variance Expression:

$$\sigma_{GMVP}^2 = \frac{1}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}}$$

# Mean-Variance Optimization (MVO)

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**Objective:** Maximize the trade-off between expected return and risk for a portfolio of assets.

$$\max_{\mathbf{w}} \left( \mathbf{w}^T \boldsymbol{\mu} - \frac{1}{2} \lambda \mathbf{w}^T \Sigma \mathbf{w} \right)$$

**Subject to:**

$$\mathbf{w}^T \mathbf{1} = 1$$

**Parameters:**

- $\mathbf{w}$ : Portfolio weights for assets.
- $\boldsymbol{\mu}$ : Vector of expected returns.
- $\Sigma$ : Covariance matrix of returns.
- $\lambda$ : Risk-aversion coefficient.

**Interpretation:** Balances maximizing expected returns and minimizing risk, controlled by  $\lambda$ .

# Solving the MVO Using Lagrangian Multipliers

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Lagrangian Function:

$$\mathcal{L}(\mathbf{w}, \gamma) = \mathbf{w}^T \boldsymbol{\mu} - \frac{1}{2} \lambda \mathbf{w}^T \Sigma \mathbf{w} + \gamma (1 - \mathbf{w}^T \mathbf{1})$$

First-Order Conditions (FOCs):

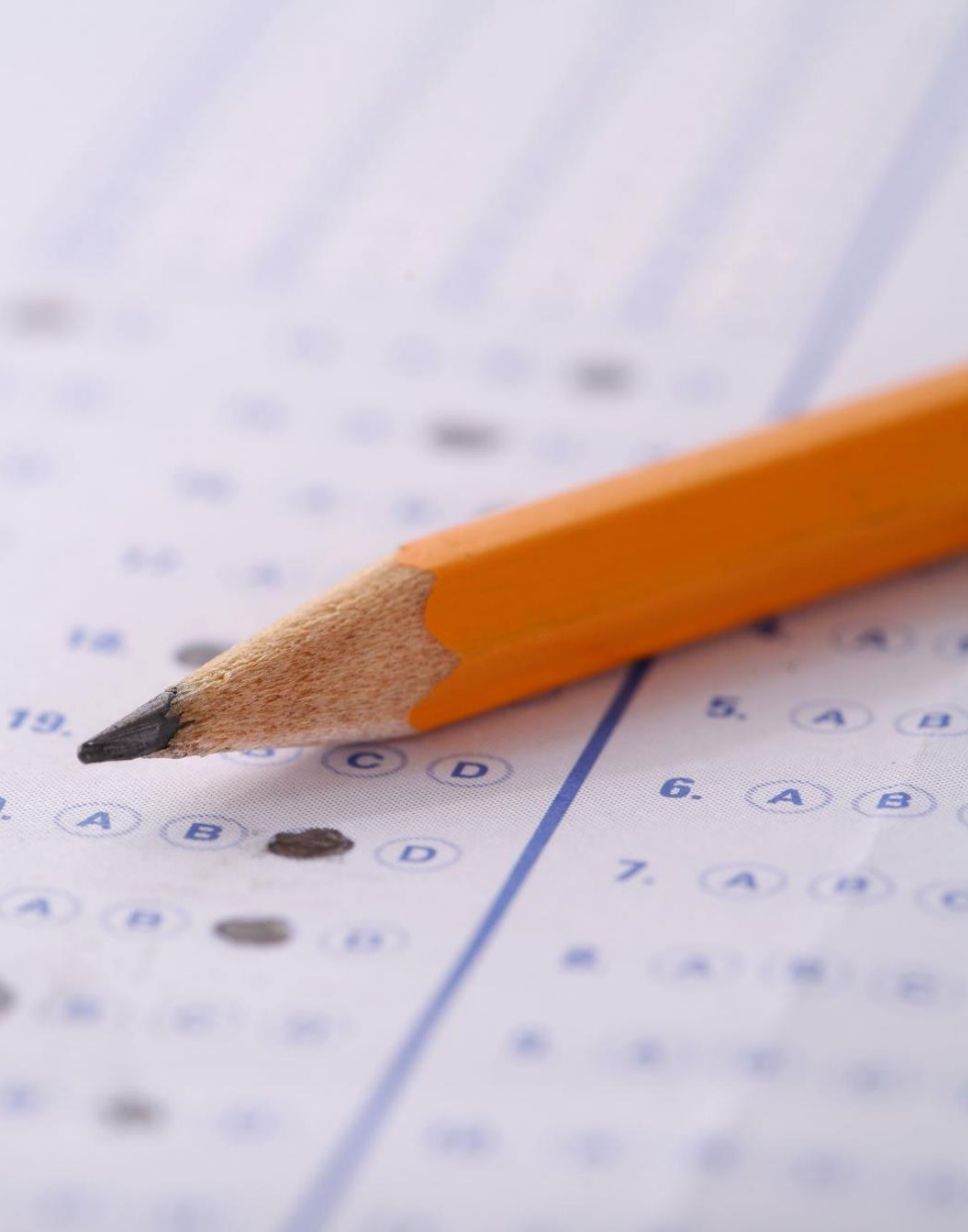
$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \boldsymbol{\mu} - \lambda \Sigma \mathbf{w} - \gamma \mathbf{1} = 0$$

Optimal Weights:

$$\mathbf{w} = \frac{1}{\lambda} \Sigma^{-1} \boldsymbol{\mu} - \frac{\gamma}{\lambda} \Sigma^{-1} \mathbf{1}$$

Determine  $\gamma$  using Budget Constraint:

$$\gamma = \frac{1}{\lambda} (\boldsymbol{\mu}^T \Sigma^{-1} \mathbf{1} - \lambda) / (\mathbf{1}^T \Sigma^{-1} \mathbf{1})$$



# In-class quiz

- Q4-7

# Maximum Sharpe Ratio Portfolio (MSRP)

**Objective:** Maximize Sharpe Ratio

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}$$

- $R_p$ : Portfolio return
- $R_f$ : Risk-free rate
- $\sigma_p$ : Portfolio standard deviation (risk)

**Optimization Problem:**

$$\max_{\mathbf{w}} \frac{\mathbf{w}^T \boldsymbol{\mu} - R_f}{\sqrt{\mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w}}}$$

- $\boldsymbol{\mu}$ : Expected returns vector
- $\boldsymbol{\Sigma}$ : Covariance matrix of asset returns
- Subject to:  $\mathbf{w}^T \mathbf{1} = 1$

**Challenge:**

- Non-linear objective function due to square root in the denominator, making the problem potentially non-convex.

**Workaround - Using Excess Returns:**

$$\max_{\mathbf{w}} \left( \mathbf{w}^T (\boldsymbol{\mu} - R_f \mathbf{1}) - \frac{\lambda}{2} \mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w} \right)$$

- Simplifies the optimization problem using excess returns over the risk-free rate.



# Maximum Sharpe Ratio Portfolio (MSRP) (optimal)

Lagrangian Formulation:

$$\mathcal{L}(\mathbf{w}) = \mathbf{w}^T(\boldsymbol{\mu} - R_f \mathbf{1}) - \frac{\lambda}{2} \mathbf{w}^T \Sigma \mathbf{w}$$

- $\lambda$ : Risk aversion parameter

First-Order Condition (FOC):

$$\nabla_{\mathbf{w}} \mathcal{L} = (\boldsymbol{\mu} - R_f \mathbf{1}) - \lambda \Sigma \mathbf{w} = 0$$

- Solve for  $\mathbf{w}$  to find the unconstrained solution:

$$\mathbf{w}_{unconstrained}^* = \frac{1}{\lambda} \Sigma^{-1}(\boldsymbol{\mu} - R_f \mathbf{1})$$

Normalization for Full Investment:

$$\mathbf{w}_{MSRP} = \frac{\mathbf{w}_{unconstrained}^*}{\mathbf{1}^T \mathbf{w}_{unconstrained}^*} = \frac{\Sigma^{-1}(\boldsymbol{\mu} - R_f \mathbf{1})}{\mathbf{1}^T \Sigma^{-1}(\boldsymbol{\mu} - R_f \mathbf{1})}$$

#### Portfolio Composition:

- $N$  risky assets with return vector  $\mathbf{r} = [r_1, r_2, \dots, r_N]^T$ .
- One risk-free asset (e.g., Treasury bills) with constant return  $R_f$ .

#### Portfolio Weights:

- Weights for risky assets:  $\mathbf{w} \in \mathbb{R}^N$ .
- Weight for risk-free asset:  $w_f$ .
- Budget constraint:  $\mathbf{w}^T \mathbf{1} + w_f = 1$ .

#### Portfolio Return:

$$r_p = \mathbf{w}^T \mathbf{r} + w_f R_f = \mathbf{w}^T (\mathbf{r} - R_f \mathbf{1}) + R_f$$

#### Excess Return:

$$\tilde{r}_p = r_p - R_f = \mathbf{w}^T (\mathbf{r} - R_f \mathbf{1}) = \mathbf{w}^T \tilde{\mathbf{r}}$$

- $\tilde{\mathbf{r}} = \mathbf{r} - R_f \mathbf{1}$ : Vector of excess return random variables.

#### Expected Excess Return and Variance:

$$\tilde{\mu}_p = \mathbf{w}^T \tilde{\boldsymbol{\mu}}, \quad \sigma_p^2 = \mathbf{w}^T \Sigma \mathbf{w}$$

- $\tilde{\boldsymbol{\mu}} = \boldsymbol{\mu} - R_f \mathbf{1}$ : Vector of expected excess returns.

#### Optimization Problem:

$$\min_{\mathbf{w}} \mathbf{w}^T \Sigma \mathbf{w}, \quad \text{subject to } \mathbf{w}^T \tilde{\boldsymbol{\mu}} = \tilde{\mu}_0$$

#### Lagrangian Function:

$$\mathcal{L}(\mathbf{w}, \lambda) = \mathbf{w}^T \Sigma \mathbf{w} + \lambda(\tilde{\mu}_0 - \mathbf{w}^T \tilde{\boldsymbol{\mu}})$$

#### First-Order Condition (FOC):

- Derivative w.r.t.  $\mathbf{w}$ :

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = 2\Sigma \mathbf{w} - \lambda \tilde{\boldsymbol{\mu}} = 0$$

#### Solve for $\mathbf{w}$ :

$$\mathbf{w} = \frac{1}{2} \lambda \Sigma^{-1} \tilde{\boldsymbol{\mu}}$$

#### Determine $\lambda$ Using Constraint:

- Derivative w.r.t.  $\lambda$ :

$$\frac{\partial \mathcal{L}}{\partial \lambda} = \tilde{\mu}_0 - \mathbf{w}^T \tilde{\boldsymbol{\mu}} = 0$$

- Substitution yields:

$$\lambda = \frac{2\tilde{\mu}_0}{\tilde{\boldsymbol{\mu}}^T \Sigma^{-1} \tilde{\boldsymbol{\mu}}}$$

#### Optimal Weights:

$$\mathbf{w}^* = \tilde{\mu}_0 \frac{\Sigma^{-1} \tilde{\boldsymbol{\mu}}}{\tilde{\boldsymbol{\mu}}^T \Sigma^{-1} \tilde{\boldsymbol{\mu}}}$$


#### Applying Full Investment Constraint:

- For  $\mathbf{1}^T \mathbf{w} = 1$ :

$$\mathbf{w}_{MSRP} = \frac{\Sigma^{-1}(\boldsymbol{\mu} - R_f \mathbf{1})}{\mathbf{1}^T \Sigma^{-1}(\boldsymbol{\mu} - R_f \mathbf{1})}$$

- Confirms the closed-form solution for MSRP.

An  
Alternative  
Derivation  
for MSRP  
(optional)



# Connecting MVO Weights with Other Portfolios

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Final Expression for Optimal Weights:

$$\mathbf{w}_{MVO} = \frac{1}{\lambda} \Sigma^{-1} \boldsymbol{\mu} - \left( \frac{1}{\lambda} (\boldsymbol{\mu}^T \Sigma^{-1} \mathbf{1} - \lambda) / (\mathbf{1}^T \Sigma^{-1} \mathbf{1}) \right) \Sigma^{-1} \mathbf{1}$$

Weights as a Combination of GMVP and MSRP:

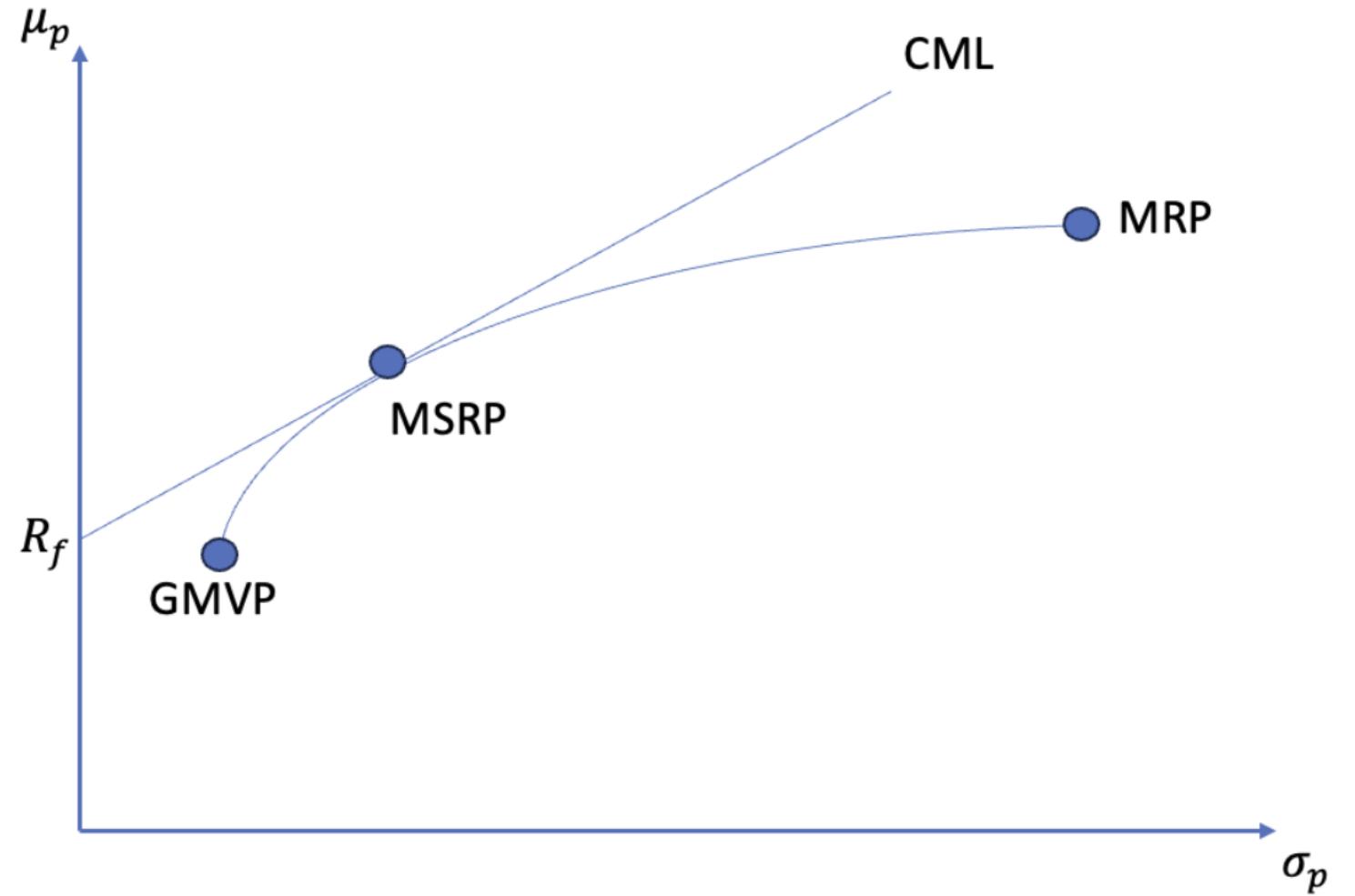
$$\mathbf{w}_{MVO} = \mathbf{w}_{GMVP} + \left( \frac{\mu_{GMVP}}{\lambda \sigma_{GMVP}^2} \right) (\mathbf{w}_{MSRP} - \mathbf{w}_{GMVP})$$

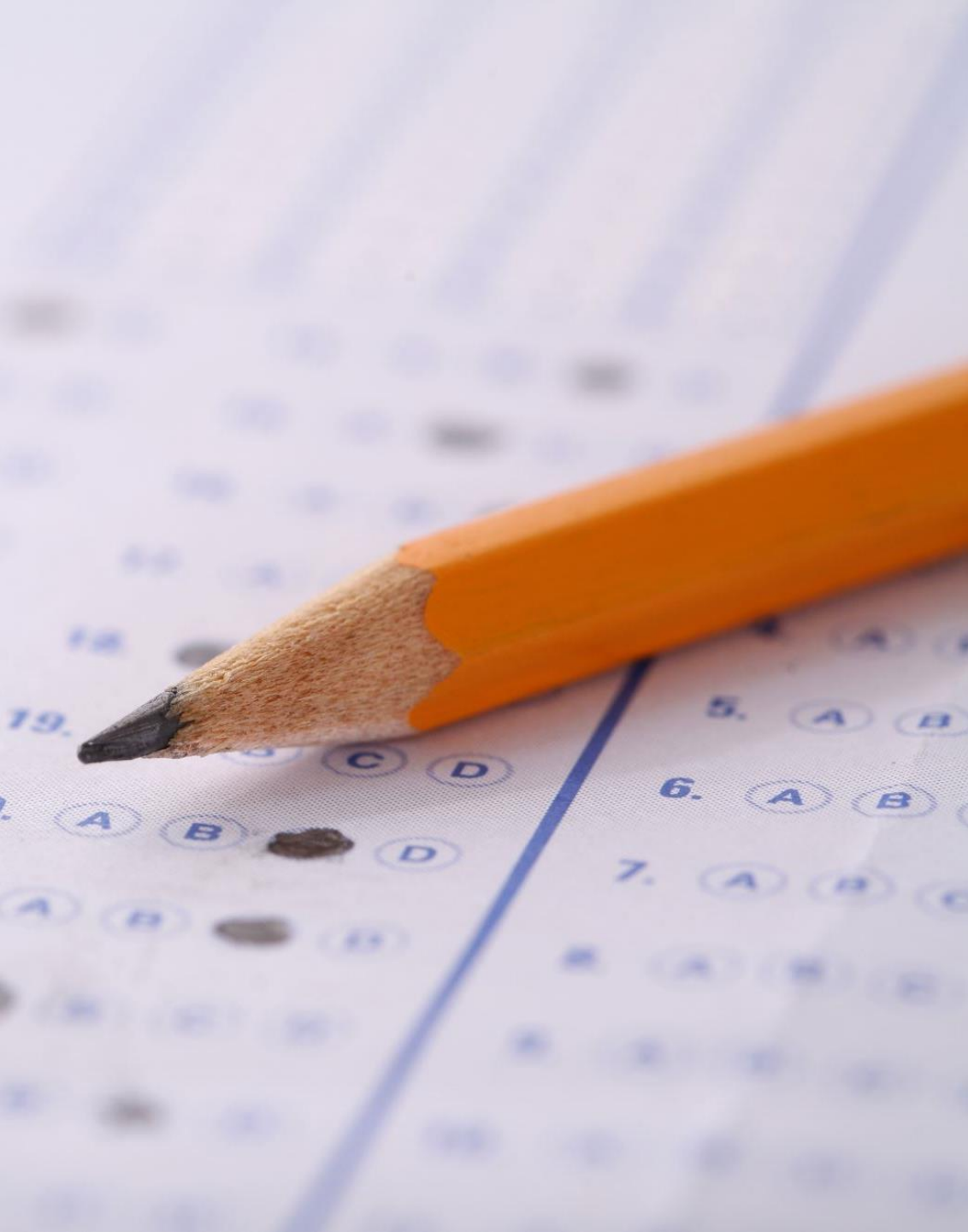
Key Insights:

- $\mathbf{w}_{MVO}$  is a blend of the Global Minimum Variance Portfolio (GMVP) and Maximum Sharpe Ratio Portfolio (MSRP).
- The allocation adjustment between GMVP and MSRP depends on the risk-return trade-off parameter  $\lambda$ , GMVP's expected return ( $\mu_{GMVP}$ ), and its variance ( $\sigma_{GMVP}^2$ ).

# Comparing Common Portfolios

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# In-class quiz

- Q8-10

```
mirror_mod = modifier_ob.  
#set mirror object to mirror  
mirror_mod.mirror_object  
operation == "MIRROR_X":  
mirror_mod.use_x = True  
mirror_mod.use_y = False  
mirror_mod.use_z = False  
operation == "MIRROR_Y":  
mirror_mod.use_x = False  
mirror_mod.use_y = True  
mirror_mod.use_z = False  
operation == "MIRROR_Z":  
mirror_mod.use_x = False  
mirror_mod.use_y = False  
mirror_mod.use_z = True
```

```
#selection at the end -add  
mirror_ob.select= 1  
modifier_ob.select=1  
context.scene.objects.active  
("Selected" + str(modifier_ob))  
mirror_ob.select = 0  
= bpy.context.selected_object  
data.objects[one.name].select  
print("please select exactly
```

--- OPERATOR CLASSES ---

```
types.Operator):  
on X mirror to the selected  
object.mirror_mirror_x"  
mirror X"
```

```
context):  
context.active_object is not
```

# Coding session

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# Group Homework – Implementing Common Portfolio Strategies

- Obtain financial data (at least three assets) of your own choice
- Strategy Implementation:
  - Implement at least three strategies
  - Use rolling window approach to obtain out-of-sample results
  - Report final performance metrics (CAGR, annual volatility, Sharpe ratio, and max drawdown)

Due one day before class starts next week



# Homework



Watch/review video tutorials  
and class recording



Post learning reflections and  
questions if any



Complete group homework