Practical Big Data Analytics

* Michael.Burgess(@qa.com)

~~1.30 — 4.30~~

9.30 — 4.30 (4 - 4.30)

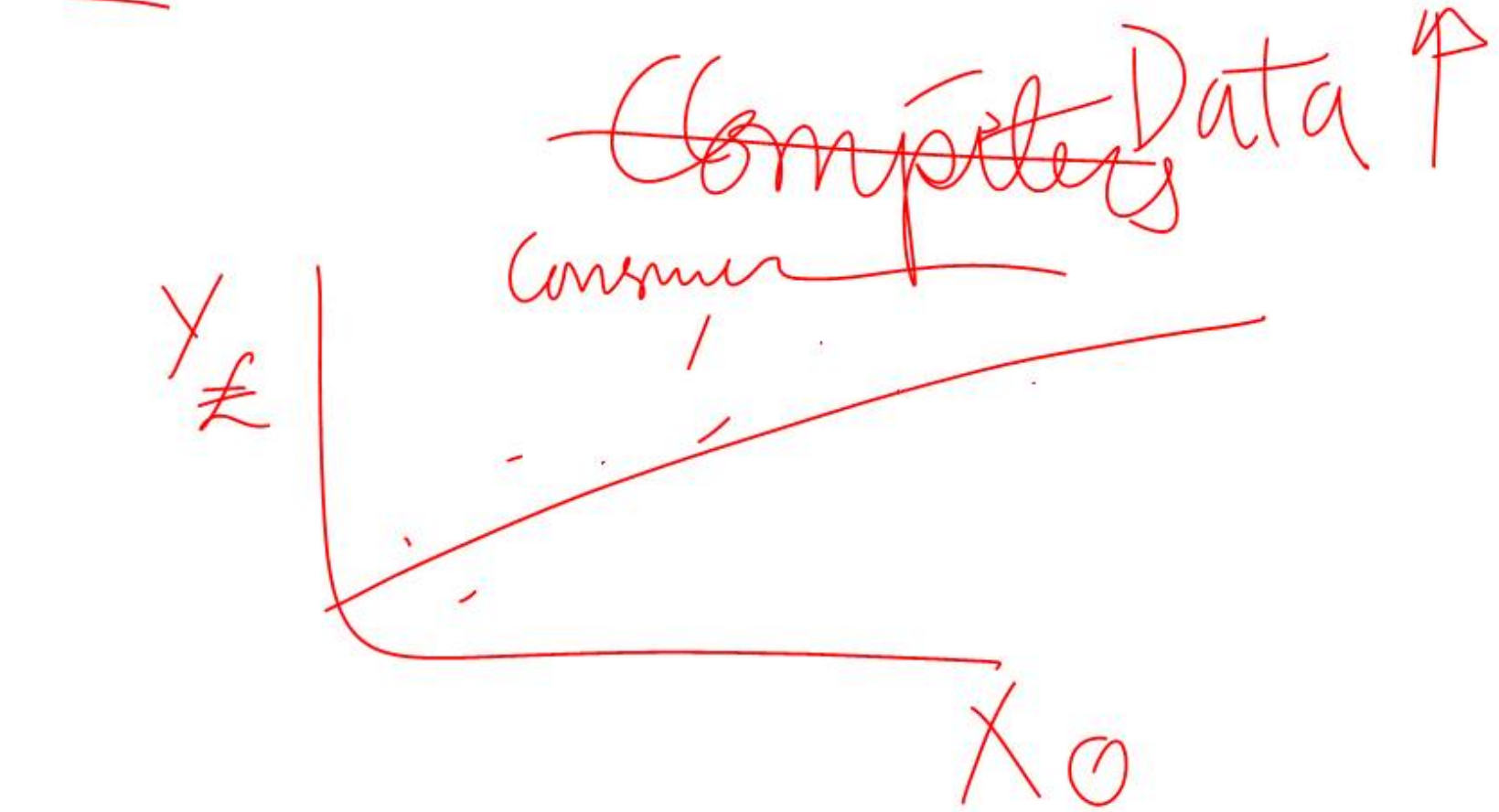
The Skills To Succeed

Train_AP

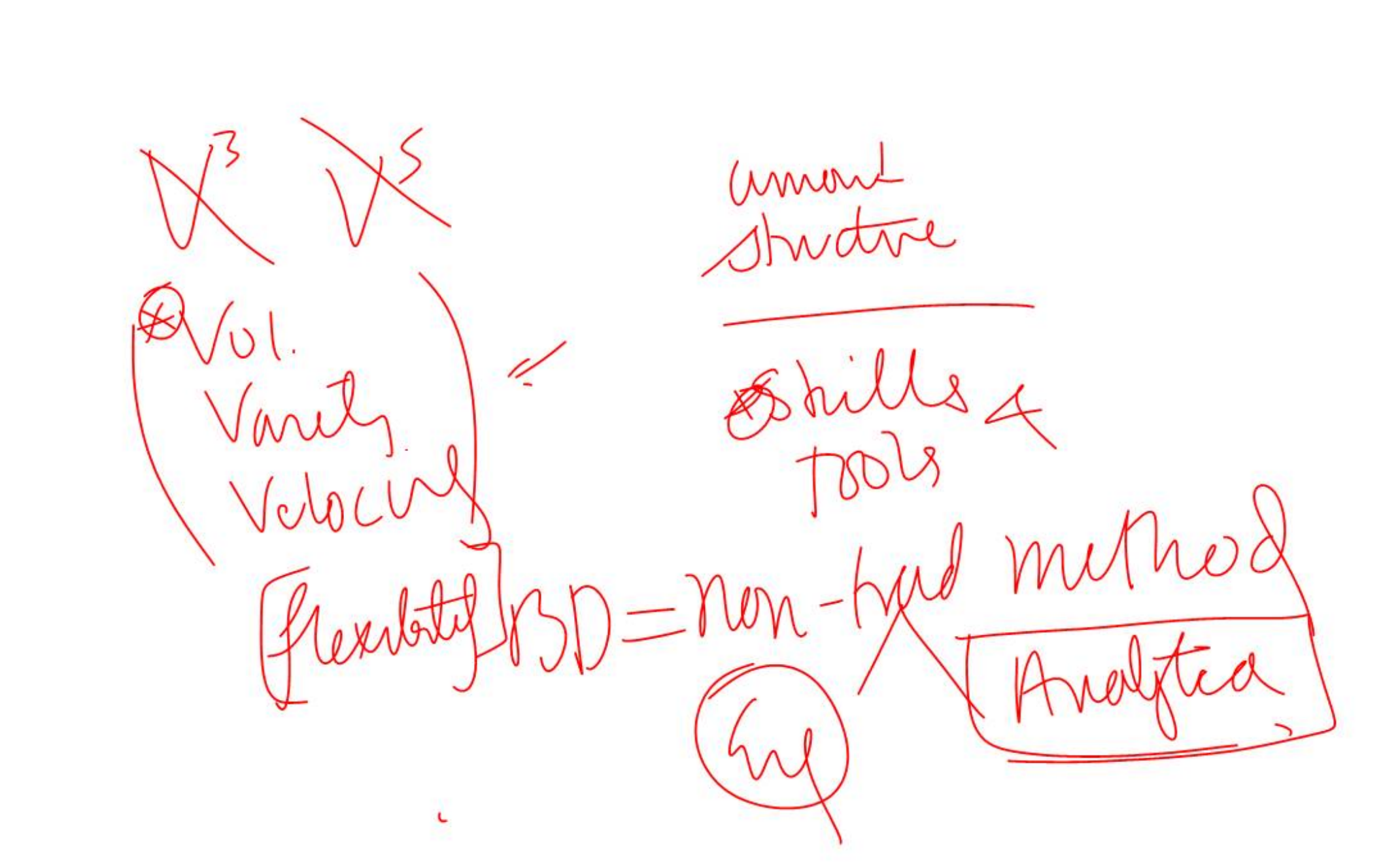
c.12/ 1pm

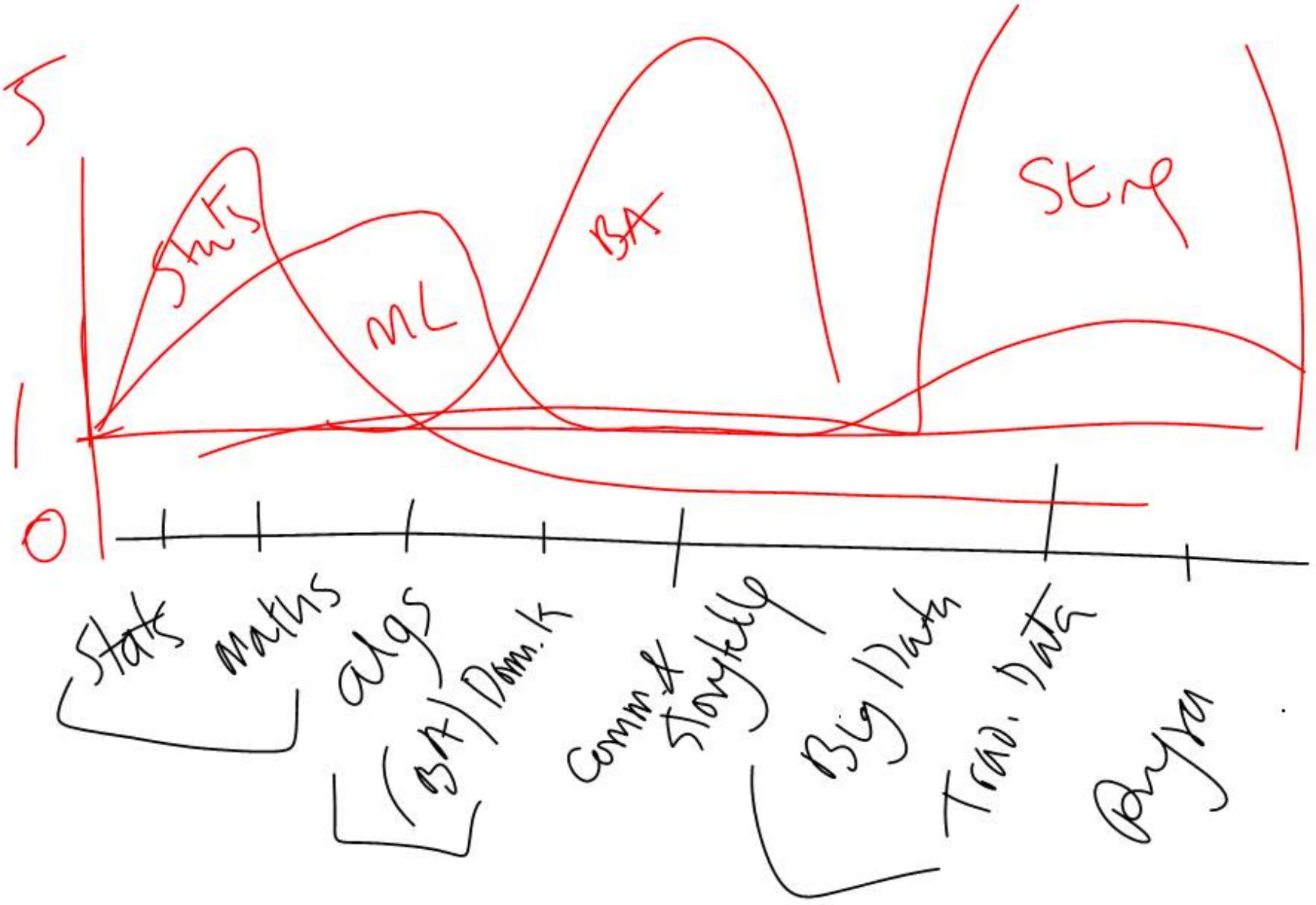
11am

c — 2.30pm


~~Computers~~ Data ↑
Consumer
Y £
X ⊙


Computational
Statistical
Big Data
Interpretup
Daten
NoSQL
AI
Insight vs. Automation
Analyst. &
Data
Inf
Science
Interesse → Produkt


V3
V5
Vol.
Variety.
Velocity
Current structure
Skills & tools
Flexibility
BD = Non-hard method
Analytical


5
1
0
Stats
ML
BA
Stop
Stats
maths
algs
(BA) Dom. k
Comm & Storytelling
Big Data
Trad. Data
Progra

1 pm

- Quick Review
- May need QAPYTH3, or eq.
- Wrap up python2 — fns — import (#2)
- Courseware Review

→ tinyurl.com/bda-10-02-20

√[√>5]

In python.

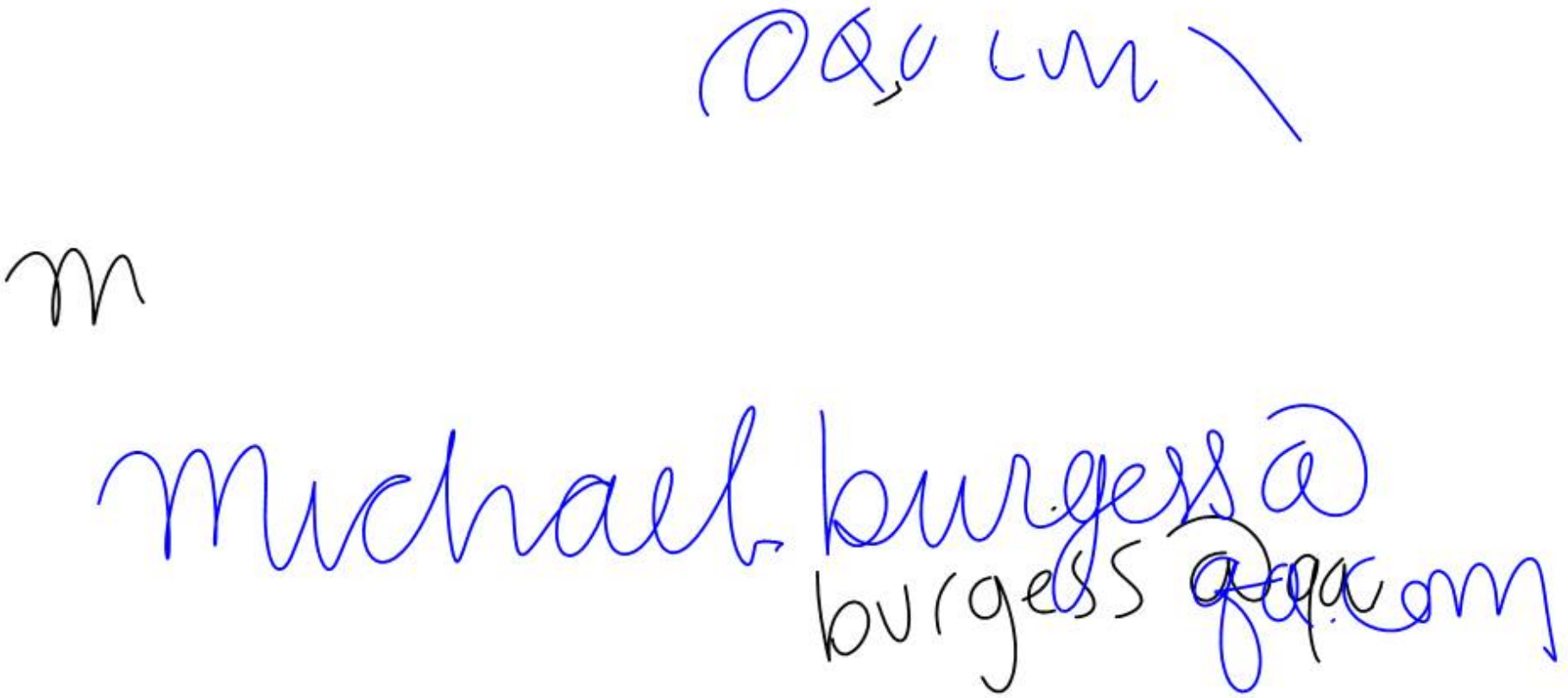
dir(x) ← lists all operations on x

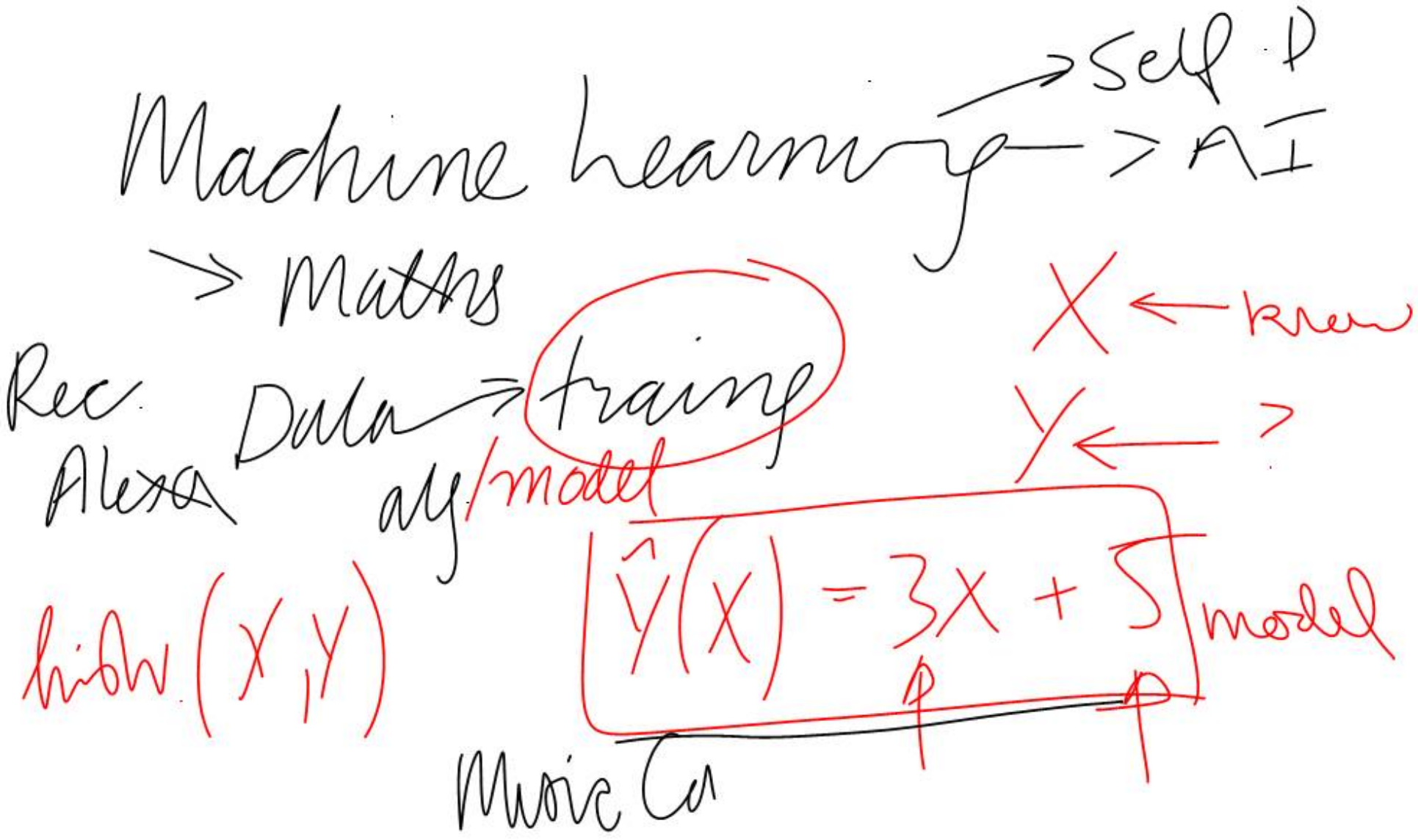
Eg dir(dataframe)

...

read_csv()

to_csv()


michael.burgess@
burgess.qaq.com


Machine learning
self P
AI
Maths
Rec
Alexa
Data
training
algorithm/model
X
known
Y
?
$\hat{Y}(X) = 3X + 5$
model
hidden (X, Y)
Music Co

Computational Stat –

Inference

Parameter Reporting

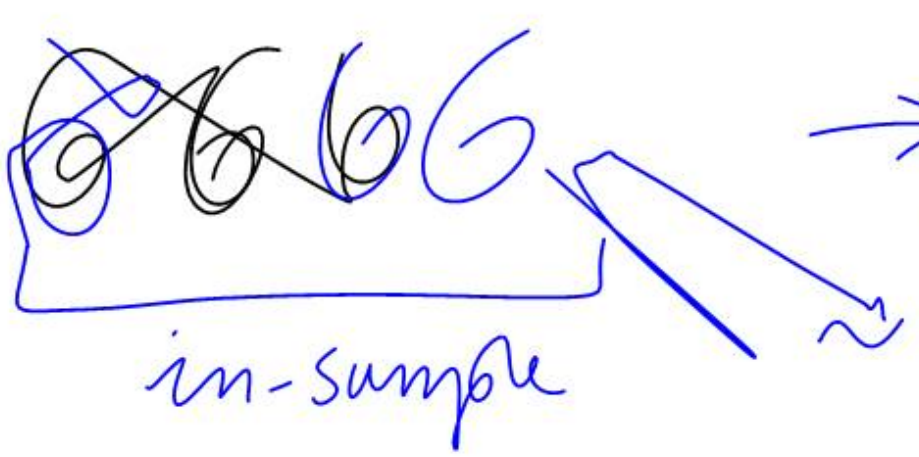
AI ?

– 90s

– 50s

00s

```
if (@ > 18):
    open()
else
    closeUX
```



£ UK ≠ € FR

① in ~ out

② in ≠ out ← unsafe

Fraud

anti

ML

1) Sup. learny

historical (X, Y) —learny / traing→ $\hat{y}(X)$ $\min \text{Loss}(\hat{Y}, Y)$

Regression ← $\hat{Y} \in \mathbb{R}$

classification. $\in \{-1, +1\}$ Binary Class

$\in \{0, 1 \dots 5 \dots\}$

2) Unsup.

t_1 t_2 t

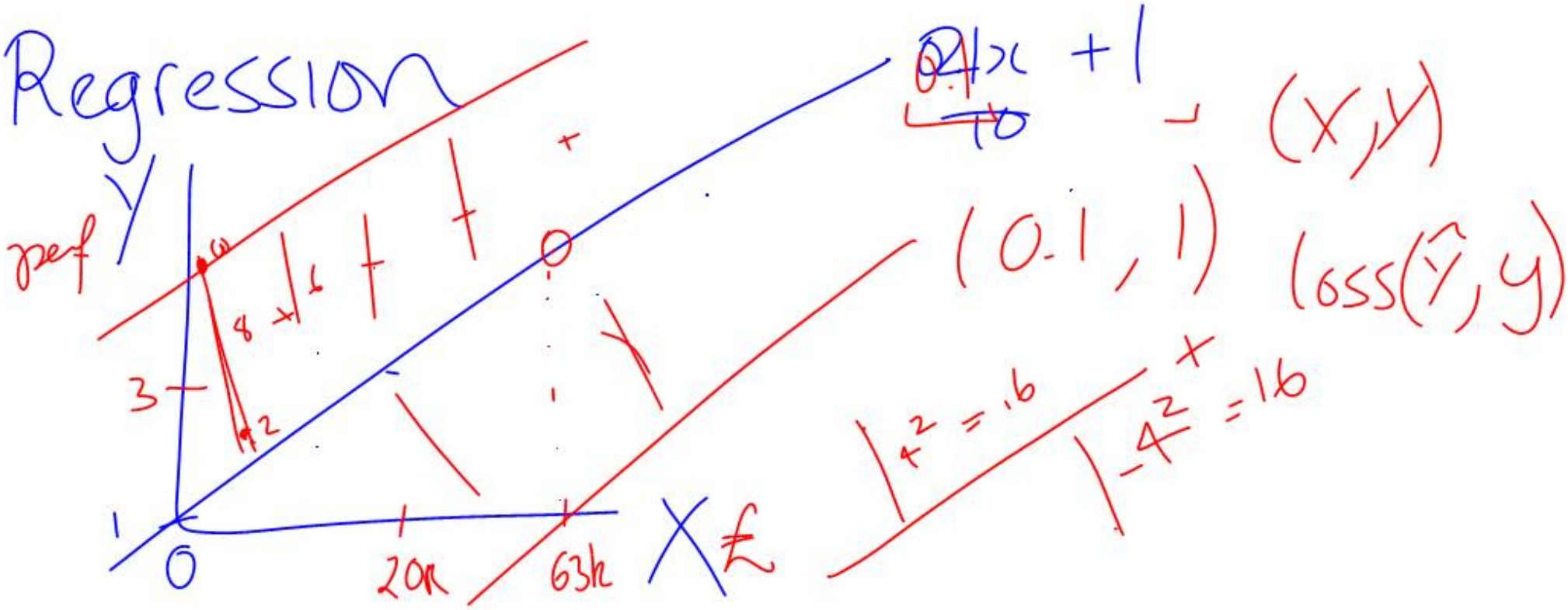
(X_1, X_2, X_3)

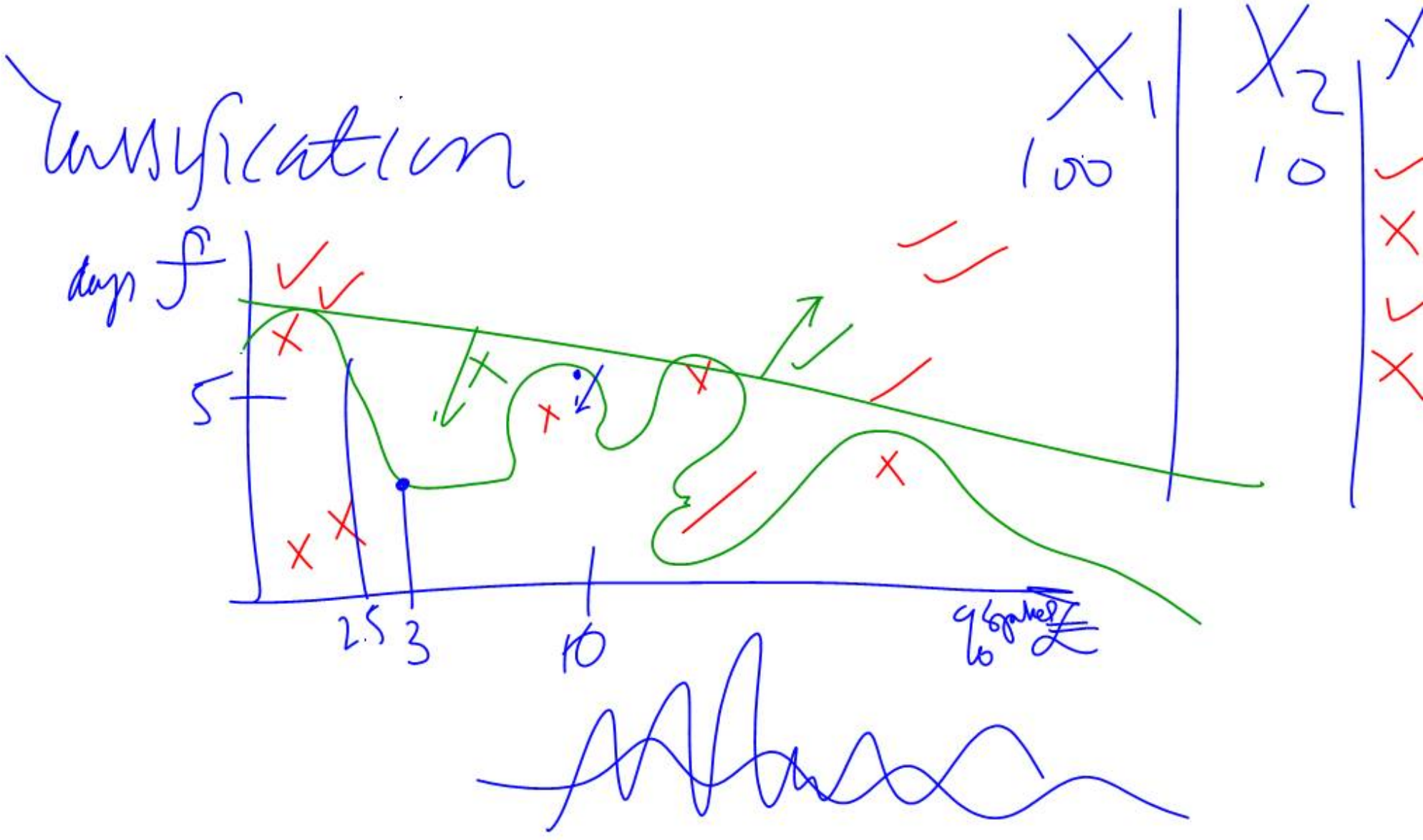
① Simplify (Dim. Reduction)

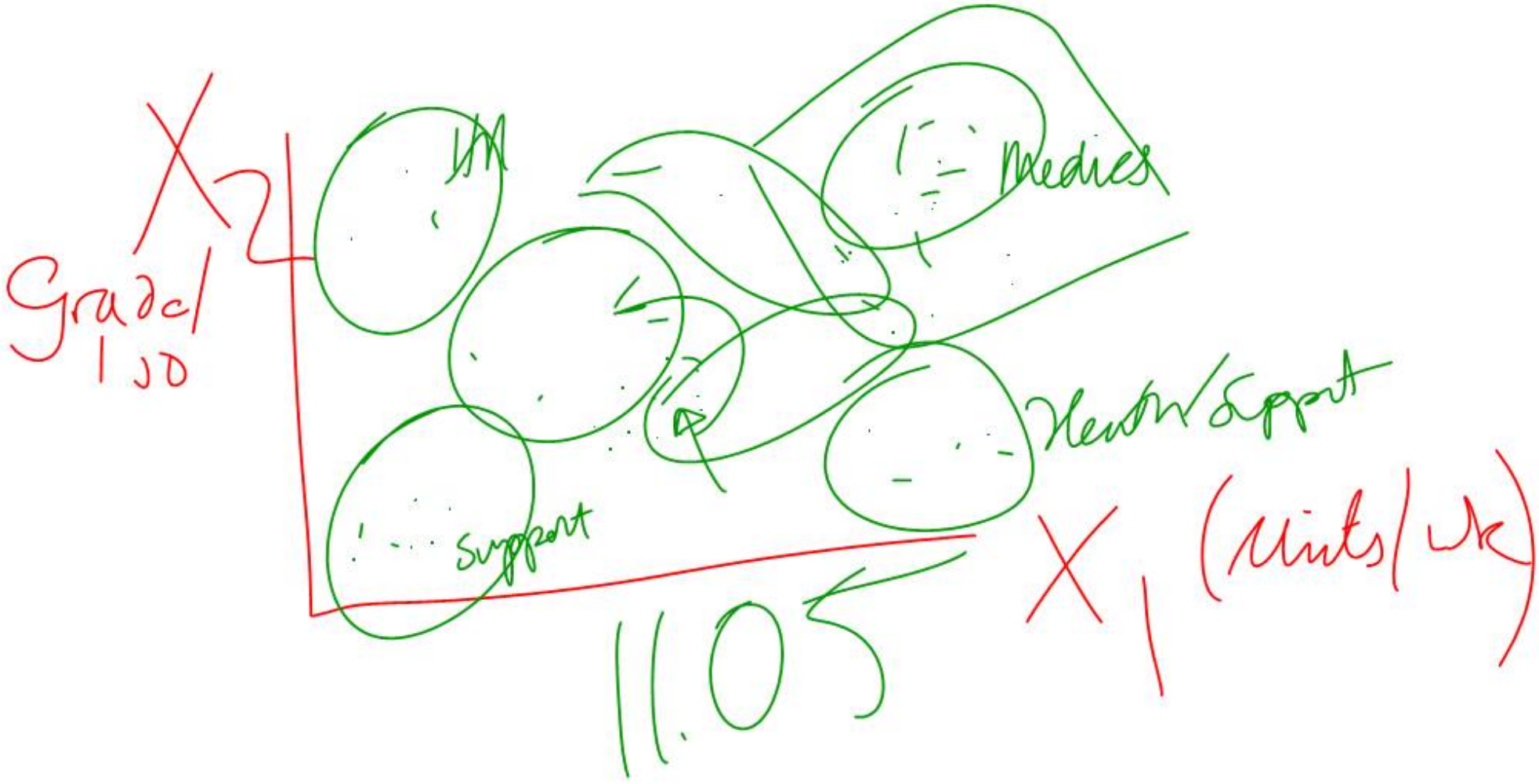
② Common Occurrence

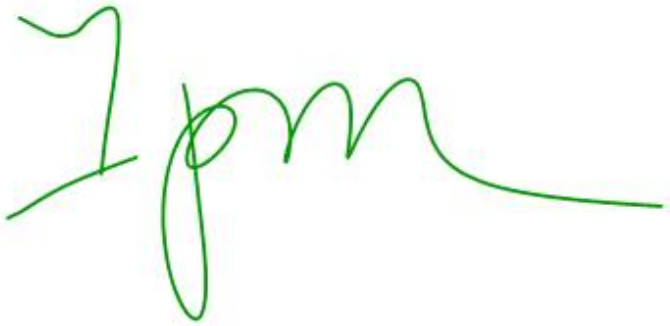
$P(X, X, X)$

Regression




X1
X2
100
10
5
2.5
3
10


X2
Grade/
150
Medical
Mental Support
Support
11.05
X1 (Units/wk)



(x^i, y^i)

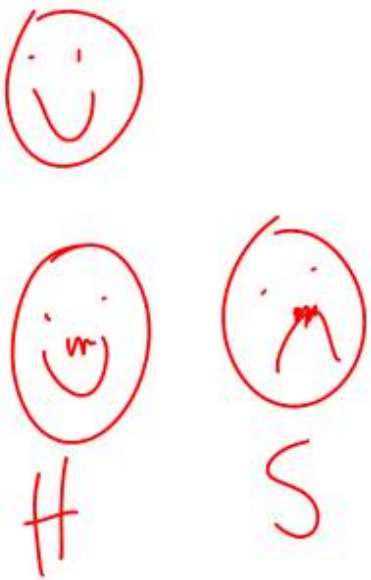
data model
Stat model — assoc
Expl

$\hat{y}(x_i, w) = w_1 x_1 + w_2 x_2 + w_3$

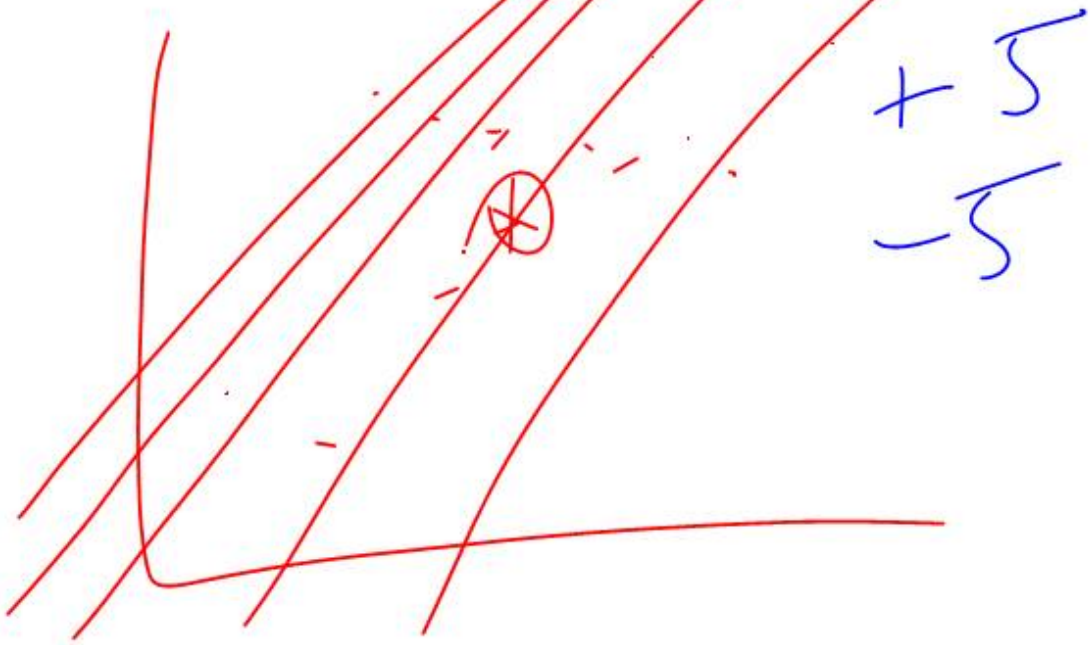
var — parameters

↘ a single number

Causal


H
S

$$loss(\hat{y}, y) = (\hat{y} - y)^2$$



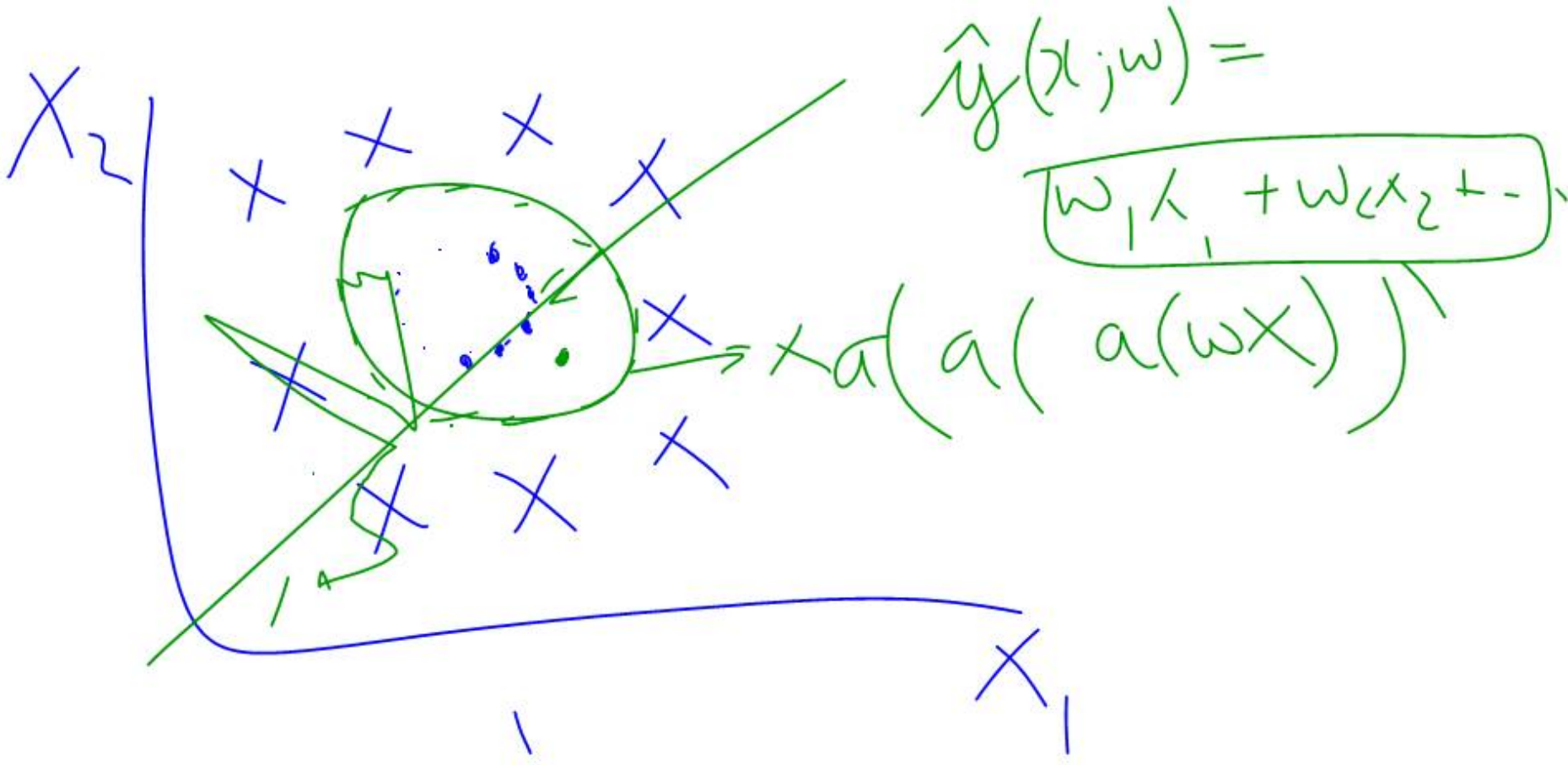
$y \in \mathbb{R}$

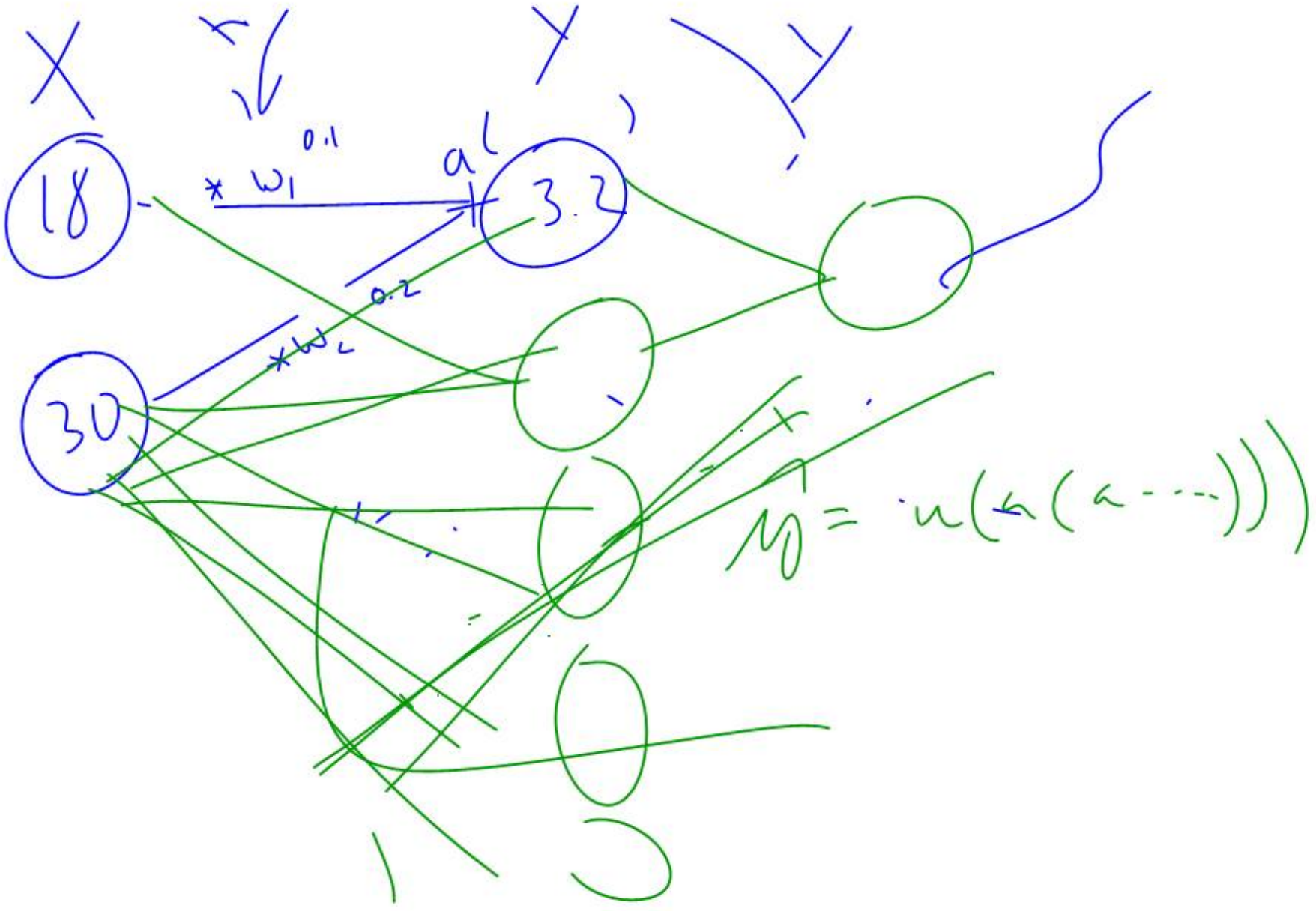
$x_1, x_2 \ldots \in \mathbb{R}$

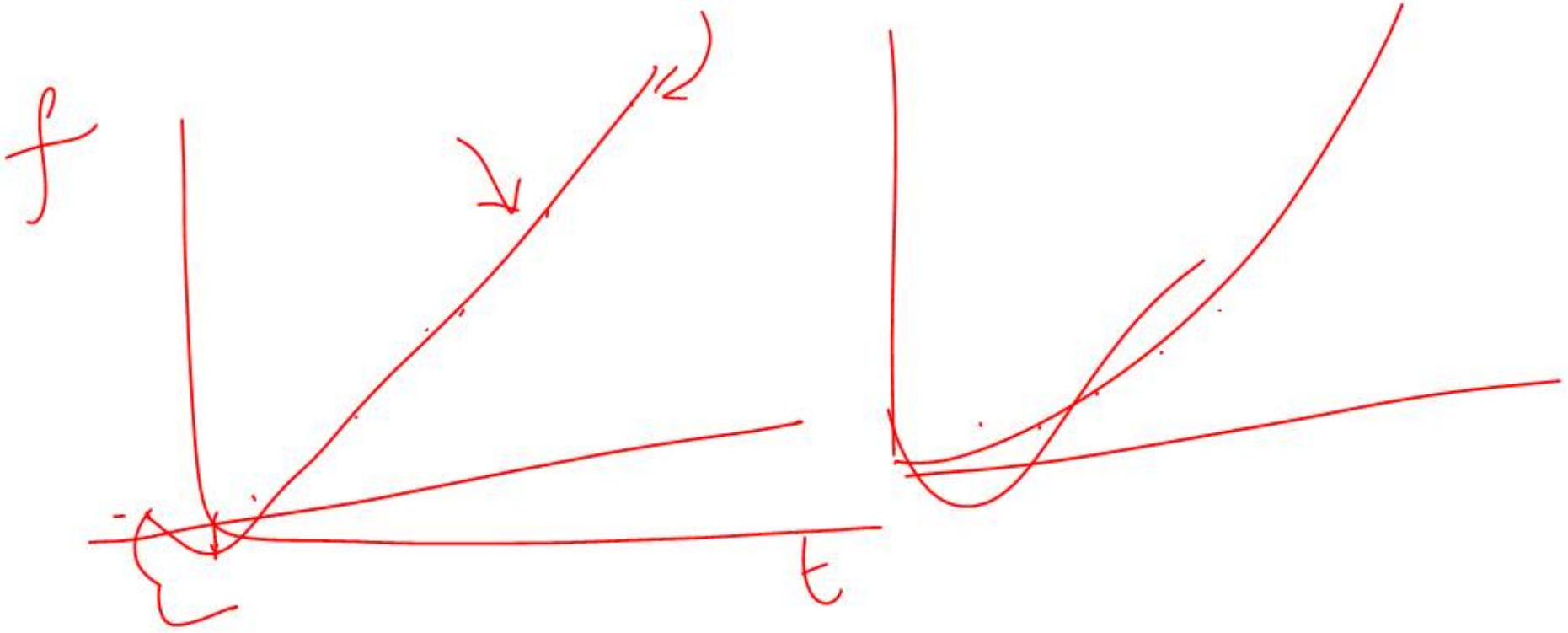
find $\hat{y}(x \ldots, w \ldots)$

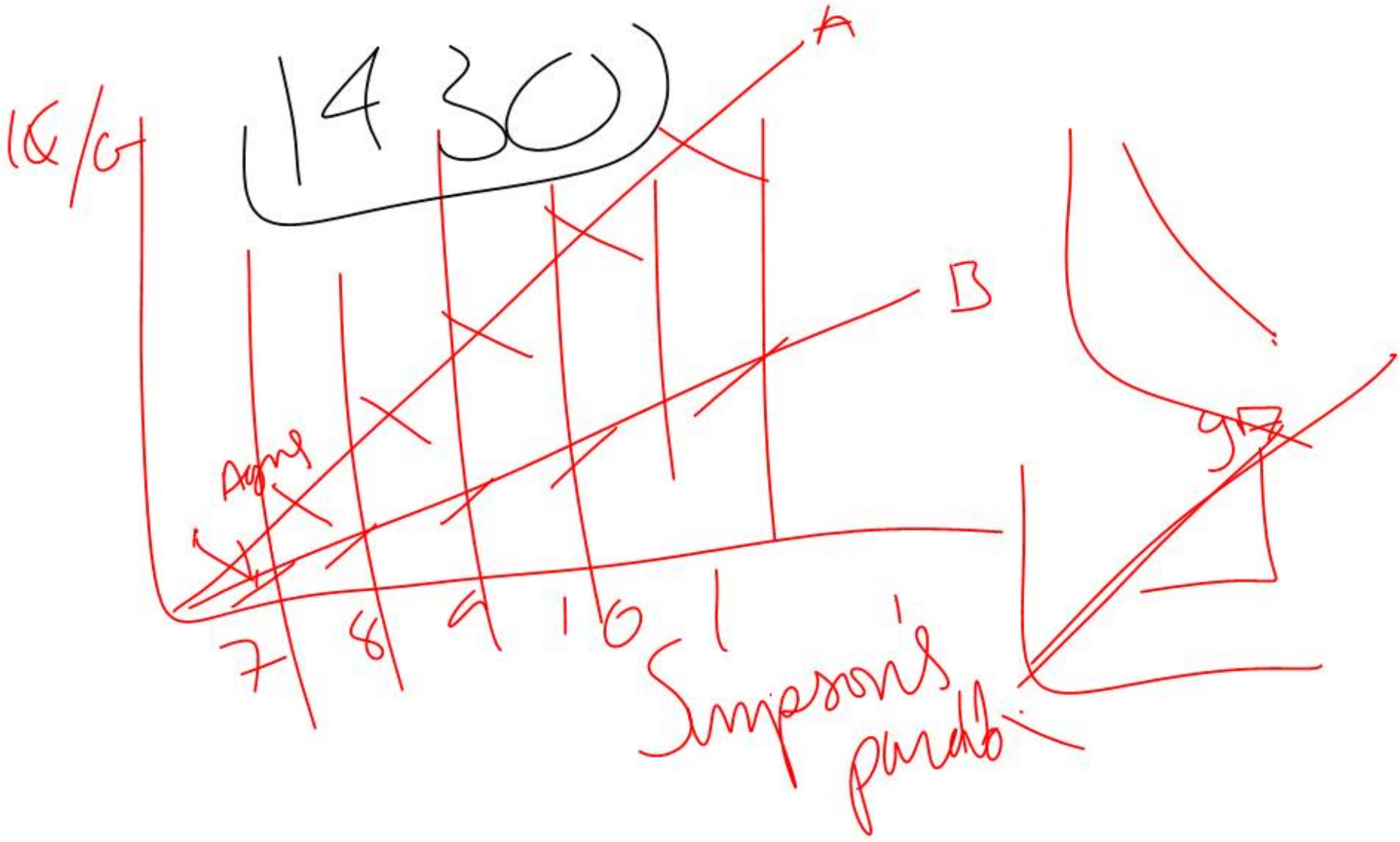
by $\min$ loss $(\hat{y}, y)$ Grad Des.

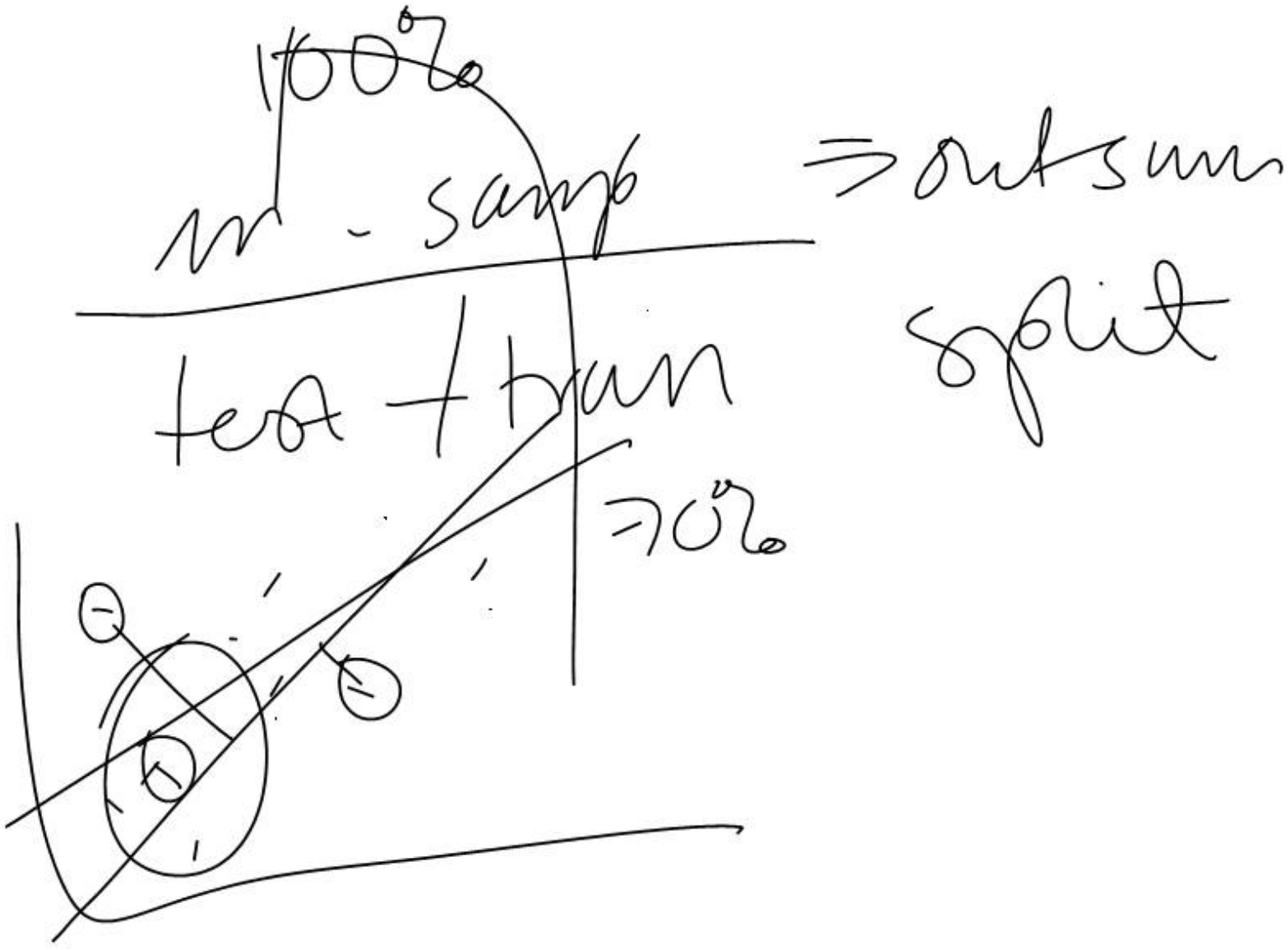
How? Alg

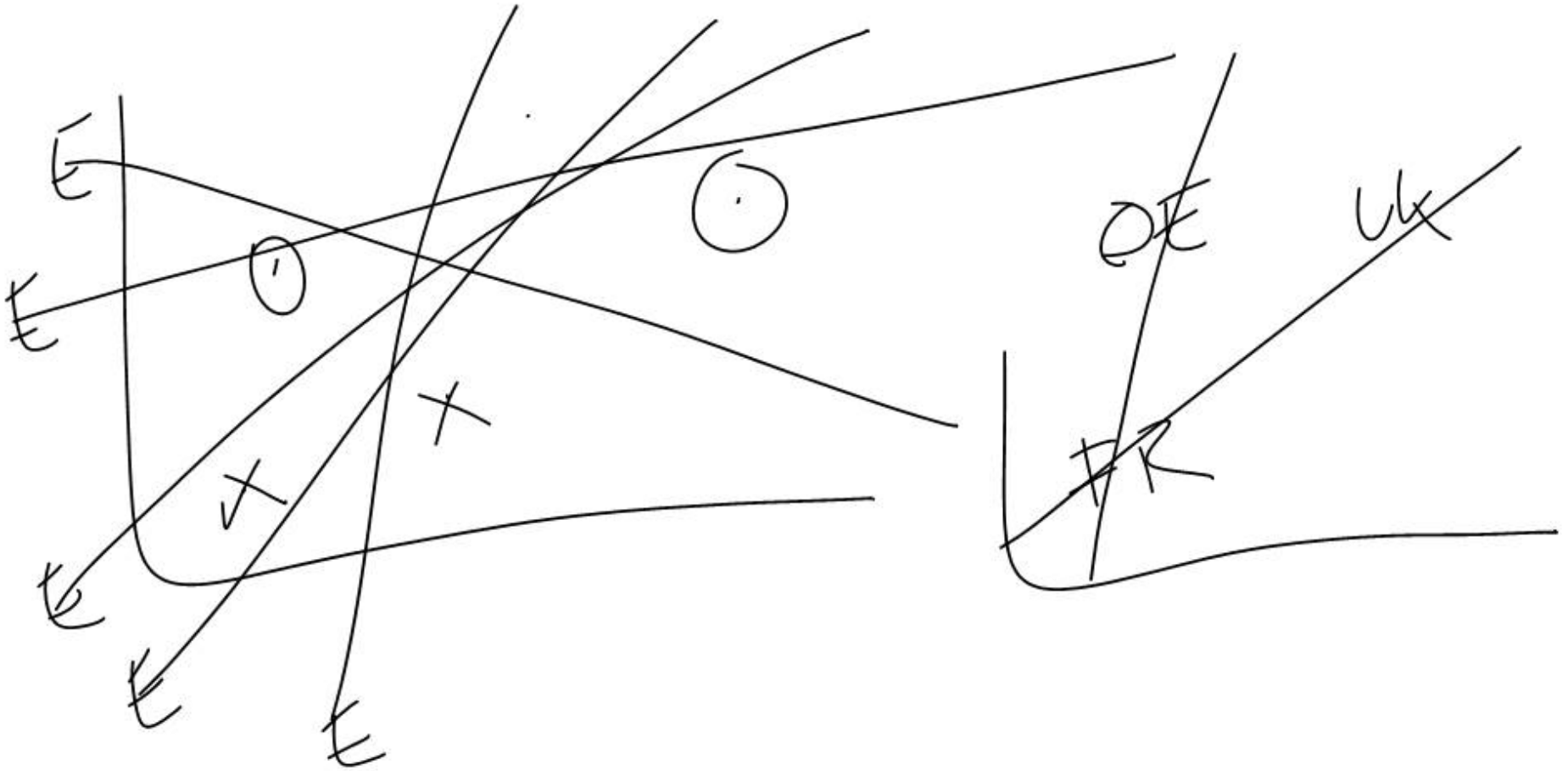

$\hat{y}(x;w) =$
$w_1 x_1 + w_2 x_2 + \cdots$
$+ a(a(a(wx)))$
X_2
X_1
1
1

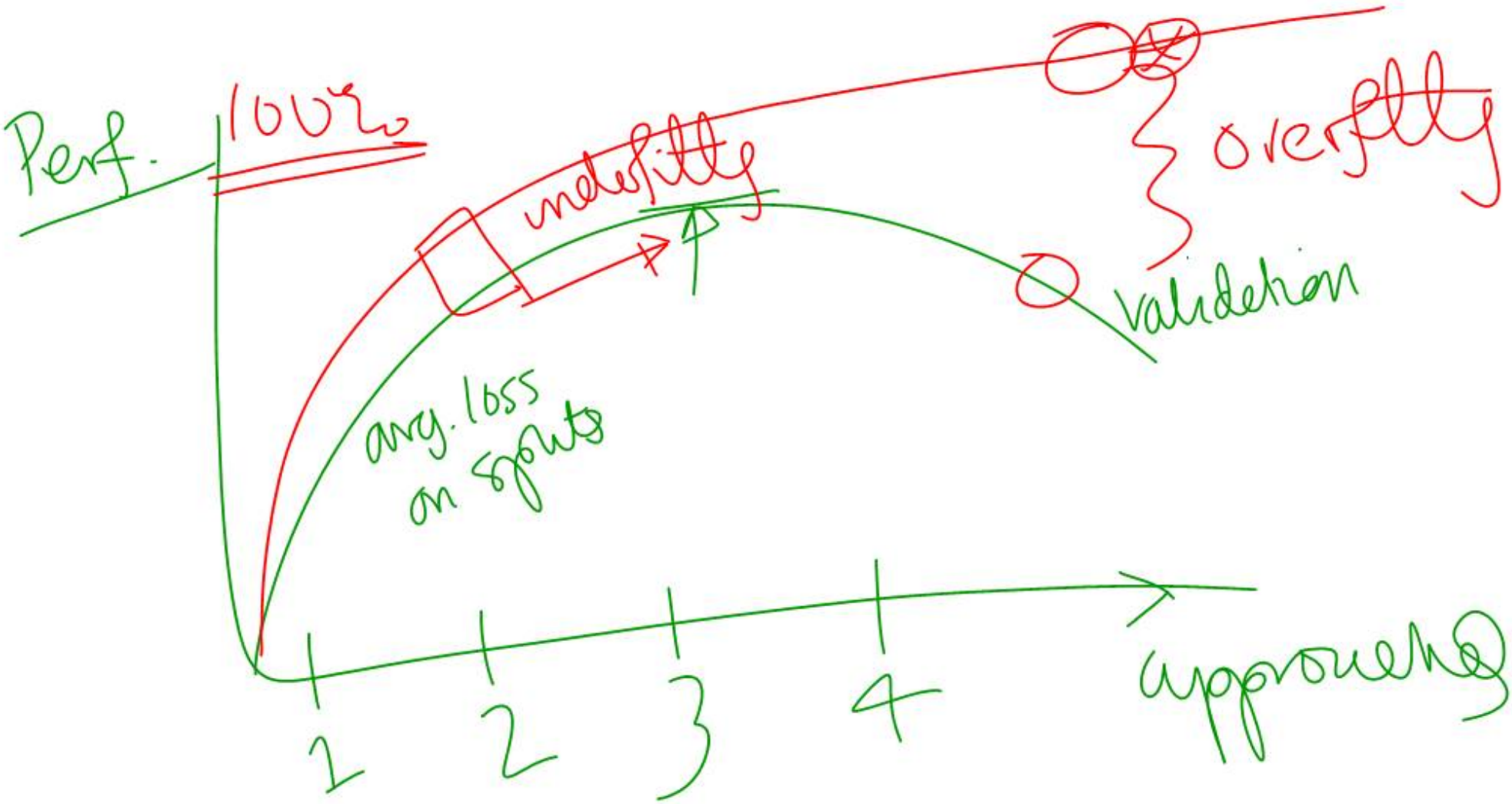

X
18
30
0.1
* w1
0.2
* w2
3.2

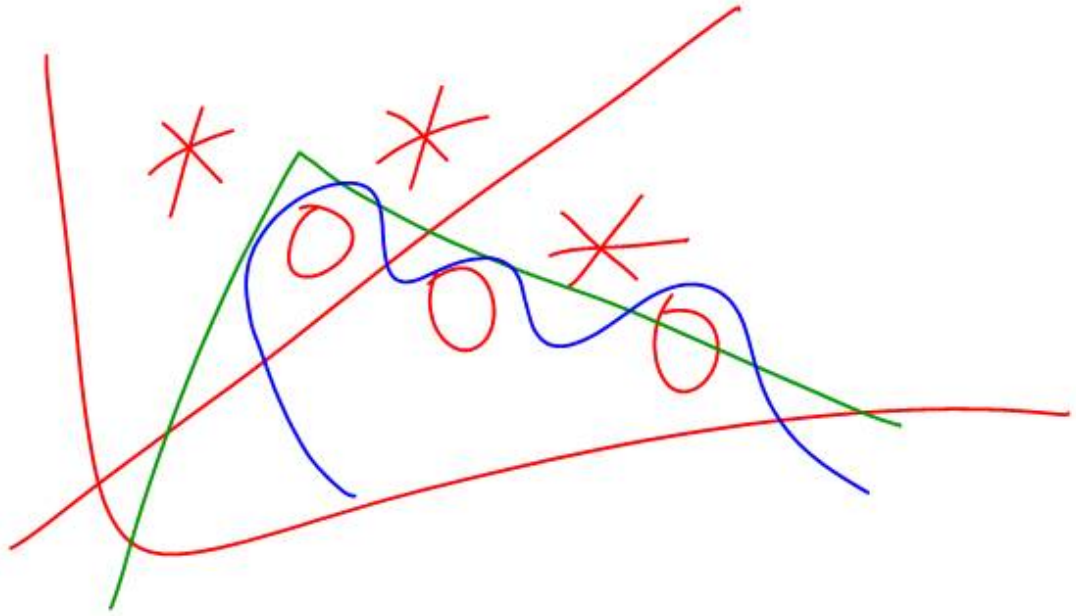

f
t


1430
A
B
Aging
7
8
9
10
1
Simpson's paradox


100%
m - samp
tea + bun
=70%
=> autsum
split


E
E
E
E
E
O
O
X
X
OE
UK
FK

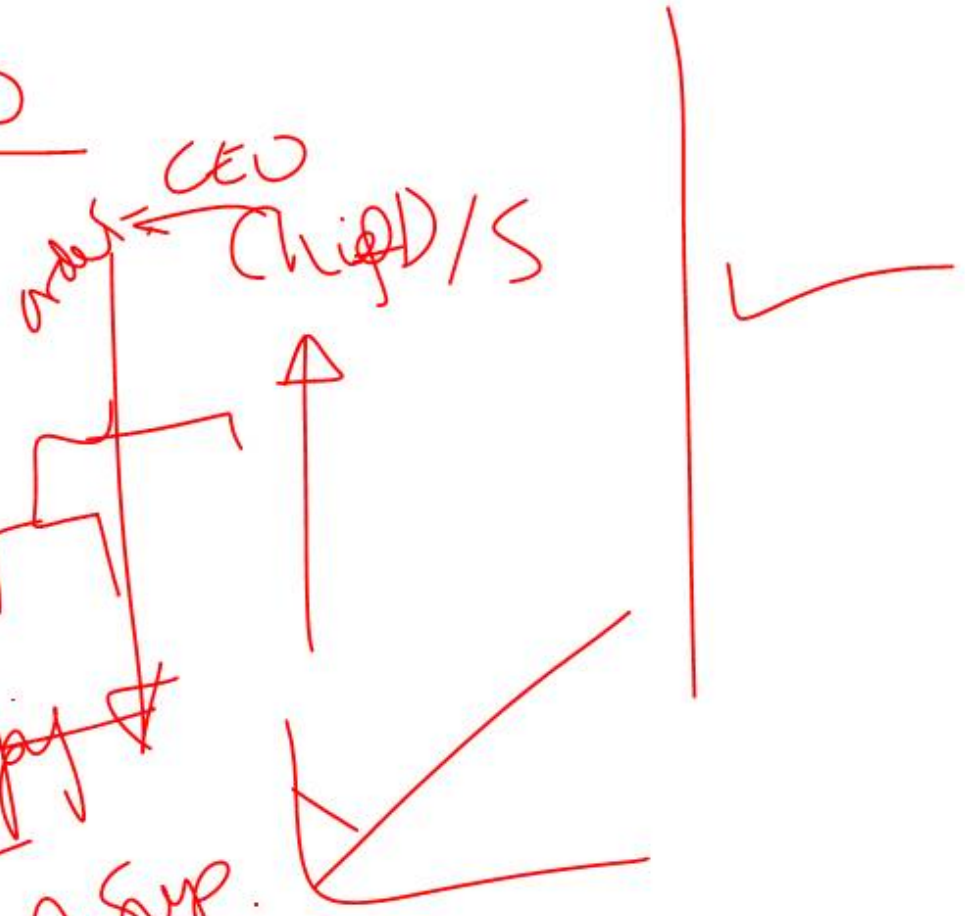

Perf.
loss
underfitting
overfitting
validation
avg. loss
on splits
1
2
3
4
approaches



1) ML workflow

2) Exploratory (x, y)

- Can we do you anything?
- Problems? ~~Gatekeeper~~ ~~HiPPO~~ Info Sup.



① Understand Data (BA)

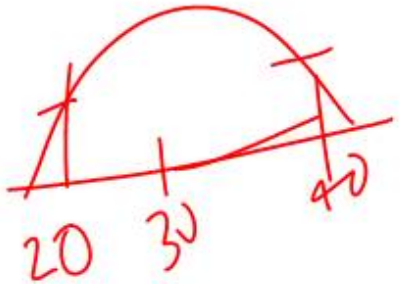
② Data Understanding

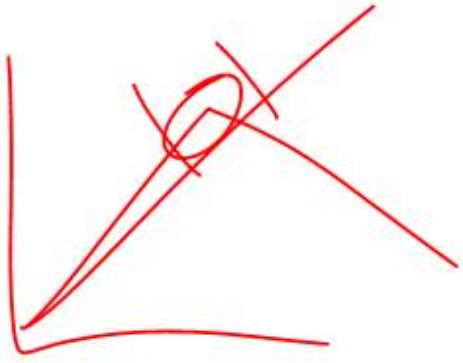
- Loan
- Ex. D A.

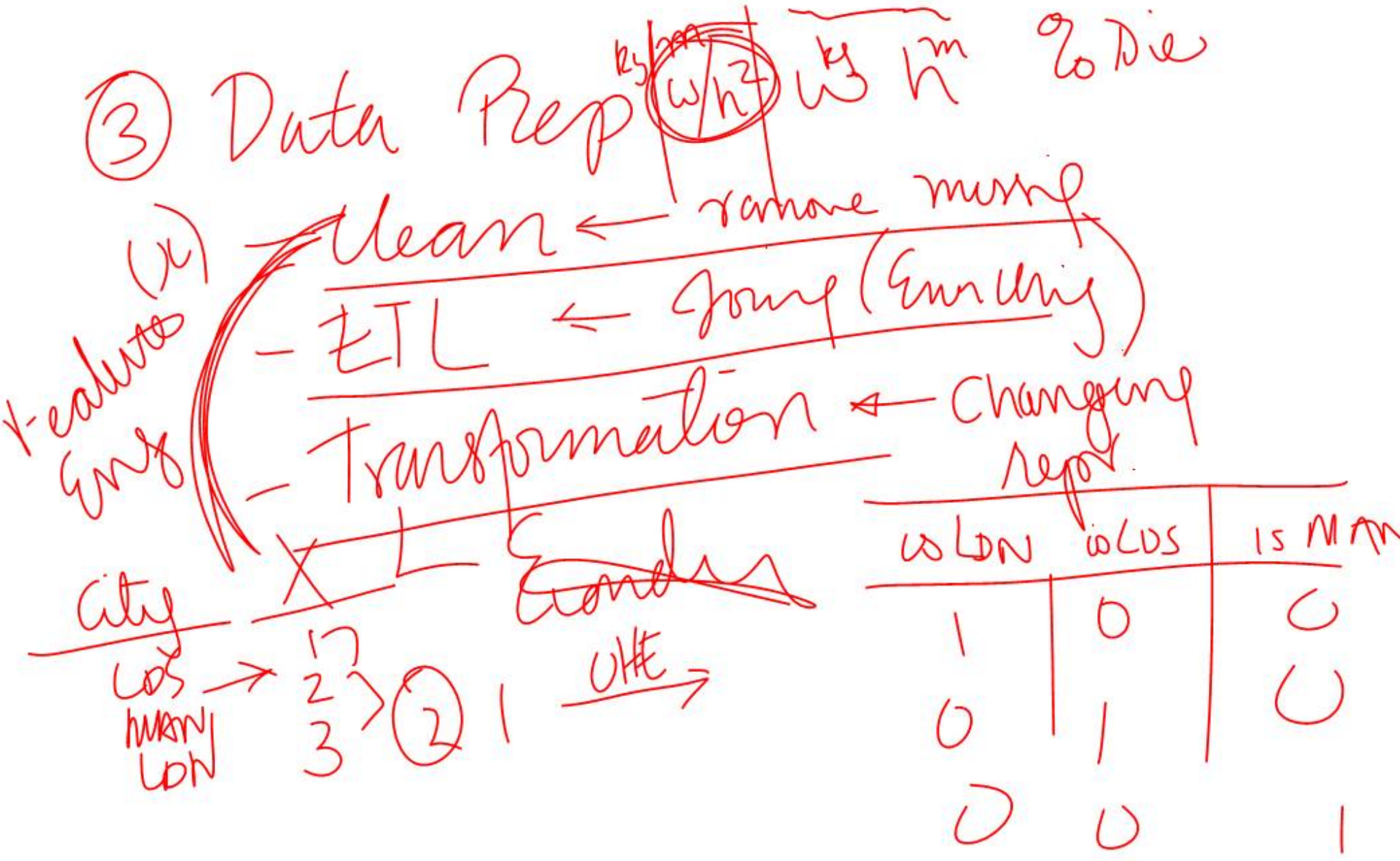
age

x_1 x_2 ...

1)

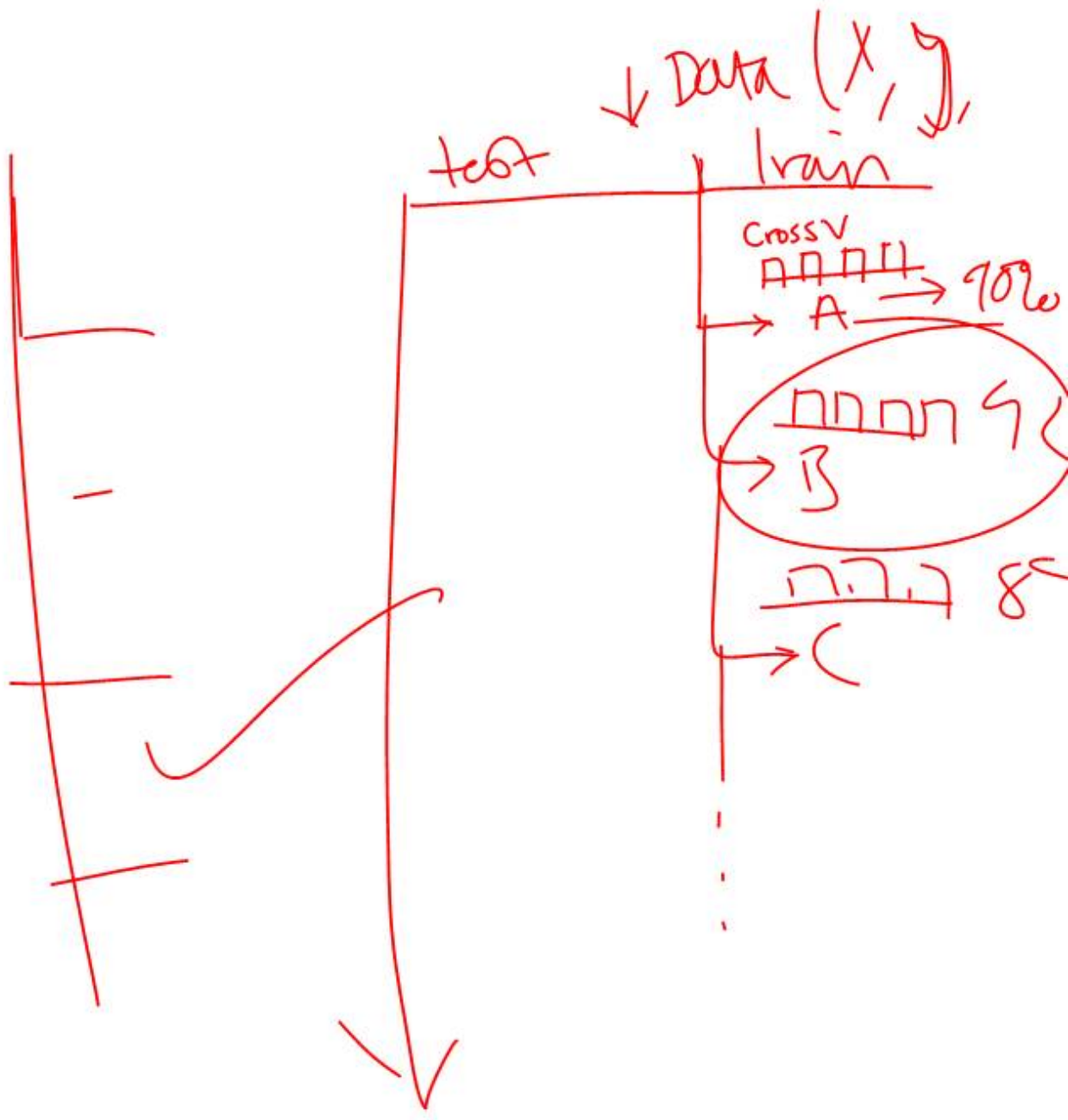


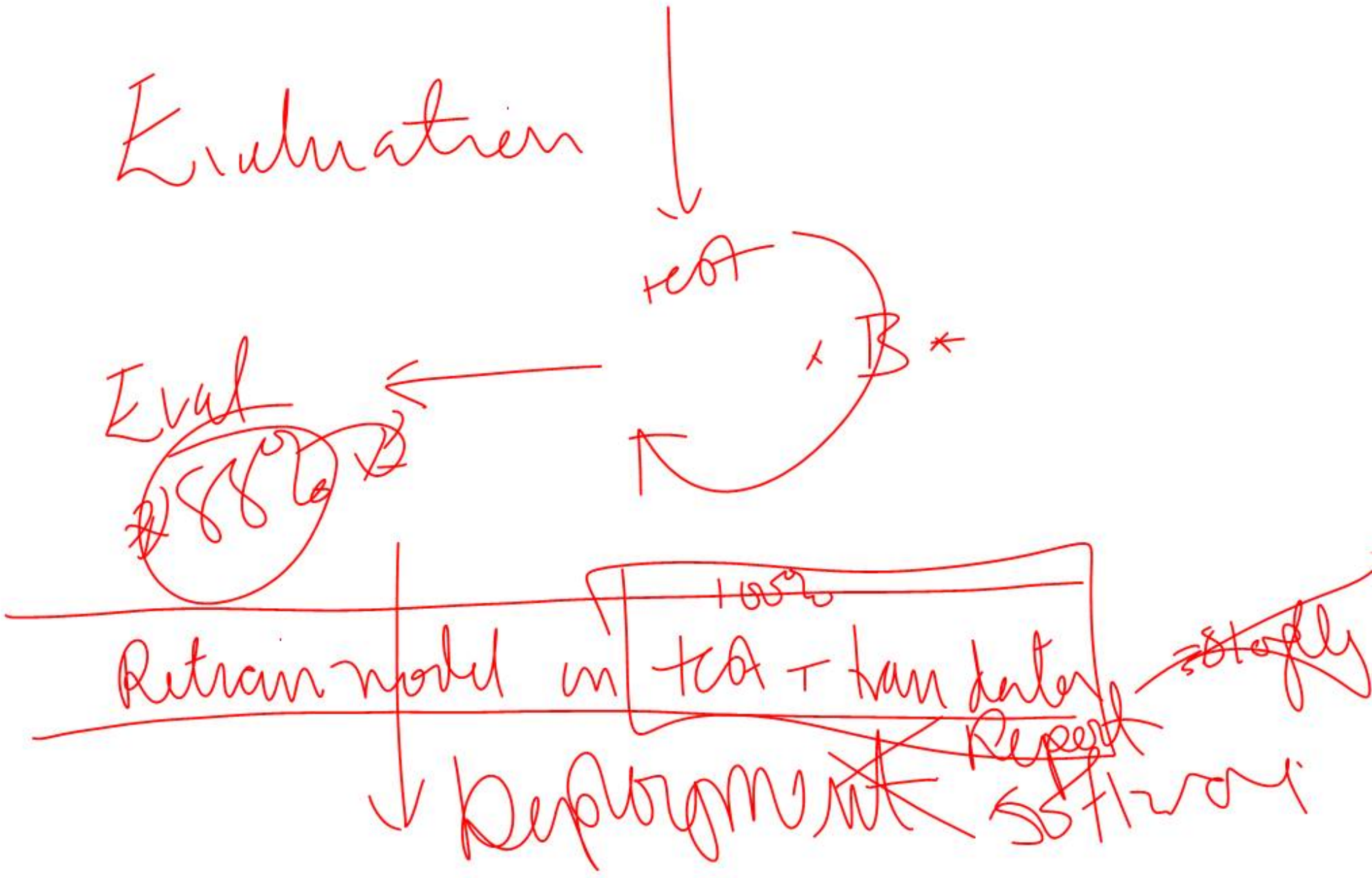


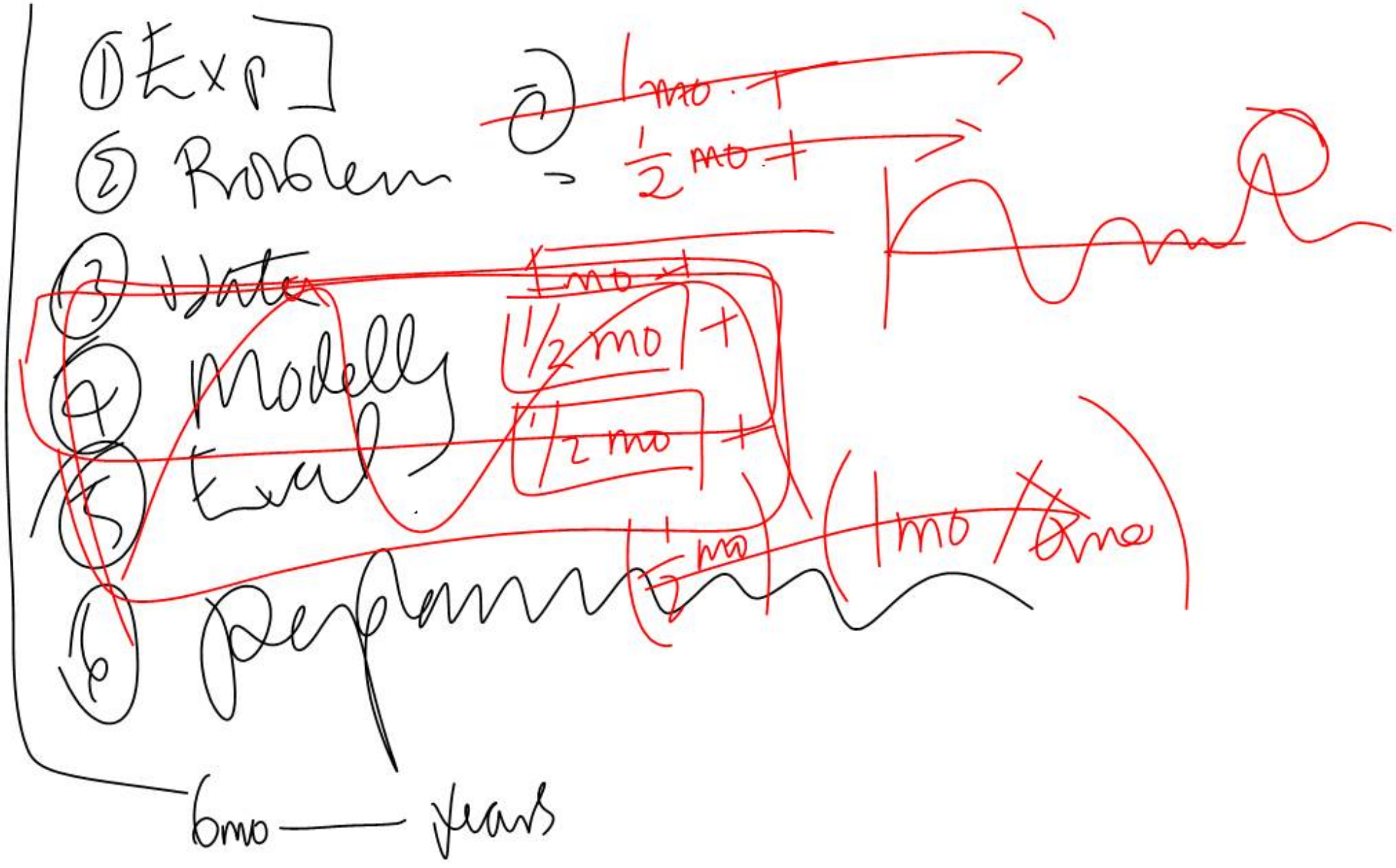

③ Data Rep
kg/m²
w/h²
kg
m
% Die
(x)
Y-value
Errs
clean ← remove missing
- ETL ← Jump (Encoding)
- Transformation ← Changing
X
Encoders
City
LOS
MAN
LON
17
2
3
2
1
OHE
Rep
is LON
is LOS
is MAN
1
0
0
0
1
0
0
1

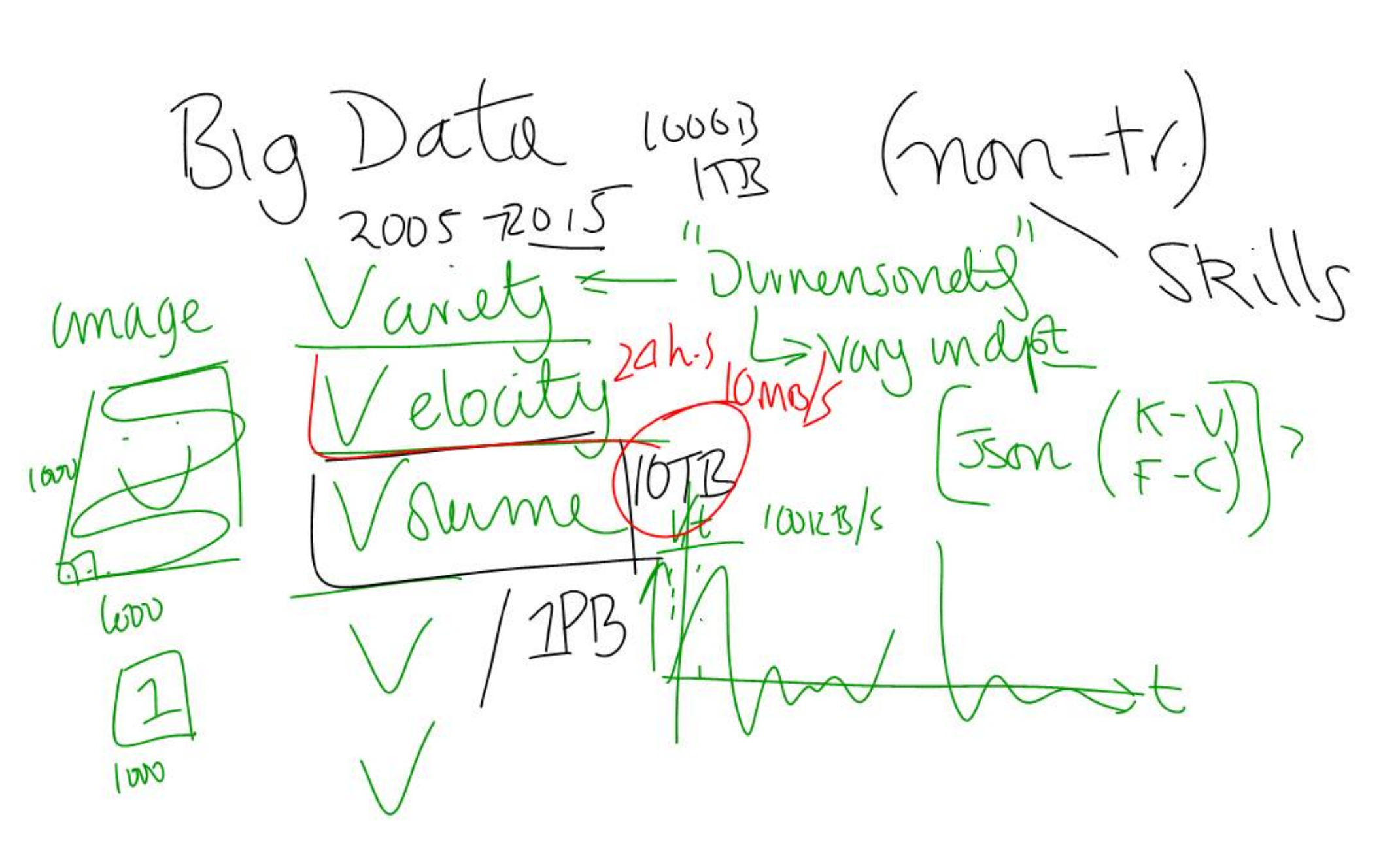
④ Modelling

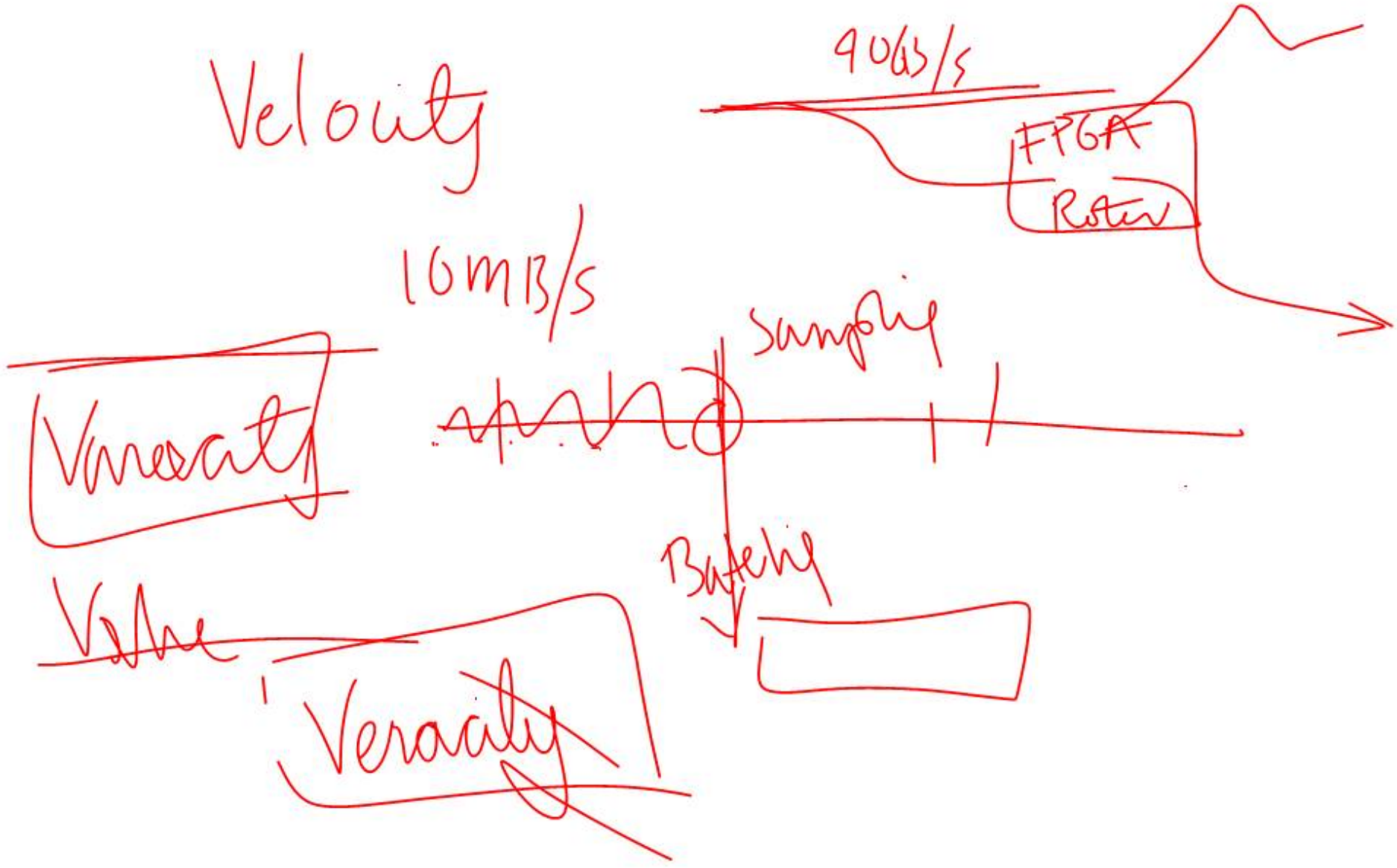
NN - 1
- 2
- 3
LR - 1




Evaluation
TCA
B*
Eval
Retrain model in TCA + transfer
Repurpose
Repeat


① Exp
② Problem
③ Hate
④ Modelly
⑤ Eval
⑥ Perform
6mo — years
1mo
1/2 mo
1/2 mo
1/2 mo
1mo
2mo


Big Data
2005 → 2015
1000 TB
(non-tr.)
"Dimensonality"
Skills
Variety
Velocity
Volume
24h.s
10MB/s
10TB
1PB
100KB/s
Image
1000
1000
1000
Json (K-V F-C)
t

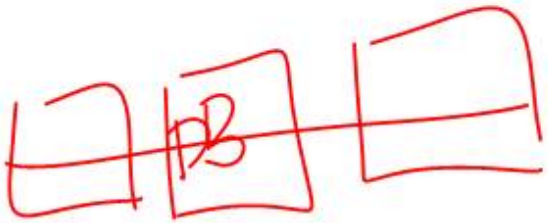

Velocity
90GB/s
FPGA
Rate
10MB/s
Veracity
Sampling
Batching
Value
Veracity

Non-traditional

BI

Relational - SQL

One Machine



Velocity

↘ injection

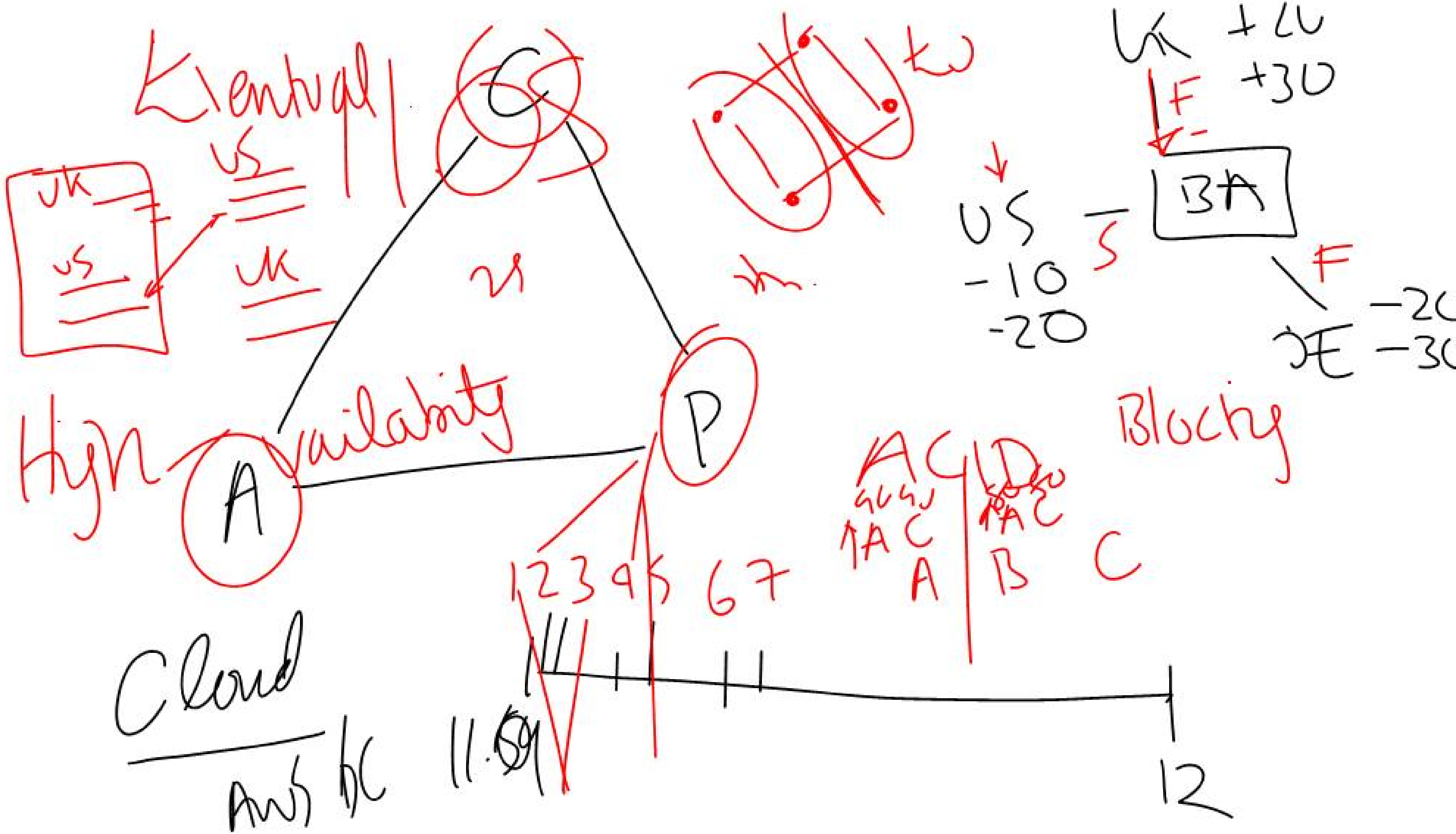
Big Data

Analysts / Engineers

1) Data Structure → CAP

2) Query Structure → Consistency
availability
partition tolerance

3) "~~Representational~~" Modelling Governing
"power"
"Readiness"

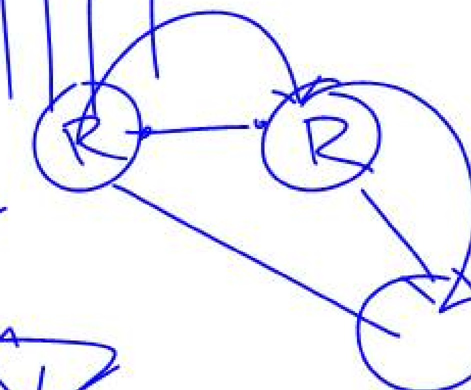


Eventual
C
A
P
High availability
UK
US
Cloud
AWS GC
11.59
12
1 2 3 4 5 6 7
ACID
A
B
C
Blocking
UK +20 +30
F
BA
US -10 -20
5
DE -20 -30

Data 11.05

Data Model

Columnar



MySQL — Table (Relation)

Neo4j — Graph (Network)

Spark (hdfs) — Unstr. / schemaless {"u.p.a" [ ] }

{"tag": } }

Redis — Key Value {name

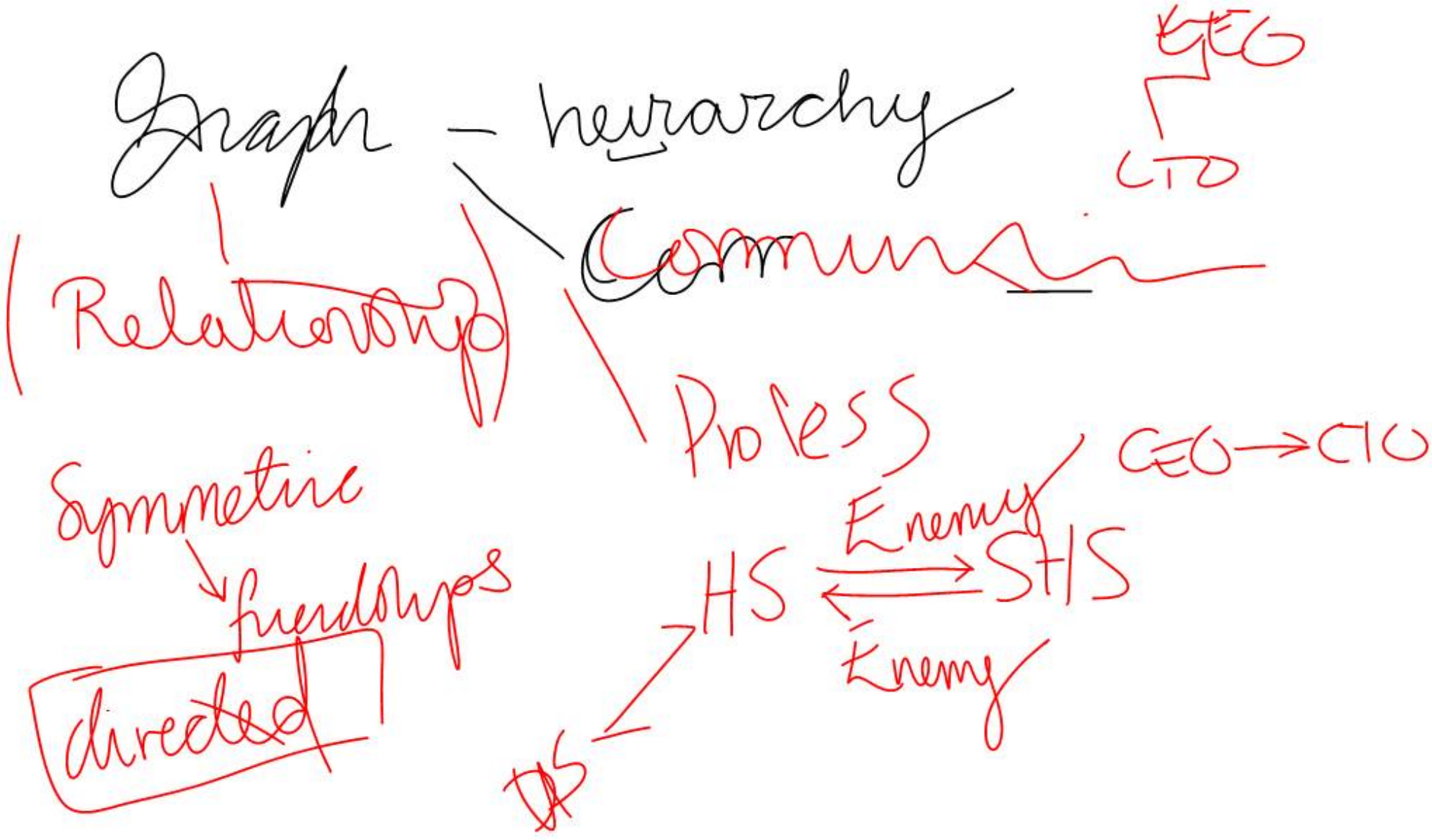
loans: {1: { }

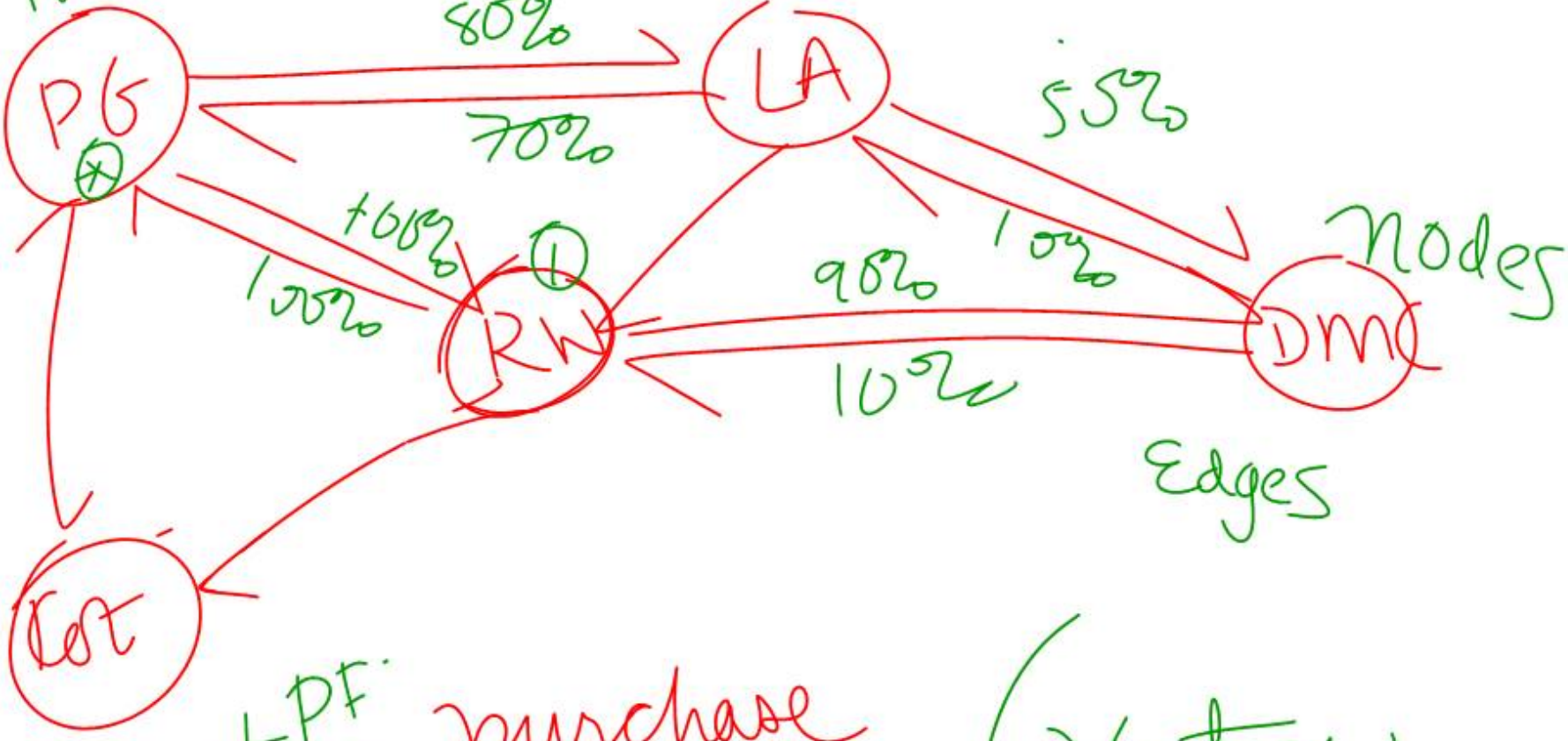
2: { } }

}

Mongo — Documents

Graphs & Graph Analytics


Graph – hierarchy
CEO
CTO
Relationship
Communication
Process
Symmetric
friendships
directed
CEO → CIO
Enemy
HS
STHS
Enemy
HS

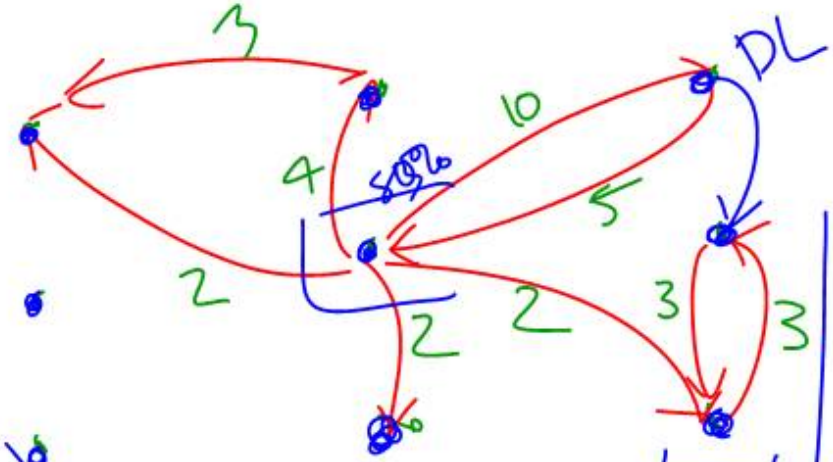


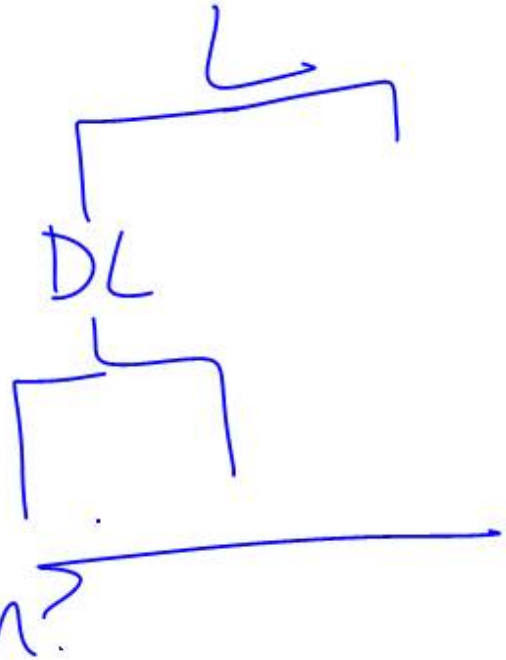
Graph + PF + BF
Traversal: weighted, purchase
(Vertex = Node)

Queen

Beer

↓ neighbor





"certainty"

(importance)

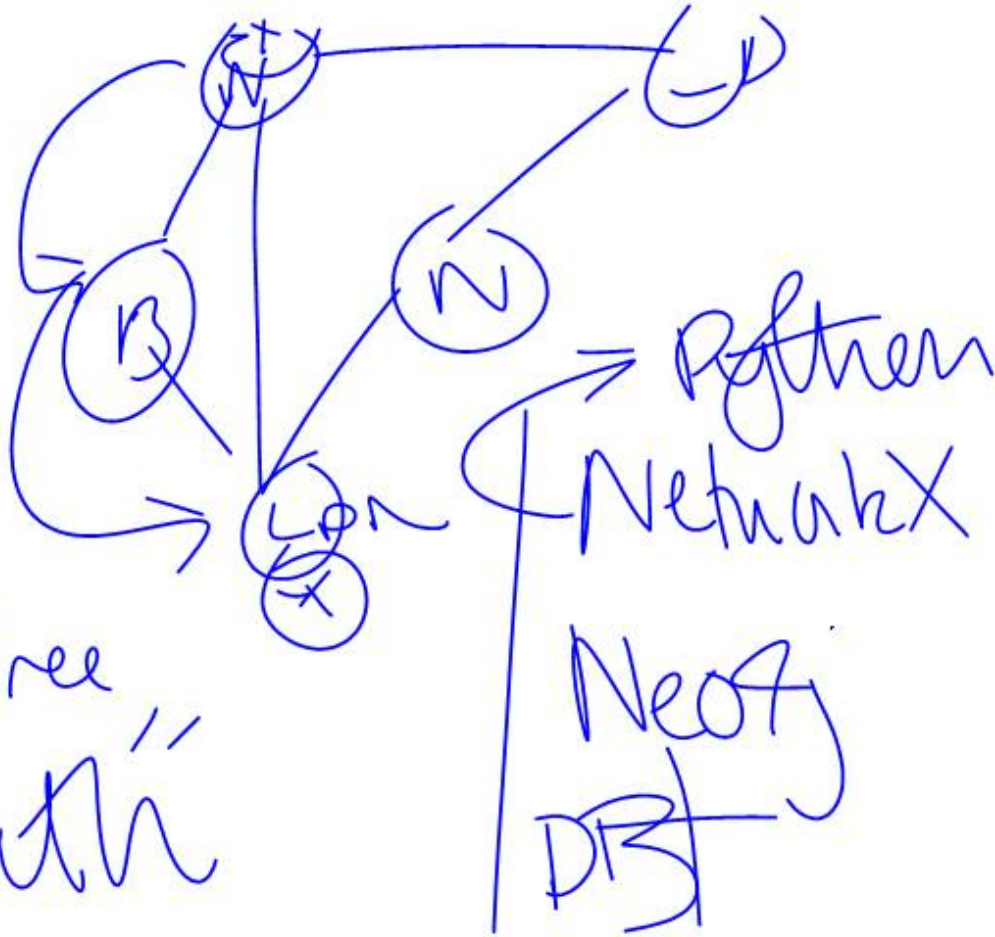
+ neighbors weighted	middle out	tenuous friendship group

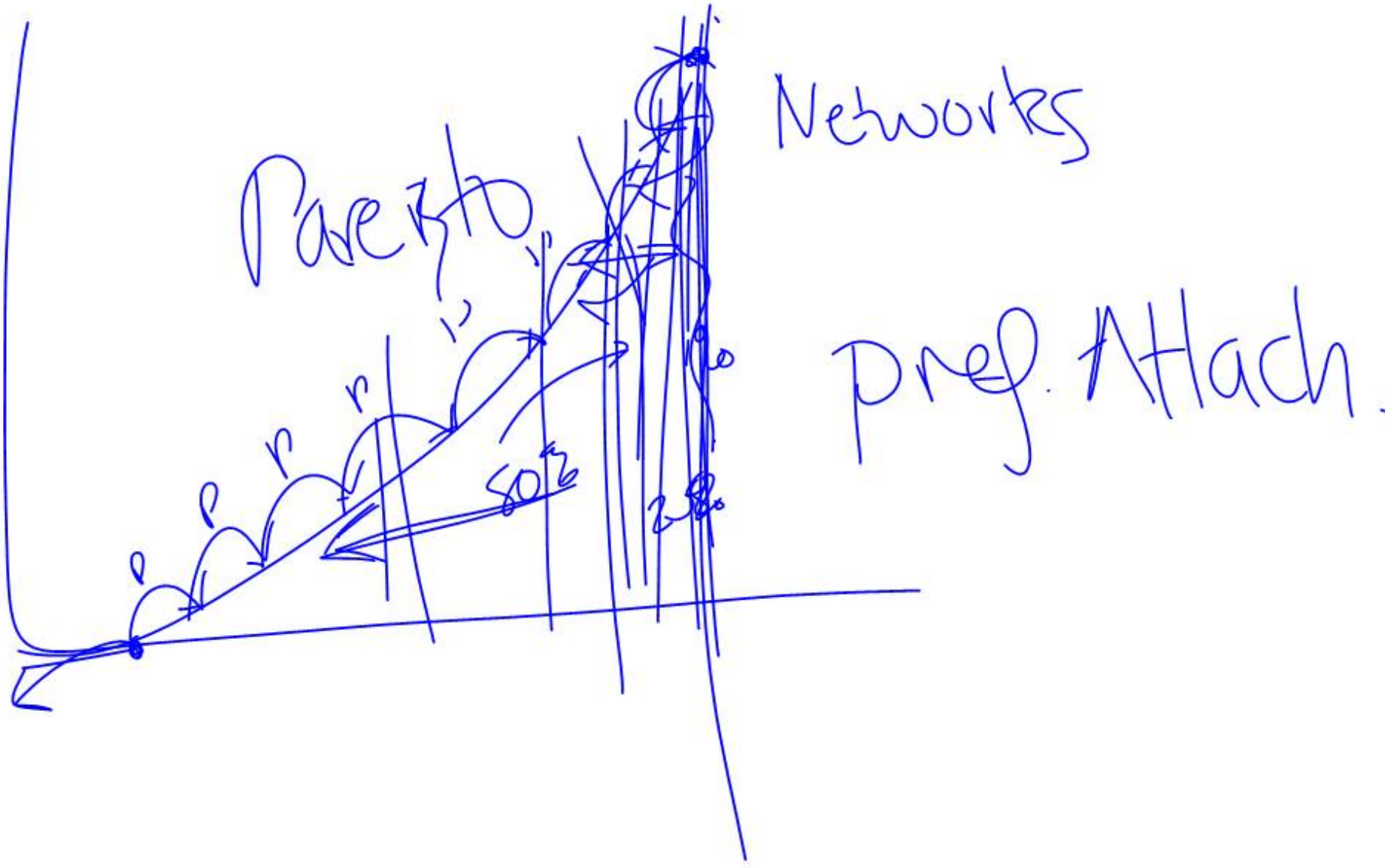
Travel / Map

Subgraph

- Min. Spn Tree

: Shortest path



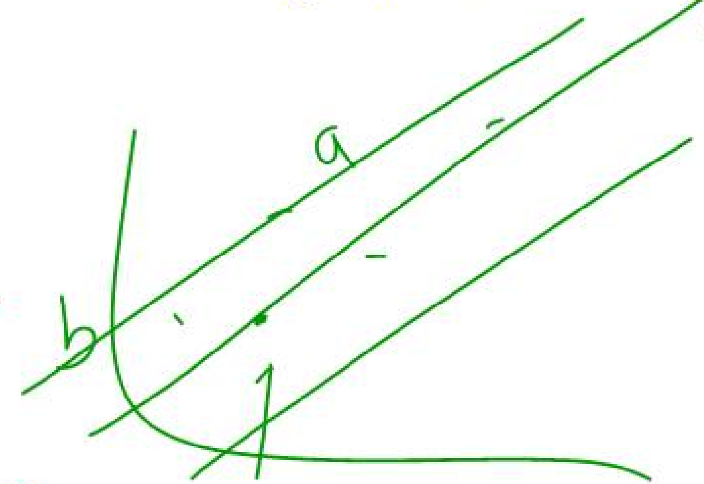

Networks
Pareto
pref. Attach.
80%
20%

T:0/2/3

$$\hat{y}(x; a, b) = ax + b \qquad (x, y)$$

$$l(\hat{y}, y) = (\hat{y} - y)^2 = l(a, b; x, y)$$

$$\min_{a,b} l(a, b; x, y)$$

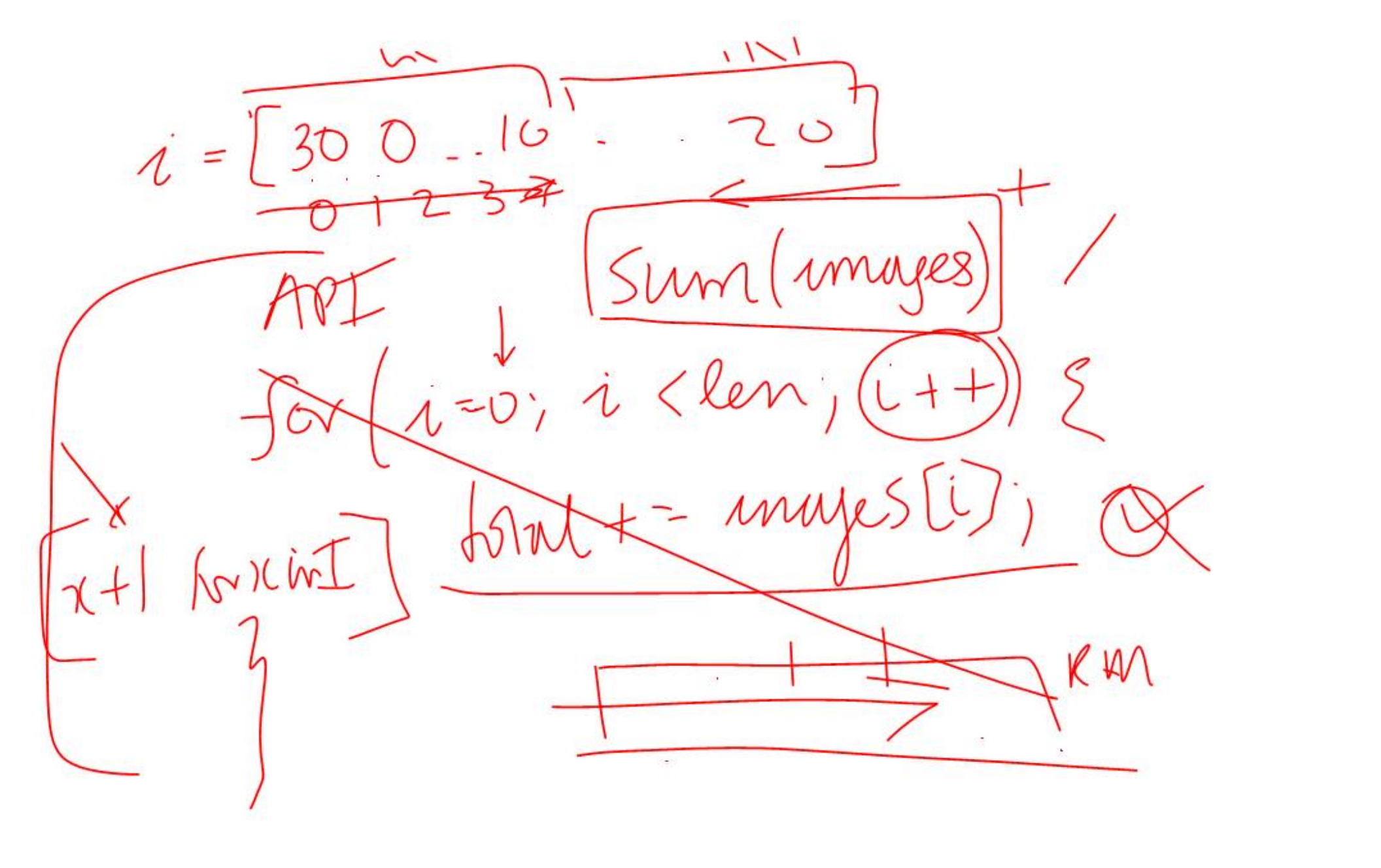


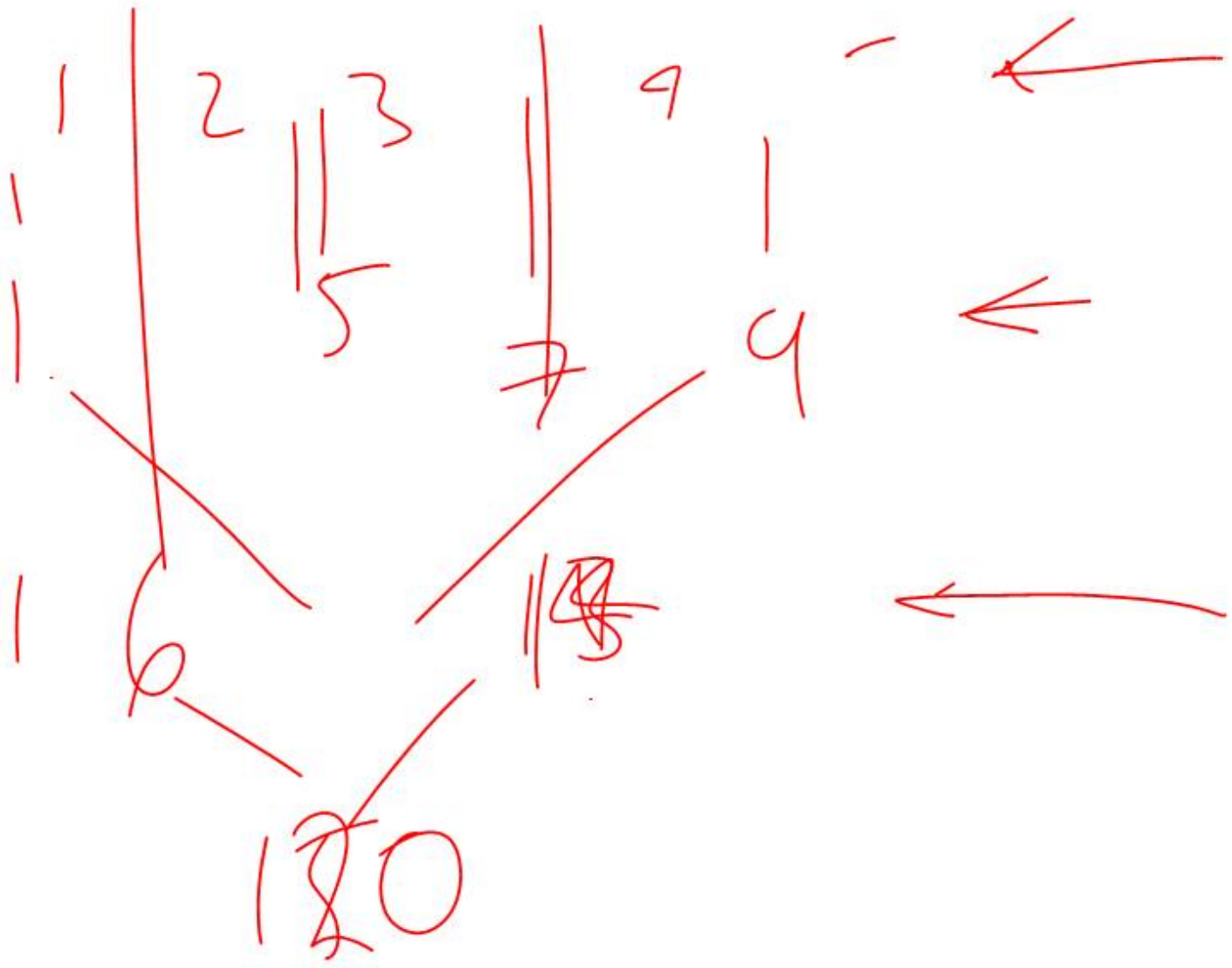
$a := \text{Rand}()$

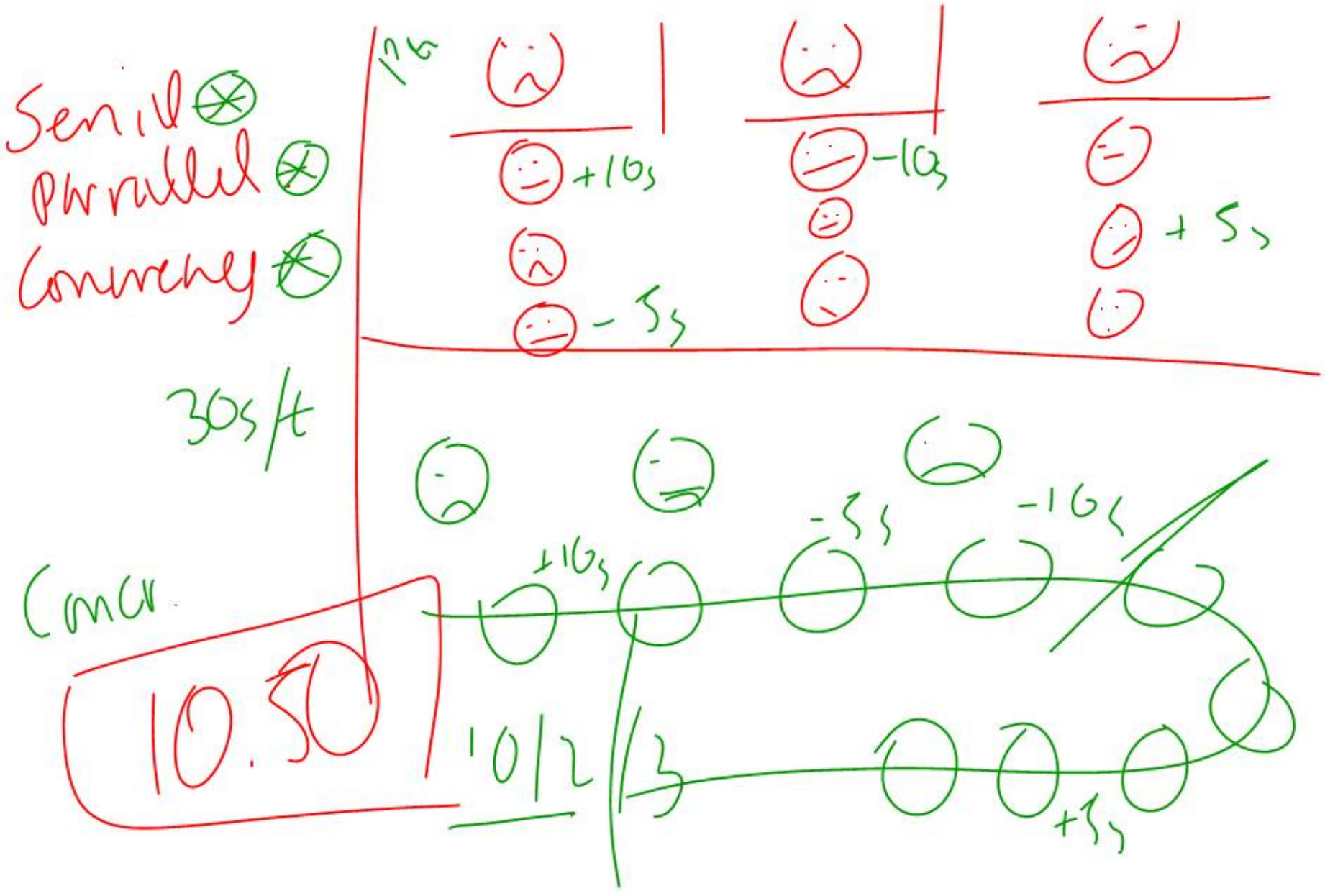
$b := \text{Rand}()$

Tiny

$a_{NEW} := a_{OLD} - \text{change}(l, a)_{OLD \to NEW}$


i = [30 0 .. 16 . . 20]
0 1 2 3 4
API
sum(images)
for(i=0; i<len; i++) {
x+1 for x in I
RM




Serial
Parallel
Concurrency
+10s
-5s
-10s
+5s
30s/t
10.50
10/2
-5s
-10s
+10s
+3s

⊗ Streaming — constant memory (RAM) — HDD

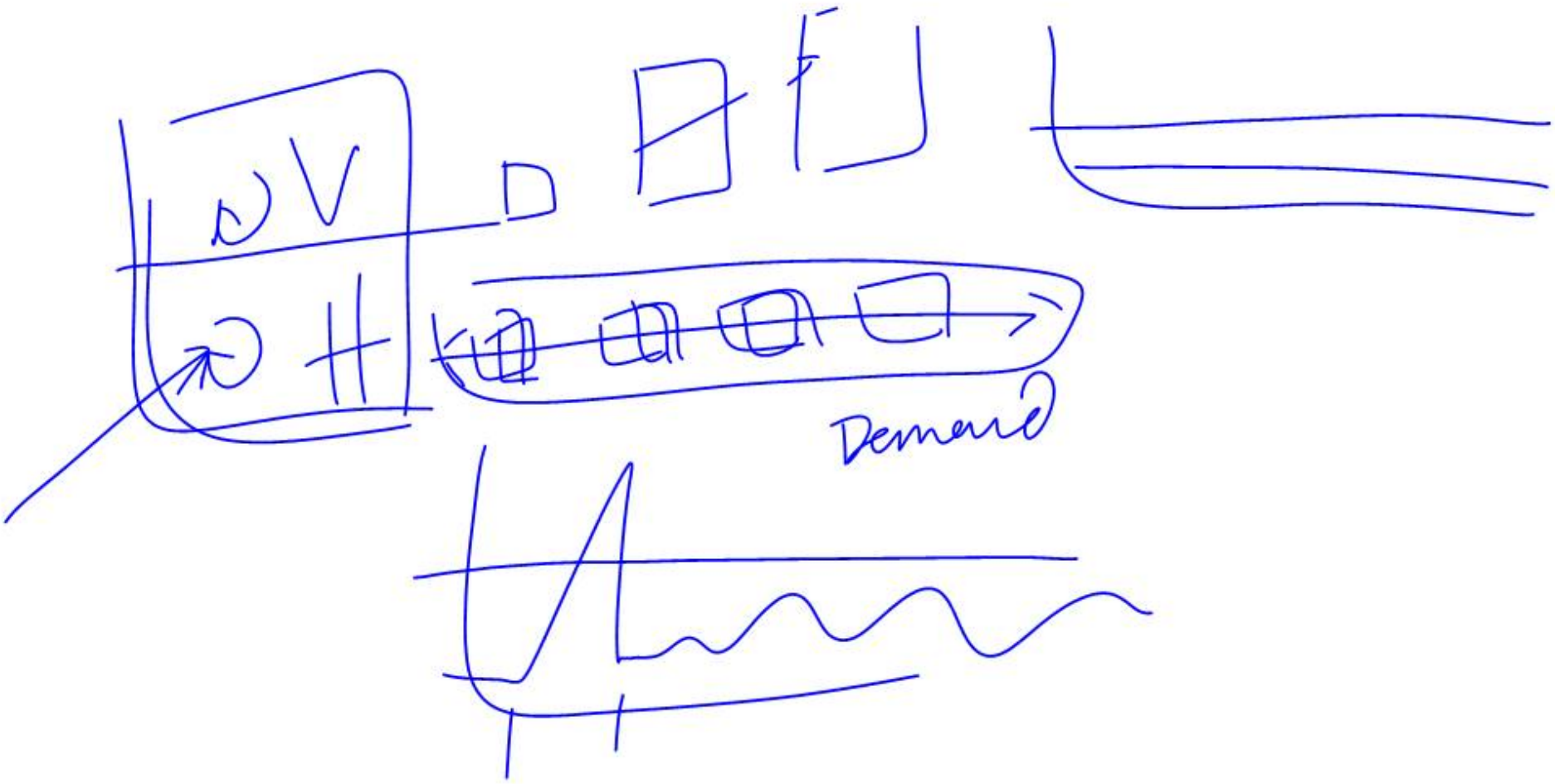
[ ] 1000

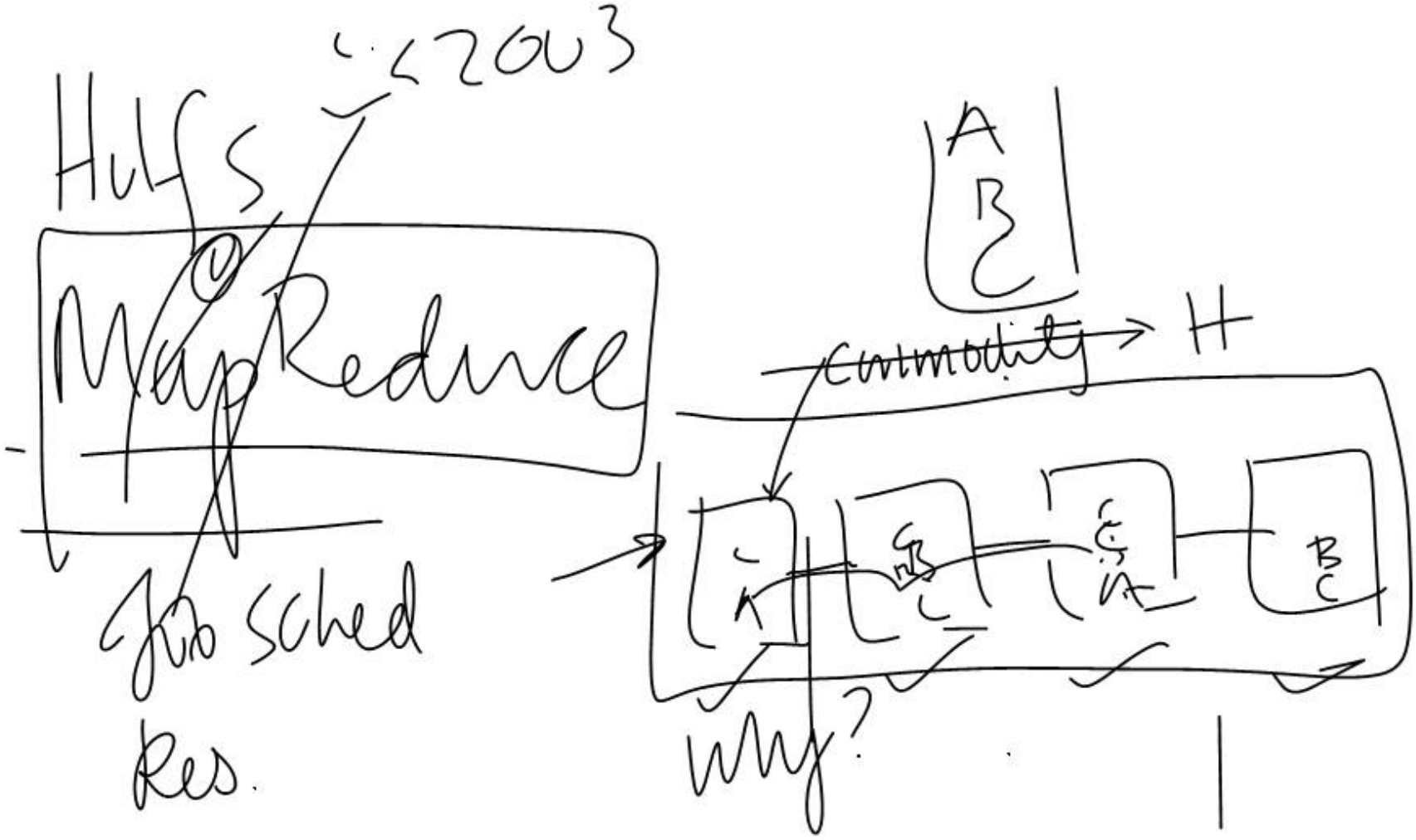
↘ Streaming API

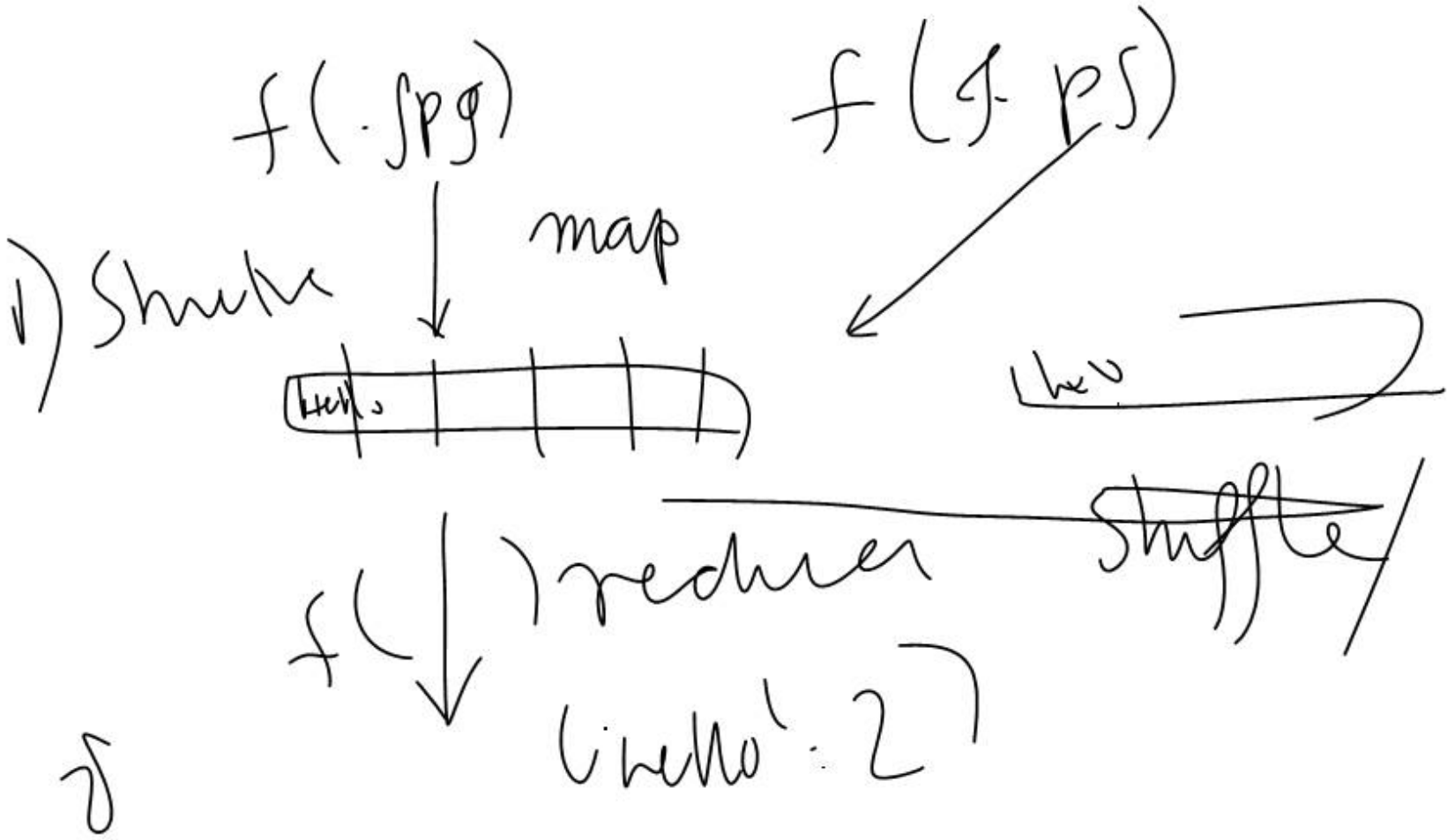
⊗ Parallelism — Merge for ds

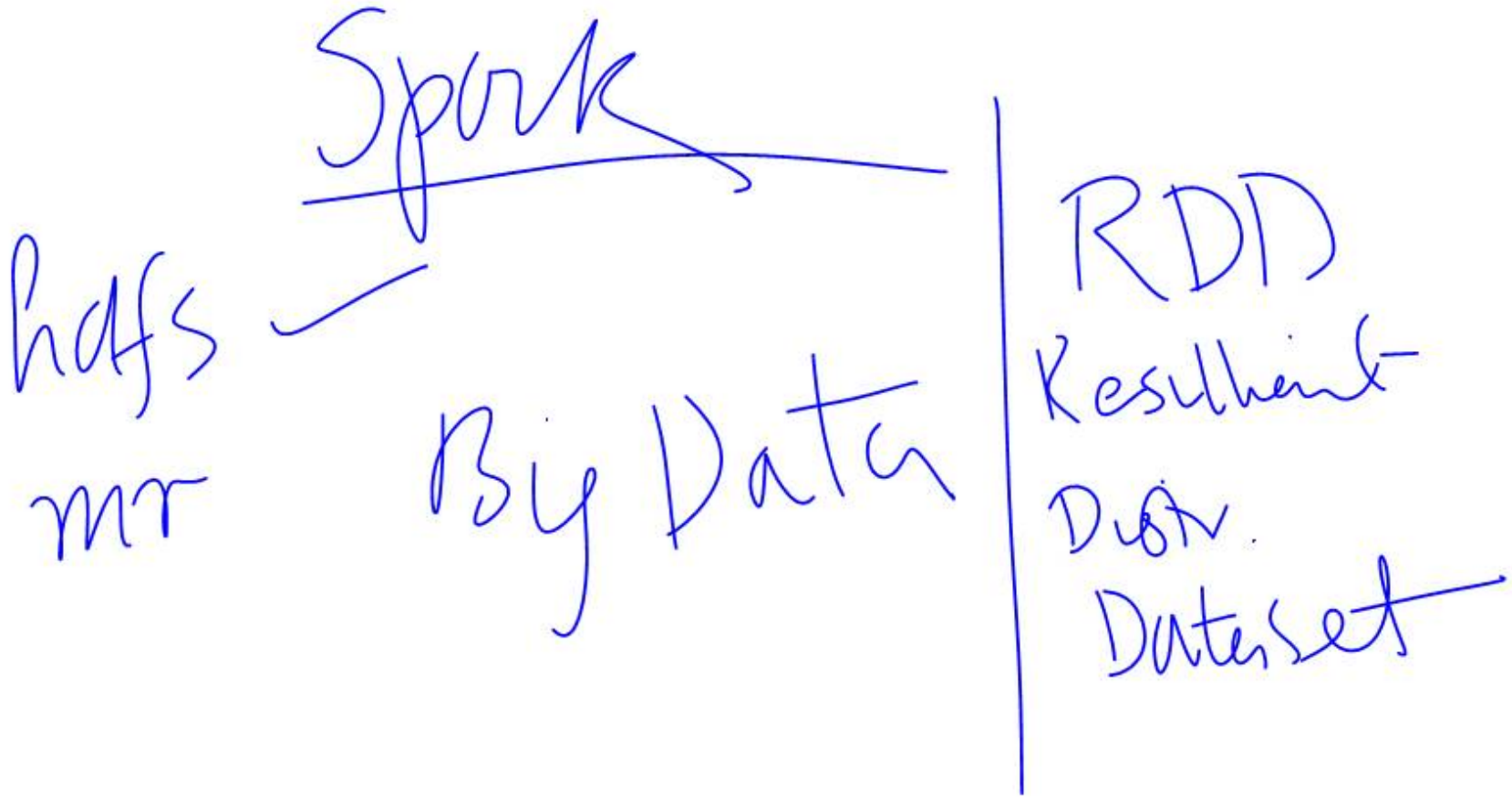
CPU +

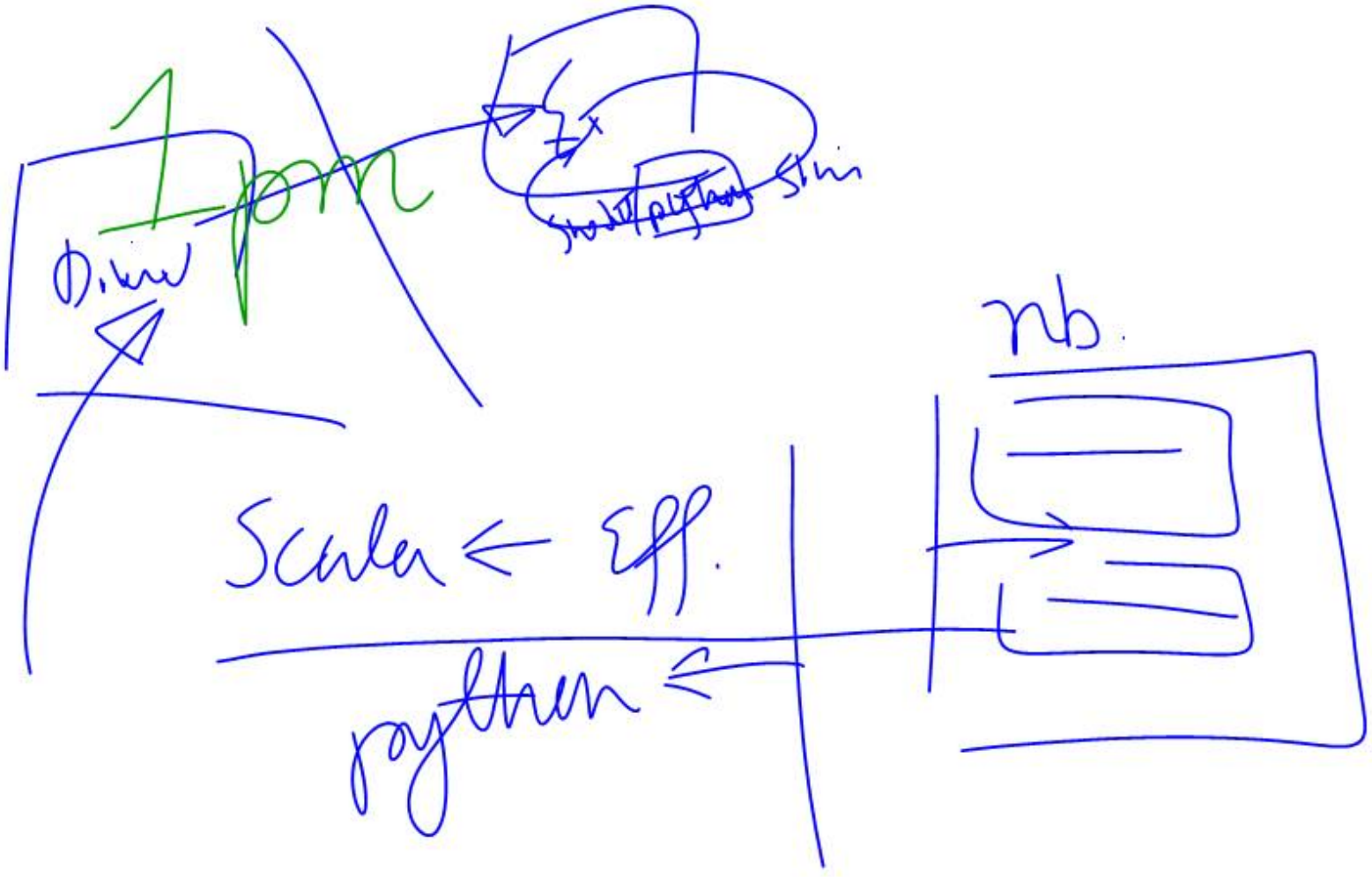
ds[i]

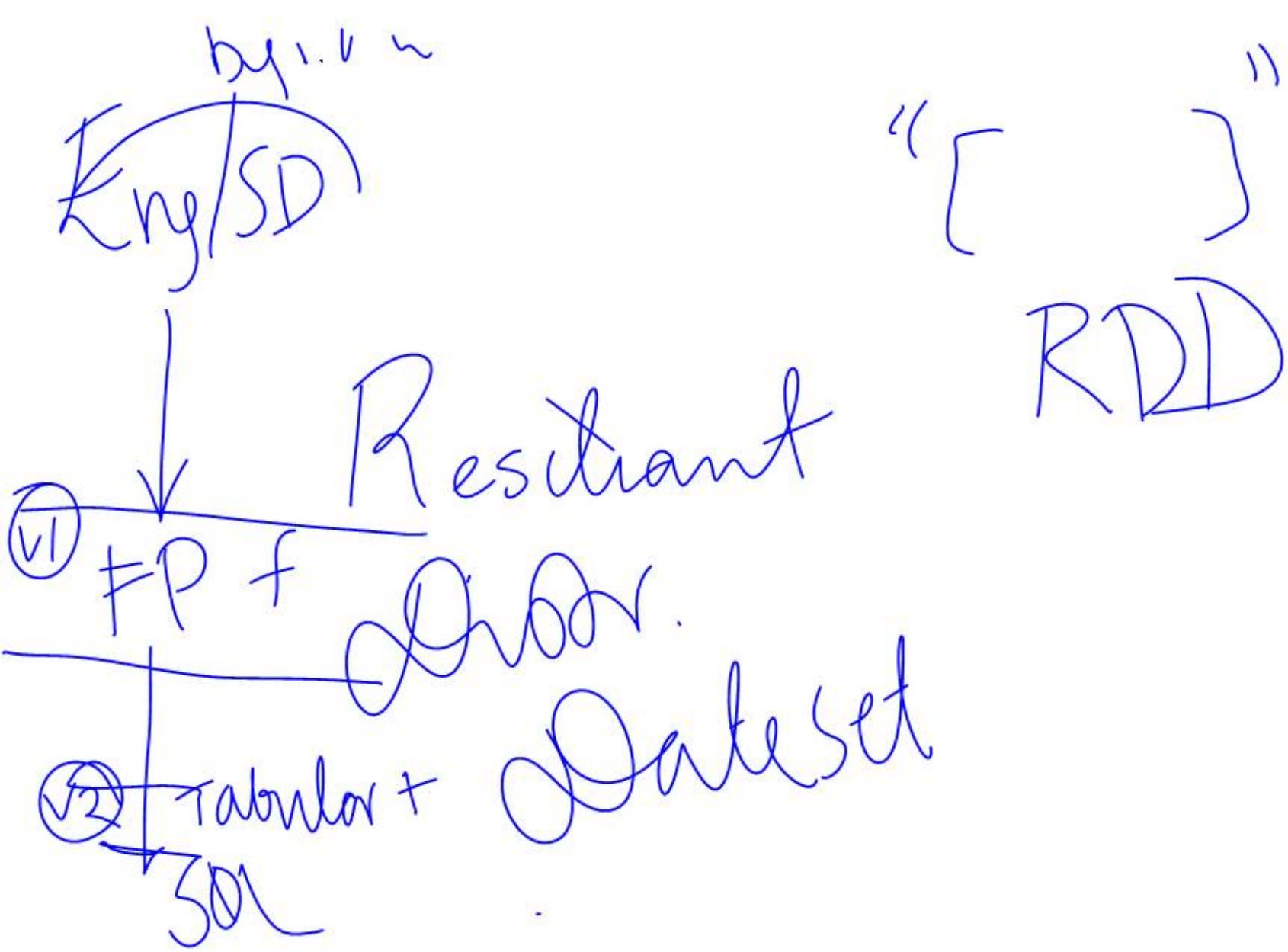

Demand


< 2003
Hulfs
MapReduce
Job sched
Res.
A
B
C
commodity
H
why?


f(.fpg)
f(.ps)
map
shuffle
hello
hello
shuffle
reducer
(hello', 2)


Spark
hdfs
mr
Big Data
RDD
Resilient
Dist.
Dataset


nb.
Scala ← Eff.
python


by.v
Kng/SD
" [ ] "
RDD
Resultant
v1
FP f
Odor.
Dataset
v2
tabular +
SQL

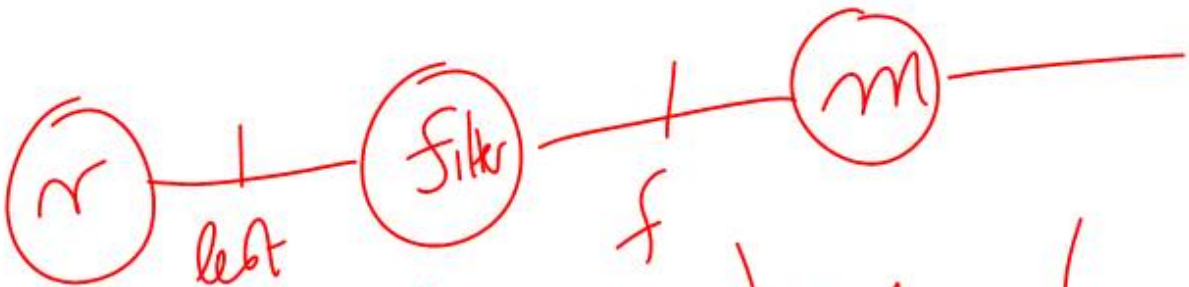
r.filter(test).map(f).collect()

Transformation

a =

a =

- a =



a = (r.map(g).filter(→)

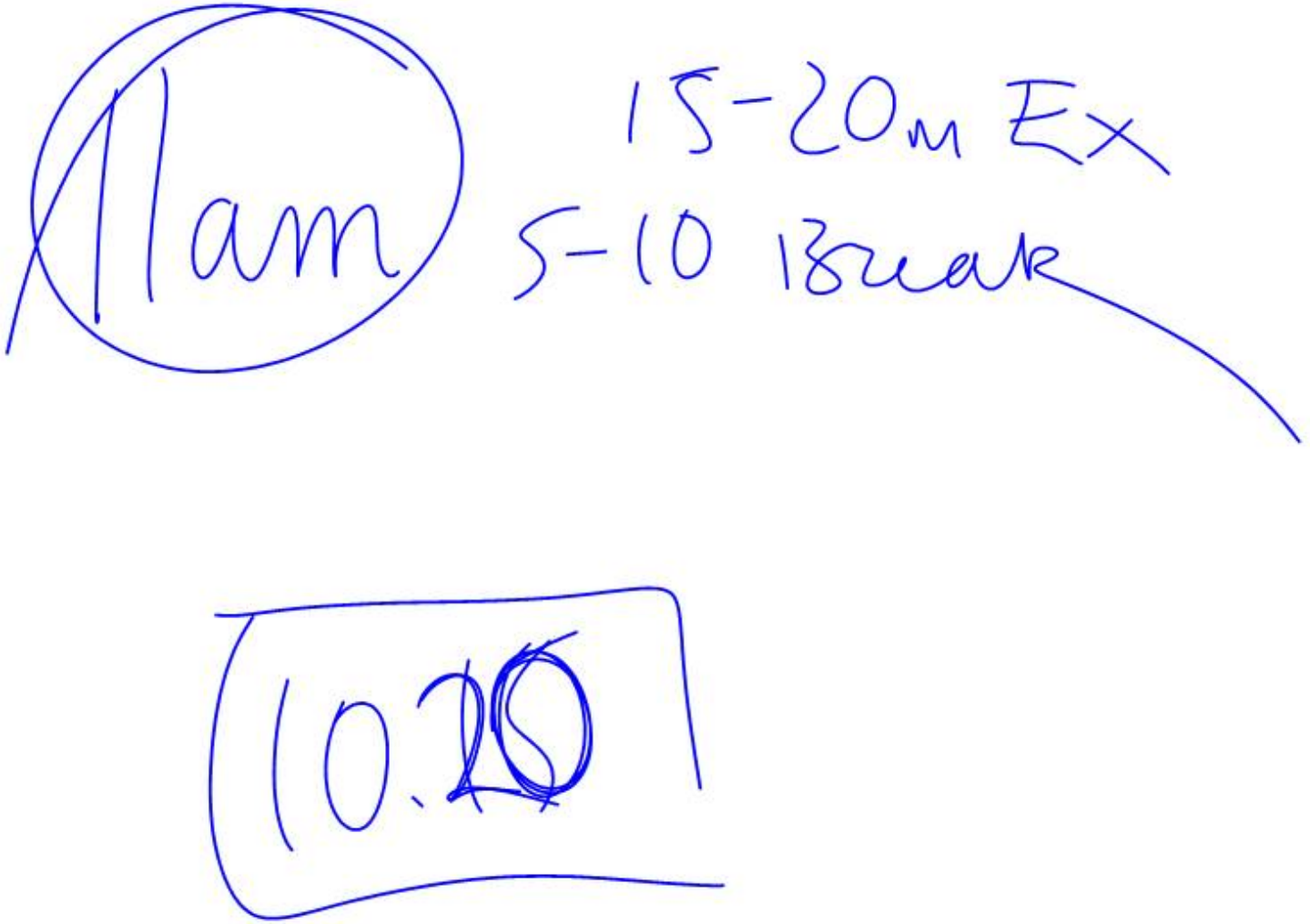
- filter (test)
- flatMap (list)
- fold → Reduce
  → aggregate
- map ← 1) Projection / "Structural"
  ← 2) Calc

- max()
- collect()
- top()

Questions

→ Next Steps

- Presentations / output ...
  - psychology
  - Evidence & argument


11am
15-20m Ex
5-10 break
10.20

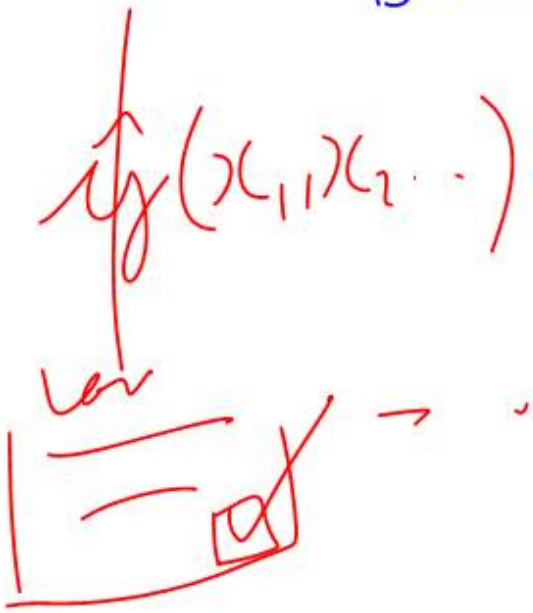
Projects / Pipelines

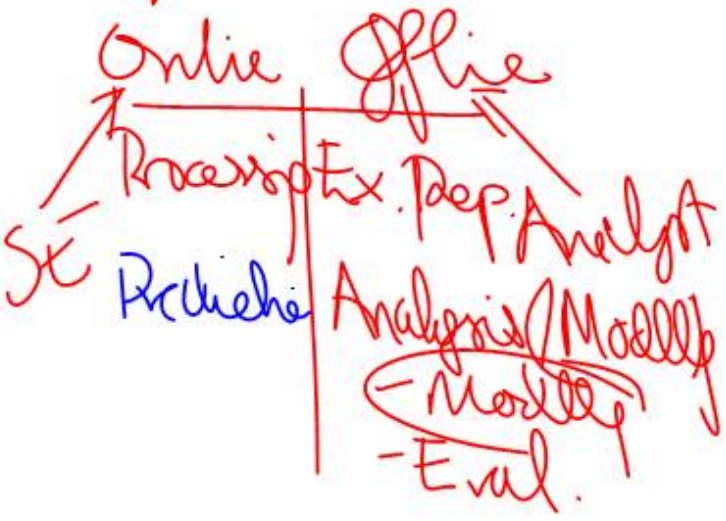
Problem

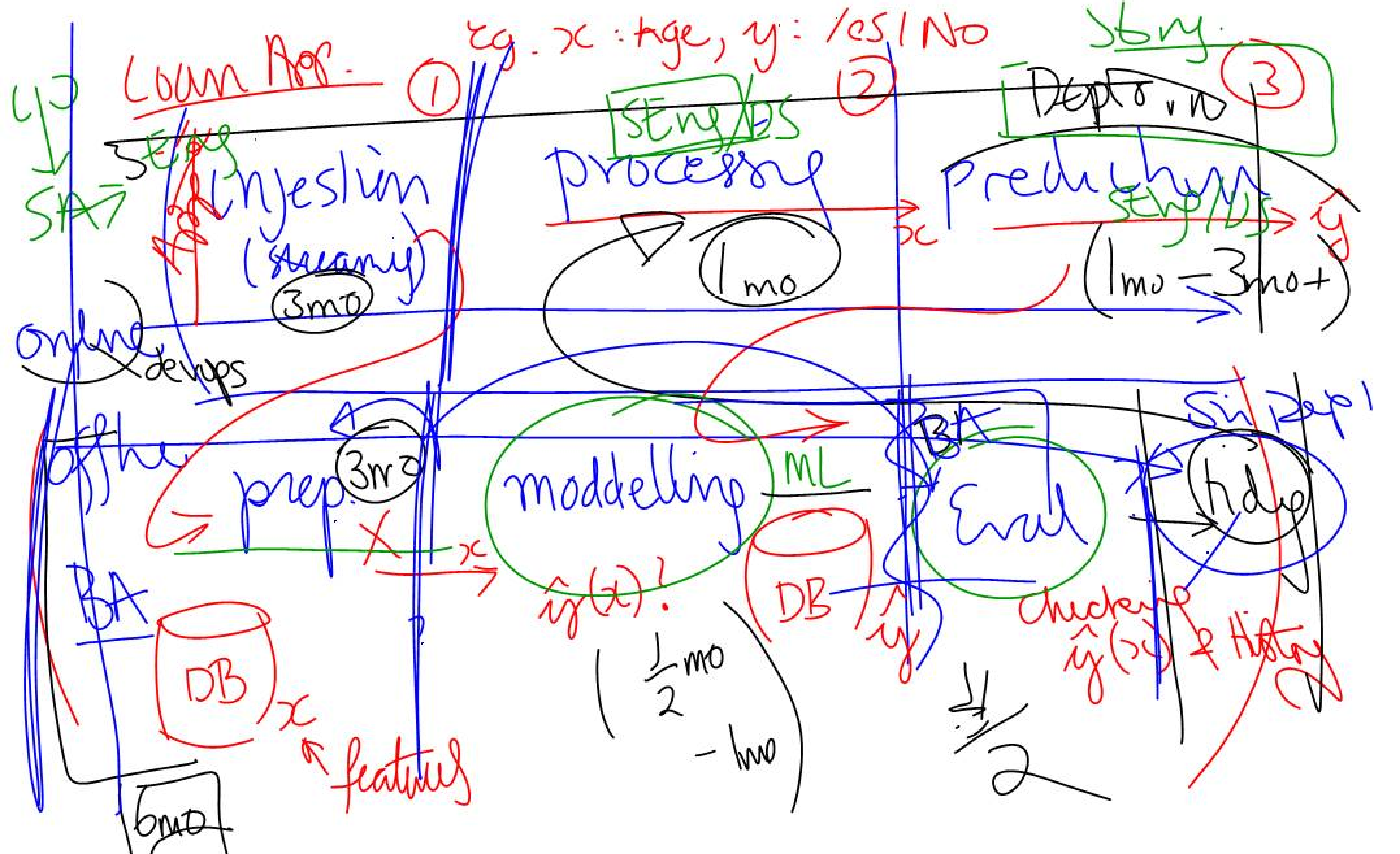
Solution

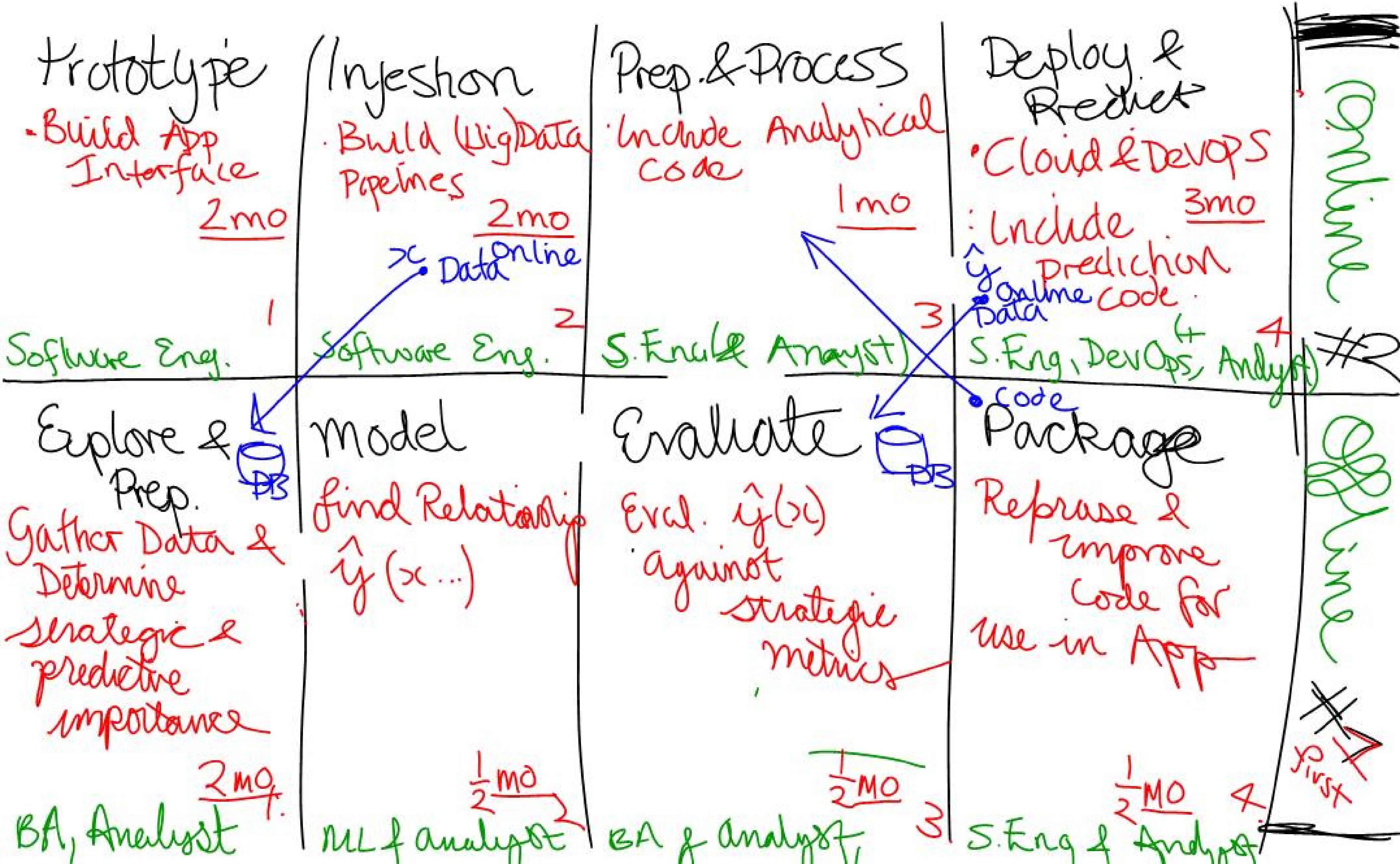
BDA

- Data
  - Streaming / online
  - Batch / DB / offline
- Injection






Loan App.
eg. x: Age, y: Yes/No
1
2
3
Injestion
(streaming)
3mo
Processing
1mo
Prediction
(1mo - 3mo+)
x
y
Online
devops
offline
prep.
3mo
modelling
ML
Eval
BA
DB
x
features
ŷ(x)?
1/2 mo
- 1mo
y
checking ŷ(x) & History
6mo
SA



Prototype
· Build App Interface
2mo
1
Software Eng.
Injeshon
· Build (Big)Data Pipelines
2mo
x Data Online
2
Software Eng.
Prep. & Process
· Include Analytical code
1mo
3
S. Eng (& Analyst)
Deploy & Predict
· Cloud & DevOPS
3mo
· Include prediction code
ŷ Online Data
4
S. Eng, DevOps, Analyst)
Online
Explore & Prep.
DB
Gather Data & Determine strategic & predictive importance
2mo
1
BA, Analyst
Model
find Relationship
ŷ (x ...)
½ mo
2
ML & analyst
Evaluate
Eval. ŷ(x) against strategic metrics
½ MO
3
BA & Analyst
DB
code
Package
Rephrase & improve Code for use in App
½ MO
4
S. Eng & Analyst
Offline
First