Date March 10th, 2022

IPO

first time offering shares = initial public offering

SEO

second and so on time offering shares = seasoned equity offering

Sessional II

from pandas-datareader import data as web

read from web — take this data — from this website

- msft = web.DataReader('MSFT', 'yahoo', '2012-0-01', '2013-12-30')

Shifting and lagging time-series data:

each time series

msft	H	L	O	C	V	Adj
Jan 1 '12						
Jan 2 '12						
Jan 3 '12						

msft remains same but time period is changing, dates.

cross-sectional data: msft changes but date remains same

	msft	aapl	yho
Jan 1 '12			

Pandas: panel data analysis

where both time-series + cross sectional data

1.063
1.065

Date

Shifting time series

mftAC = msft ['Adj Close']

- shift_forward = mftAC.shift(1) →

2012-01-03	1	→	-01-03	NaN
04	2		01-04	1
05	3		01-3	2

last value gets lost.

- shift_backward = msftAC.shift(-2)
  (2 indices back)

2012-01-03	1	→	2012-01-03	3
-04	2		-04	
-05	3		-05	

- Shift_1sec = msftAC.shift(1, freq = 'S')
  1 second — seconds
  shift from 1 sec forward
  (no value lost, no NaNs)

Theory

Investors
- → Return ↑
- → Risk ↓

net return : when we subtract -1 from returns val
→ gross return : own investment + profit

Google

returns

Jan-1-2022 → \$10 → -1 = 0.1 we standardise using ratios.
-2- → \$11 → $\frac{11}{10}$ = 1.10 we can see return on
-3- → \$11.5 → 1.045 -1 = 0.45 our \$1 investment
-4- → \$10.25 → 0.89 -1 = -0.11
-5- → \$12 → 1.17 -1 = 0.17

1.1 means yesterday the share had \$1 now today its was \$1.1 worth

1.1 × 1.045 → 1.1495
1.1495 × 0.89 → 1.023
1.023 × 1.17 → 1.197 - 1
= → = 0.197

$\frac{12}{10}$ = 1.2 ←

commulative Product ≈ 0.2 ←

+ 0.1
+ 0.45
− 0.11
+ 0.17
0.205

→ commulative return

Date		Return	Net return	
1-Jan-22 →	$10 →	~~[illegible]~~	~~[illegible]~~	Cum product
2 →	11 →	$\frac{11}{10} = 1.1$	$-1 = 0.1$	
3 →	11.5 →	$11.5/11 = 1.045$	$-1 = 0.045$	$1.1 \times 1.045 = 1.1495$
4 →	10.25 →	$10.25/11.5 = 0.89$	$= -0.11$	$1.1495 \times 0.89 = 1.023$
5 →	12 →	$12/10.25 = 1.17$	$+\ 0.17$	$1.023 \times 1.17 = 1.197$
			0.205	$1.197 - 1 = 0.197 \approx 0.2$

$\frac{12}{10} = 1.2$ ← commulative return

- msftAC / msftAC.shift(1) → first shift
  Then divide

10		NaN		NaN
11	shift →	10	÷ →	11 / 10
11.5		11		11.5 / 11
10.25		11.5		10.25 / 11.25

- np.cumprod(msftAC / msftAC.shift(1)) → gives value ~~at last date~~ 30-Dec-23 of ~~stock~~ $1 that was invested on Jan 1st
  ↓
  commulative product

- can plot cumprod and compare investment strategies of diff companies

- net return = msft / msft.shift(1) - 1

net return.asfreq('H') → gives hourly

12am	1.12
1am	NaN
2am	NaN

.asfreq('H', method = 'ffill')

Jan 1	12am	1.12
	1am	1.12
	2am	1.12
		1.41

Scanned with CamScanner

Date March 30th, 2022.

Resampling of time Series:
DIY
New NB
Technical Analysis → • which stock to buy + which to sell.
• finding pattern in charts / graphs
+ determine which stocks to buy or sell

find undervalued stocks + investing in them = Fundamental Accounting

$10 item is undervalued to $8, you buy it after you research that $10 is true value so it will converge to $10 + it will give profit of $2.

---

cc = 'BTC - USD' → bitcoin USD
tickers = ['GOOG', 'AMZN', 'AAPL'].

```
plt.figure(figsize=(12, 8))
ax1 = plt.subplot2grid((7,1), (0,0), rowspan=4, colspan=1, title='Amazon')
ax2 =    ''     ((7,1), (5,0),     = 3,     =1, sharex=ax1

ax1.plot(data['Adj Close'], label='Price')
 ax2.bar(data.index, data['Volume'], label='Volume')

ax1.legend()
 ax1.legend(loc='upper right')
plt.show
```

Date

- 'import matplotlib.dates as mdates

- Jan 2020 → Sept 2020 trend analysis

$\frac{Sept}{Jan}$ → almost 78% return

= 1.78 → $1 in Jan is now of worth $1.78 in Sept

Moving Averages : → to smooth out fluctuations in graphs (prices)

→ first 20's mean

```
data['SMA 20'] = data ['Adj Close'] .rolling(20) .mean()
  "  [' "  120'] = "              .rolling(120) .mean()
```

longer trend

SMA 20 surpasses / exceeds SMA 120 → signal = buy

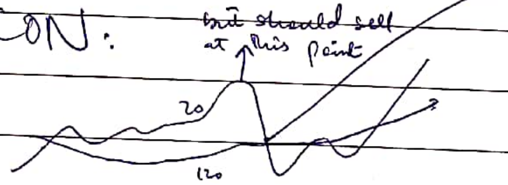
↓ shorter trend

hold it till till 20>120

when 120 > 20 almost, sell it + make profit

- investors are demanding more + more shares
- buying pressure
- price goes up so buying signal that in near future price will go up

CON:



- buy + hold is better than SMAs
- but in moving avgs your rule SMAs do better than buy + hold

data = data.drop (columns = ['High']) → remove unneeded cols

Date

- Shift vals of Adj Close
- ~~to~~ after shift 03-01 (24.7) — after shift 02-01 (24.9) → -ve value tells loss

after shift 0~~2~~-01 24.9

March 31st, 2022.

$\frac{24.7}{24.9}$ → 0.99 → ~~profit~~ $1's worth

daily return

data['invested_SMA'] = np.where(data['SMA20'] > data['SMA120'], 0, 1)

data(data['invested_SMA'] == 1)

↓

we want cumreturn in this frame of time

$1 grow from $1 to $2.9

a	a
b	a x b = c
d	c x d = e
f	e x f = g

} commulative return

Buy + hold strategy

data['buy_hold'] = np.cumprod(data['change'])

$1 grew from $1 to $4.~~8~~. in example

so, buy + hold is better than SMA. maybe he gives 1 or 2 x. but SMA (→ simple moving avg) would multiple buys + sells so more time paid we find cumprod of all data so we can plot it + see the graph. If we do $\frac{2012}{2011}$ then gives only one value.

Date

Exponential weigted moving avg:

in notebook — gives values from start not from row 20 or 120 like SMA.

EWM12 > EWM26 → buy
< → sell

$1 to $7 ⟶ commulative product

- EWM better than buy + hold which is better than SMA for AAPL only. It varies for every firm.

- Example Comparison of Amazon, coke, Tesa, MSFT, apple in notebook

MPT = modern portfolio theory
Harry Markowitz (1952)
William Sharpe (1964)

μ population parameter
$\bar{x}$ sample statistic

April 6th, 2022 — Probabilistic Model

$E(R_A) = 15\%$
exp. return of A

Prob. P_i	stock returns X_i	P_iX_i
0.1	30%	3%
0.2	25%	5%
0.4	18%	7.2%
0.2	-10%	-2%
0.1	-25%	-2.5%
		10.7%

10.7% → average, expected return

we don't divide by 5 cuz that would mean we give equal weight to all returns which is wrong

Std. deviation of small sample space + not population $= \sqrt{\dfrac{\Sigma(x_i - \bar{x})^2}{N-1}}$

$\dfrac{(3-10.7)^2 + (5-10.7)^2 \ldots}{4}$

↓ if population? then 'N'
'μ'

μ	$\bar{x}$
30%	25%
	18%

↓ ~~underestimation~~

we do N-1 to ~~decrease denominator~~ + increase variance which decreases biasness in sample.

- if we have past returns + not probabilistic returns then we take avg of past returns

$E(R_{Tesla}) = 15\%$ $\qquad$ $E(R_{BoA}) = 10\%$

$\sigma_{Tesla} = 17\%$ $\qquad$ $\sigma_{BoA} = 9\%$

- investing in BoA because less risk (9%) = conservative approach, can't tolerate higher risk
- investing in Tesla cuz more exp. return but more risky = risk tolerance
- ~~make portfolio: contains shares of proportion of both BoA + Tesla~~ ~~(different risk aversion levels)~~ = Diversification

simple finance : Return & Risk
Portfolio : no compromise on return + decrease risk

Date

Portfolio Scenario

60% investment in Tesla, 40% in BoA

$$E(R_p) = \underbrace{W_{Tesla}}_{\text{weight}} \cdot E(R_{Tesla}) + W_{BoA} \cdot E(R_{BoA})$$

$$= 60\% \times 15\% + 40\% \times 10\%$$

$$Cov_{T,BCA} = \sigma_T \cdot \sigma_{BCA} \cdot corr_{T,BCA}$$

$$\sigma_p^2 = W_T^2 \cdot \sigma_T^2 + W_{BoA}^2 \cdot \sigma_{BCA}^2 + 2 W_{Tesla} W_{BoA} Cov_{T,BoA}$$

$$= 60\% \cdot 17\% + 40\% \cdot 9\%$$

$Cov_{T,BoA}$ b/w returns of A, B

~~$\sigma_T \cdot \sigma_{BoA}$~~

~~Cov can be replaced by corelation $_{T,BoA}$~~

covariance : what happens to the other variable when 1st variable changes

+ve covariance

GPA	# hours
1.1	1
2.3	2
3.0	3
3.5	5

+ve ↓ +ve ↓

corelation : -1 — 0 — 1

-ve relation: if return of one firm ↑ other's return ↓ — 1st inc. by 1%, 2nd dec. by 1% — weak

no relation

+ve relation: one ↑ by 1%, 2nd ↑ by 1% — Strong

Example: covariance has no definition so value of 900 can't tell if relation b/w variable is strong or weak or not. Corelation tells us about relationship b/w variables.

- In σ_p^2, if cov. is -ve than risk is decreased

$E(R_p) \uparrow \quad \sigma_p^2 \downarrow$.

This is why portfolio is better than investing only in Tesla or BoA

- If we change weights, exp. return$_p$ + σ_p^2 changes as well so this tells we can make infinite portfolios. It is crucial to find best portfolio.

Assign 2 { weighted moving avg, simple moving avg, buy + hold for any 1 firm

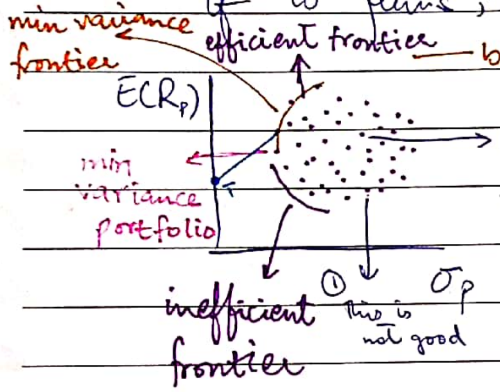
Date April 7th, 2022.

3 firms

$$\sigma_p^2 = W_T^2 \cdot \sigma_T^2 + W_{BAC}^2 \cdot \sigma_{BAC}^2 + W_{AAPL}^2 \cdot \sigma_{AAPL}^2 +$$
$$+ 2 W_T \cdot W_{BAC} \, cov_{T,BAC}$$
$$+ 2 W_T \cdot W_{AAPL} \, cov_{T,AAPL}$$
$$+ 2 W_{BAC} \cdot W_{AAPL} \, cov_{BAC,AAPL}$$

- covariance Tells us more about risk.

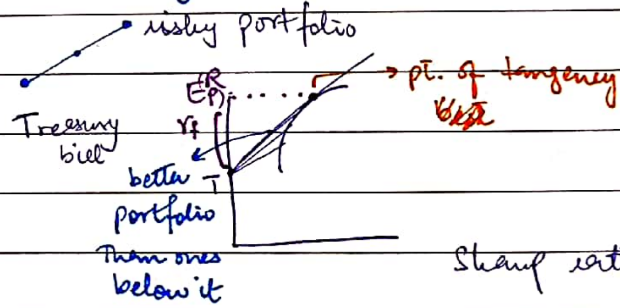
If 10 firms, 10 Ws and 90 Covs → more imp!



- investors are interested in maximising return + minimising risk
- from min variance frontier investors choose portfolio which falls in their preferred risk. Risk aversion level

William Sharp

T : treasury bills



Sharp ratio $= \dfrac{E(R_p) - r_f}{\sigma_p}$; r_f → risk free rate ; $= 1.3$

sharp ratio at tangent line of portfolios is higher

for every 1 unit of std. your return ↑ 1.3 above risk premium

Scanned with CamScanner

Date April 13th, 2022.

Variance Covariance Matrix

	W_A A	W_B B
W_A A	$W_A \cdot W_A = W_A^2$ $\sigma_A \cdot \sigma_A = \sigma^2_A$	$W_A \cdot W_B$ $\sigma_A \cdot \sigma_B$ $cov_{A,B}$
W_B B	$W_B \cdot W_A$ $\sigma_B \cdot \sigma_A$ $cov_{A,B}$	$W_B \cdot W_B = W_B^2$ $\sigma_B \cdot \sigma_B = \sigma^2_B$

In covariance
self variance

A's A's

25 25

∴ when we calculate A's covariance w/ A it's equal to variance of A

- variance

Date # Portfolio Optimization

- returns → .pct_change()
- returns.mean() → investing $1 will give return $0.002 on daily returns

- random weights
  np.sum(random weights)
- sharp ratio maximum = best portfolio

$E(R_p)$ = daily mean return$_T$ * weight$_T$ + dMR$_{BAC}$ * W$_{BAC}$.

(== = 0.001428 → $1 will give $0.0014 return

np.sum(returns.mean * weights)

// * 252 = 0.36
(stock market is open) for days in a year

- $1 investment gives $0.36 returns annually when user invests 0.528 in T and rest in BAC.
  0.472

36% per annum

- returns.cov() ← covariance matrix

- weights.T

Scanned with CamScanner

stock mkt is open for 252 days/year

Date April 20th, 2022

$$\text{sharp ratio} = \frac{\text{return}}{\text{std (risk)}}$$

$$\sigma_p^2 = W_A^2 \sigma_A^2 + W_A 1 \ldots$$

variance

$\sqrt{\sigma^2} \rightarrow$ gives standard deviation/risk

annual return 0.31
risk 0.32

- std + variance both are measures of spread/dispersion so both can be used for risk
- but std is used cuz diff. in interpretation.
- variance units in square so difficult.

Next year return is going to be 0.31

\$ 100 $\rightarrow$ to 0.31 \$31

actual return could deviate by 0.32

31% + 32.8% = 64%

31% − 32.8% = −1.5% $\rightarrow$ −1.5% to 64%

Example: $E(GPA) = 3.3$

data points $\sigma = 0.5 \rightarrow$ spread/deviation

$3.3 + 0.5 = 3.8$

$3.3 - 0.5 = 2.8$

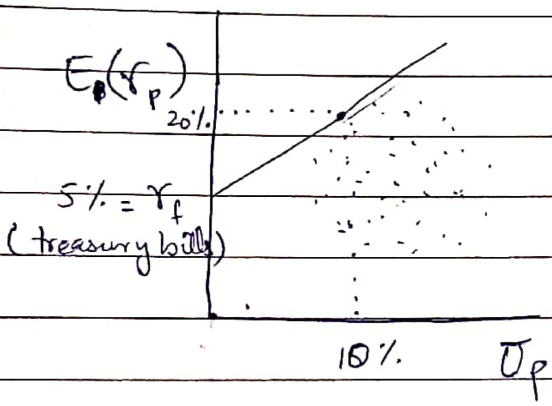
mean = 3.3
equal to E(GPA)

Date April 21st, 2022.

risk free rate'

annual return − risk free rate

$$\text{sharpe ratio} = \frac{\text{annual return} - r_f}{\text{portfolio std}}$$



risk premium: user ~~willing~~ getting ↑ return are we willing to take 10% risk

$$\frac{E(r_p) - r_f}{\sigma_p} = \frac{20-5}{10}$$

$$= \frac{15}{10} = 1.6\%$$

'interpret ~~consider~~ it as 1

'~~interpret~~ ~~consider~~ it for numerator

minimum risk / variance portfolio:
having the minimum risk in datapoints

1% risk increase → return increases by 1.5%.

1% risk → return by 1.2

1.5% one is better portfolio