

Generativ ki og højere uddannelse

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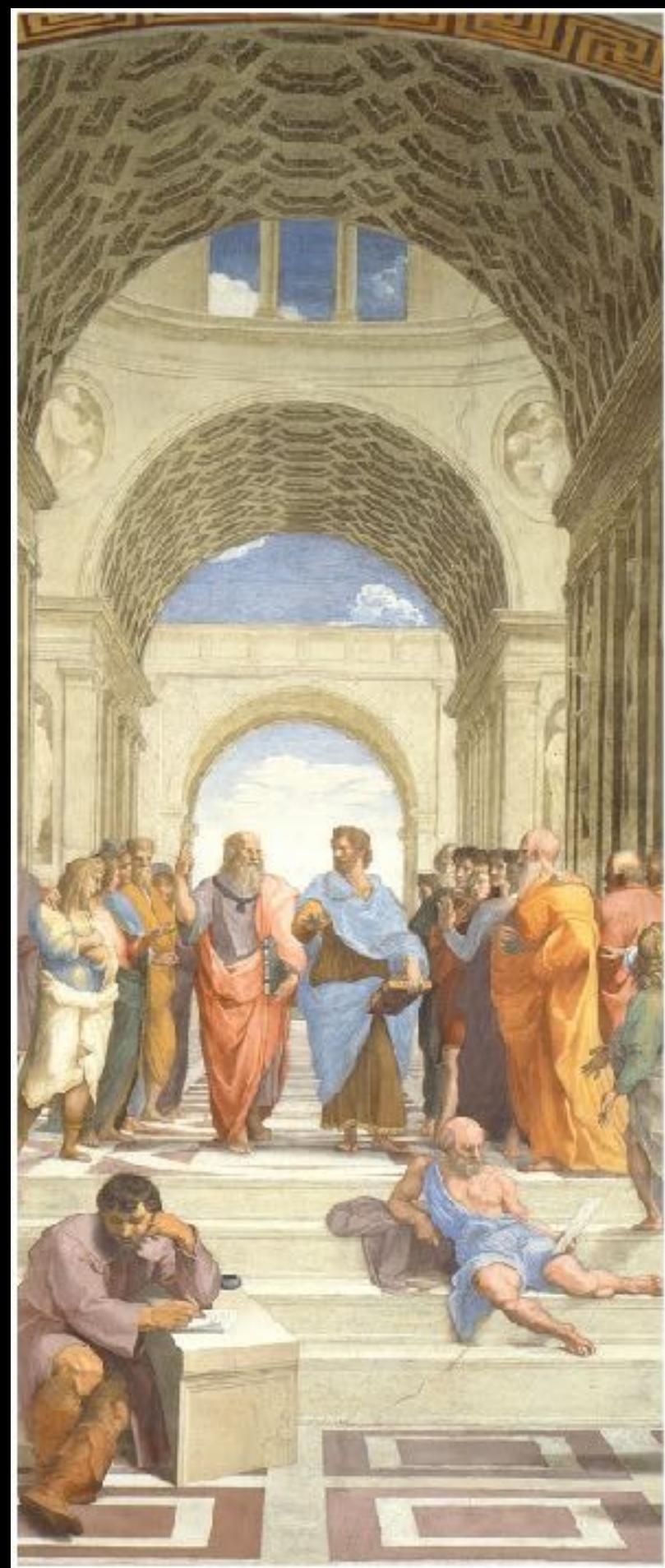
Basic Algorithms Research Copenhagen

(2023–): UFM ekspertgruppe for ki, CBS *advisory board*



2 timer

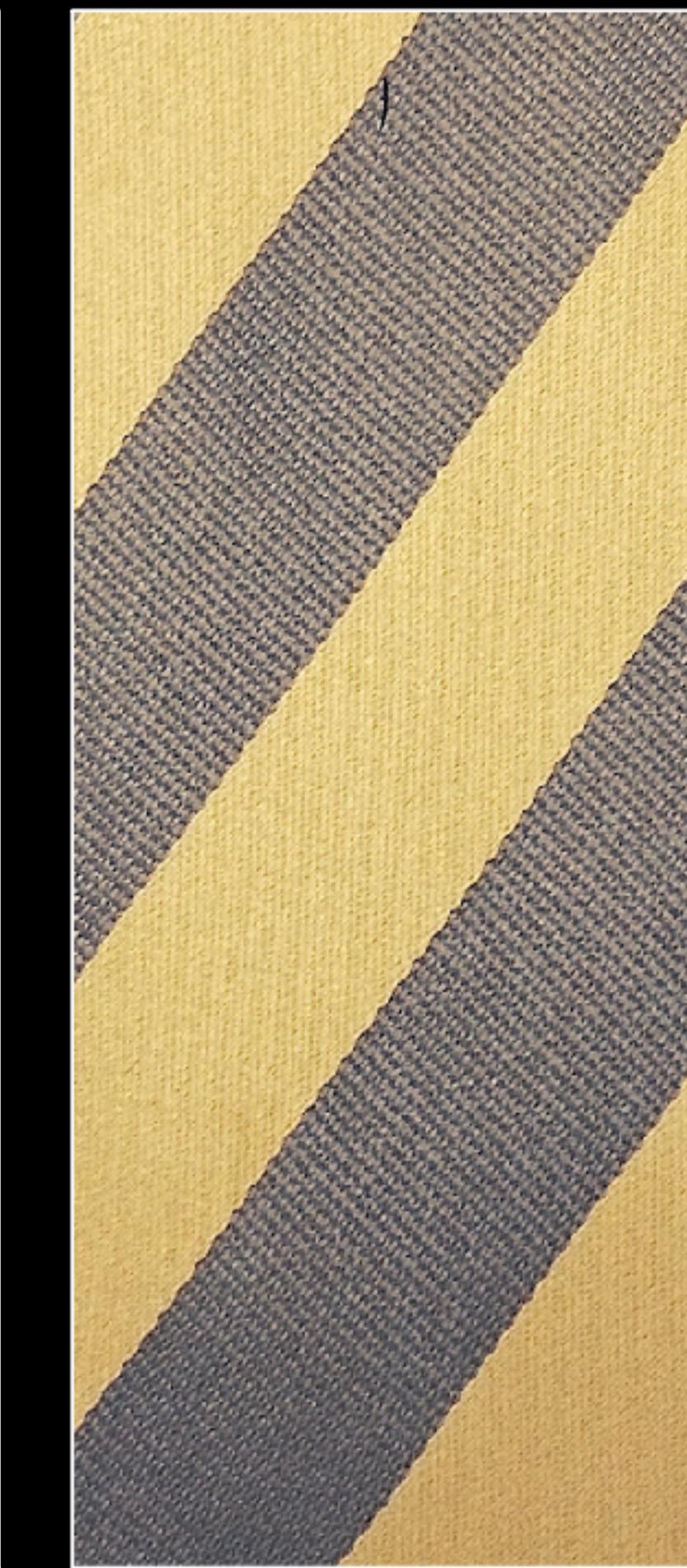
Oplysning



Økonomi



Status



Oplevelse



Værktøj



Dannelse

Humankapital

Netværk

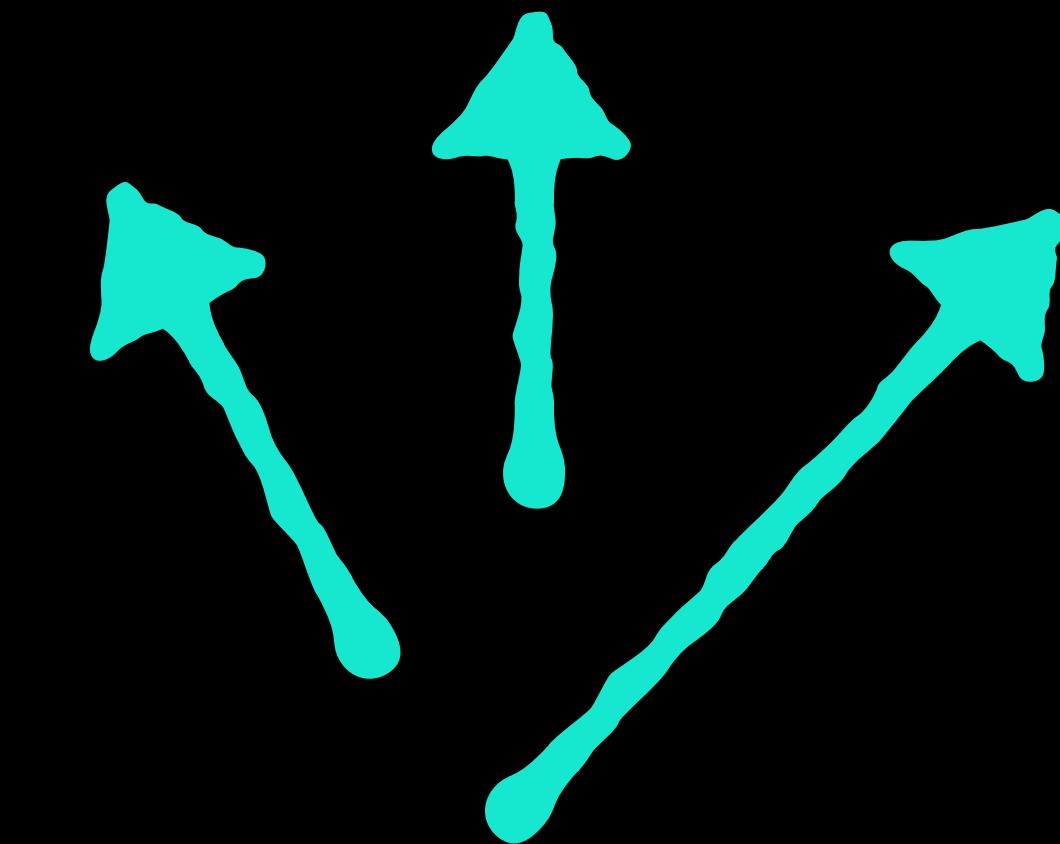
Selvrealisering

Andre mål

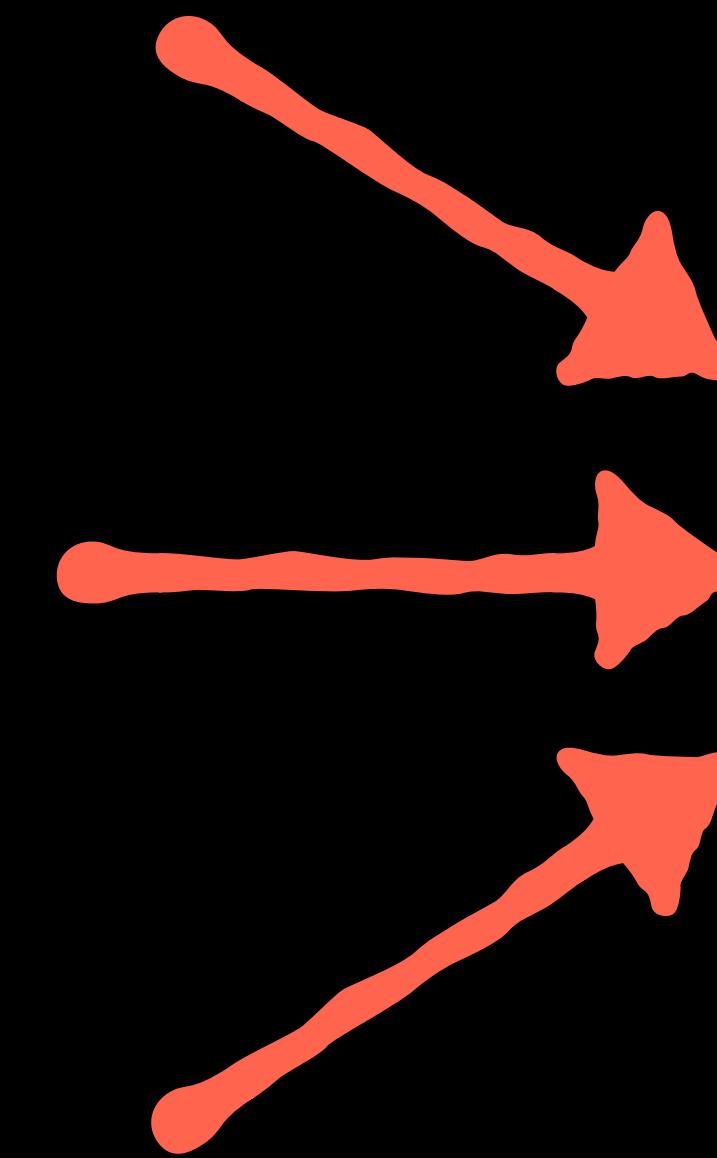
Dygtiggørelse



Personlig udvikling



Socialisering



Studieforberende

Viden

Kompetence

Akademia

Drivkraft

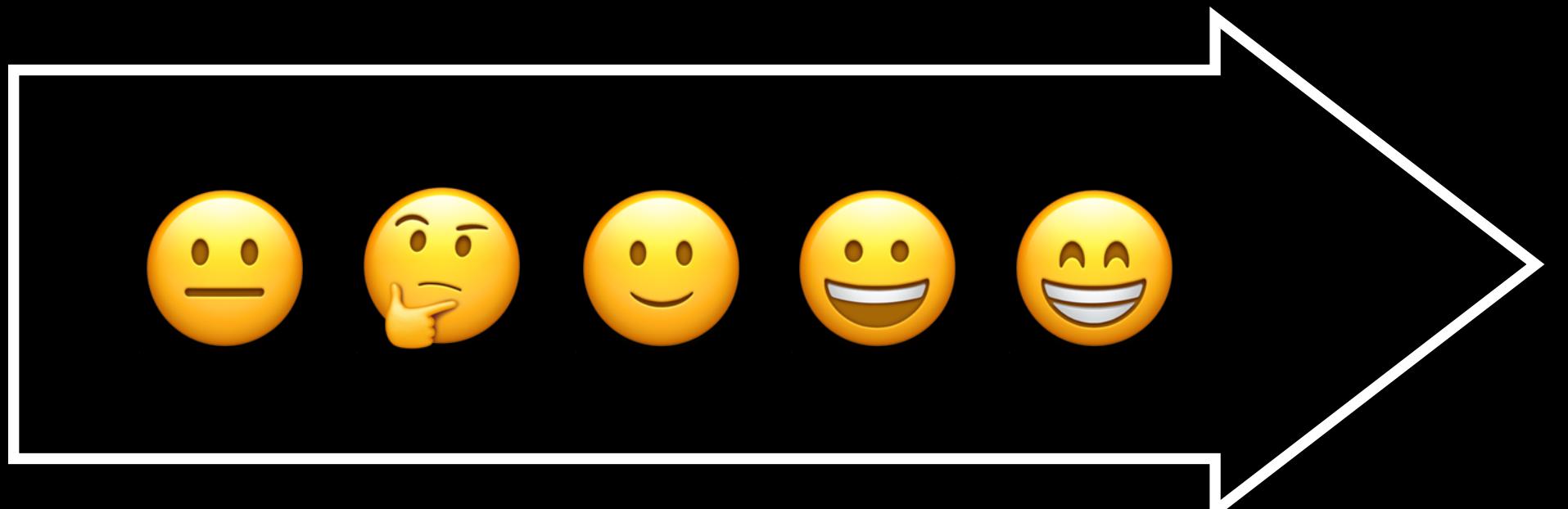
Det sande jeg

Udfaldsighed

Rarhed

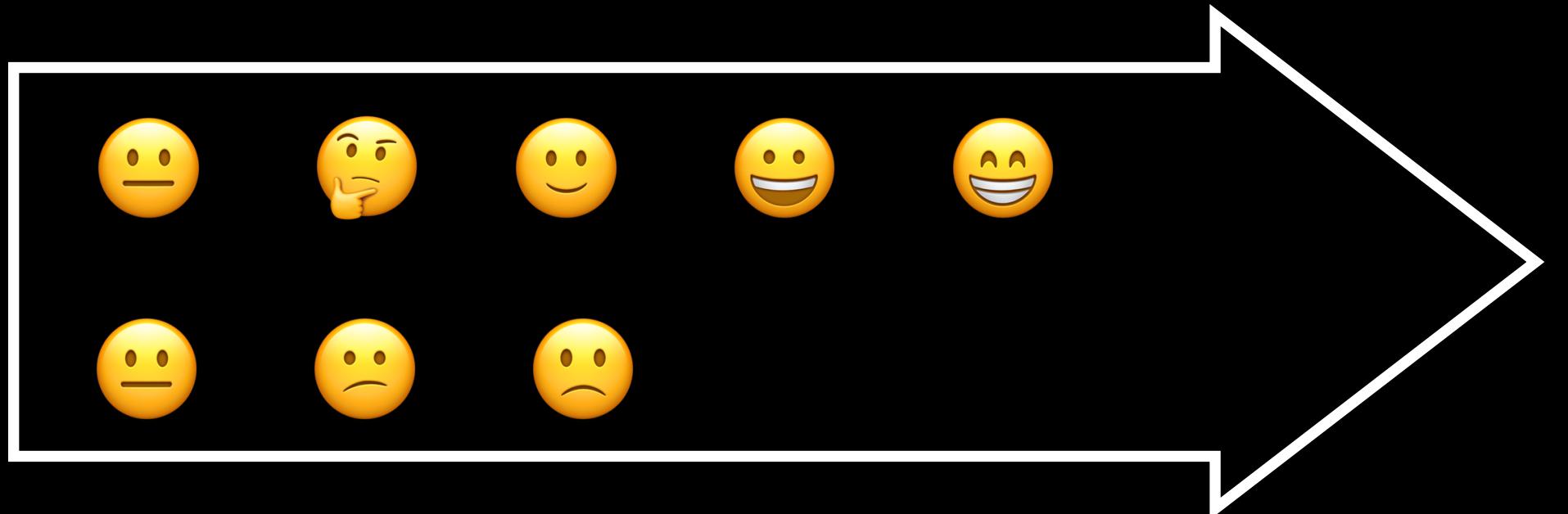
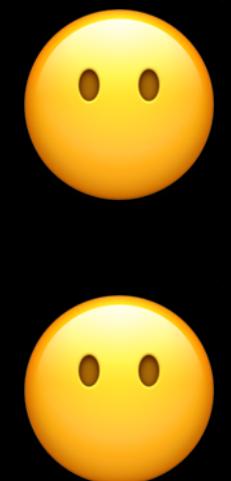
Arbejdsmarked

Læring



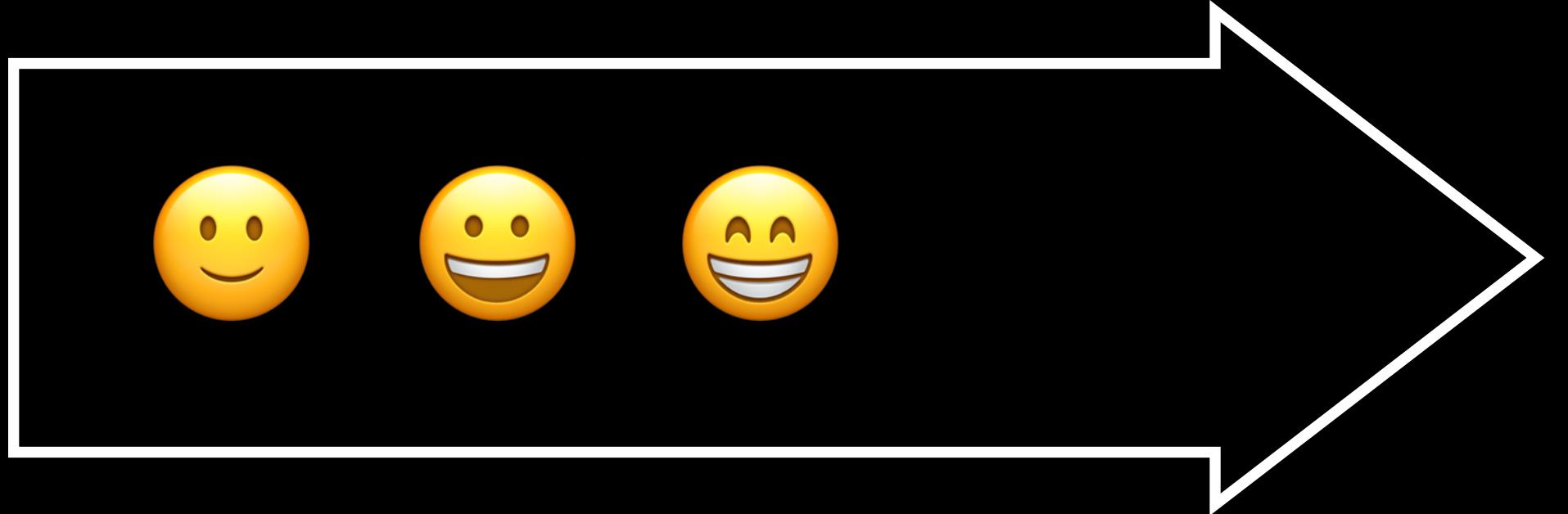
😊 har visse
egenskaber og
færdigheder

Frafald



Hvilke?

Udtagelse



Er der brug for 😊?

Om at frembringe violinlyde



Tilgængelighed

Lav

Høj



Resultatkvalitet

Afhænger af
brugeren

Gennemgående
fremragende

Signalværdi: Brugeren

... kan spille violin

... kan lære noget
vanskeligt

... har adgang til

en grammofon

Undervisning (læringsteknologi,
lærergerning, læremidler, elevadfærd, ...)



Grundlag for tilbagekobling (»bedømmelse«)



Egenskaber og færdigheder (»læringsmål«)



~~Undervisning (læringsteknologi,
lærerergerning, elevadfærd, ...)~~

Grundlag for tilbagekobling (»bedømmelse«)

Egenskaber og færdigheder (»læringsmål«)

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Grundlag for tilbagekobling (»bedømmelse«)

Egenskaber og færdigheder (»læringsmål«)

Ærlighed



»Bedømmelsesgrundlaget skal være gyldigt«

Holdbarhed



» The amount of energy needed
to refute bullshit is
an order of magnitude bigger than that needed
to produce it.

— Alberto Brandolini, 2013.

» Ils peuvent
en quelques mots exposer une vérité incomplète ; et,
pour montrer qu'elle est incomplète,
il nous faut de longues et arides dissertations.

— Frédéric Bastiat, *Sophismes économique*, 1863.

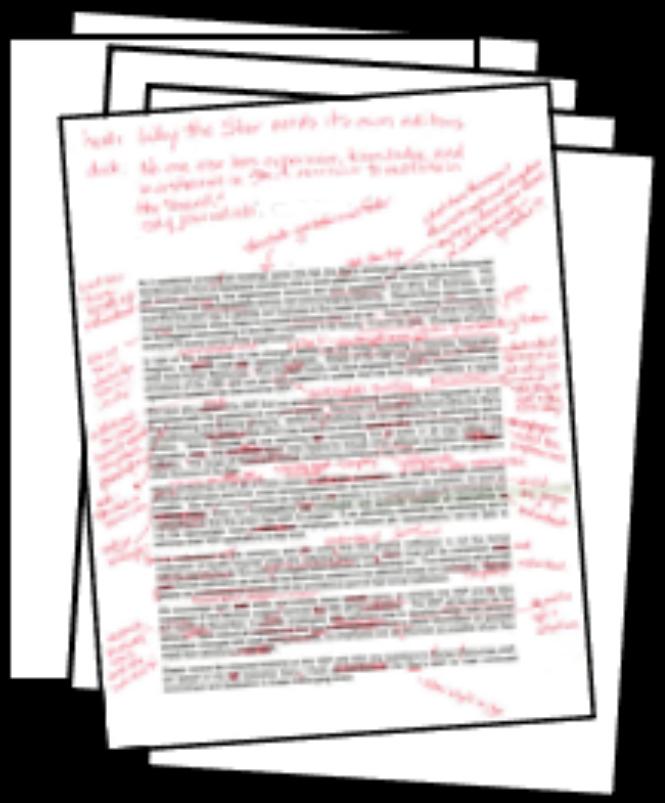
	før 2022	efter 2022
t(produktion)	dage	sekunder
t(feedback)	timer	dage
signalerer	verbal intelligens konformitet investeteret tid social kapital	adgang til en stor sprogmodel

»Bedømmelsesgrundlaget skal kunne behandles effektivt.«

Holdbarhed

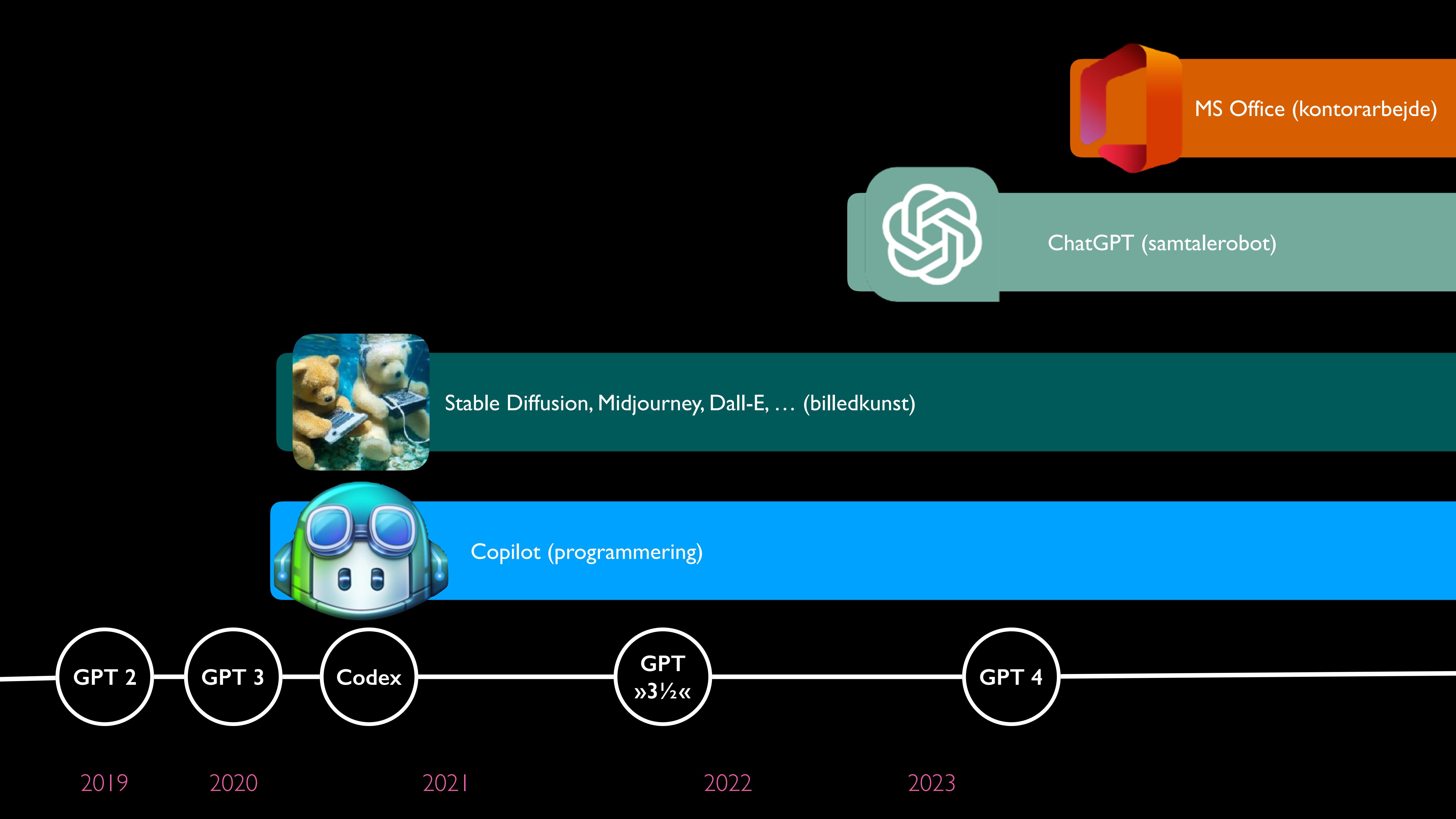
HVORNÅR FALDT KONSTANTINOPEL?

1066



Grundlag for tilbagekobling (»bedømmelse«)

Egenskaber og færdigheder (»læringsmåkk)



Generativ ki er en »styrkefordobler«



+



=



+



=



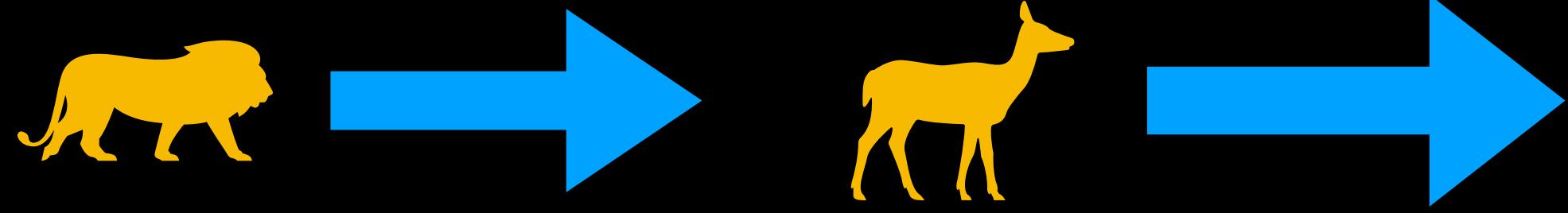
Hvilke færdigheder?

Signaler



»Signalet er ikke egenskaben«

Egenskab



Kan i otte timer løbe vandret

Signal

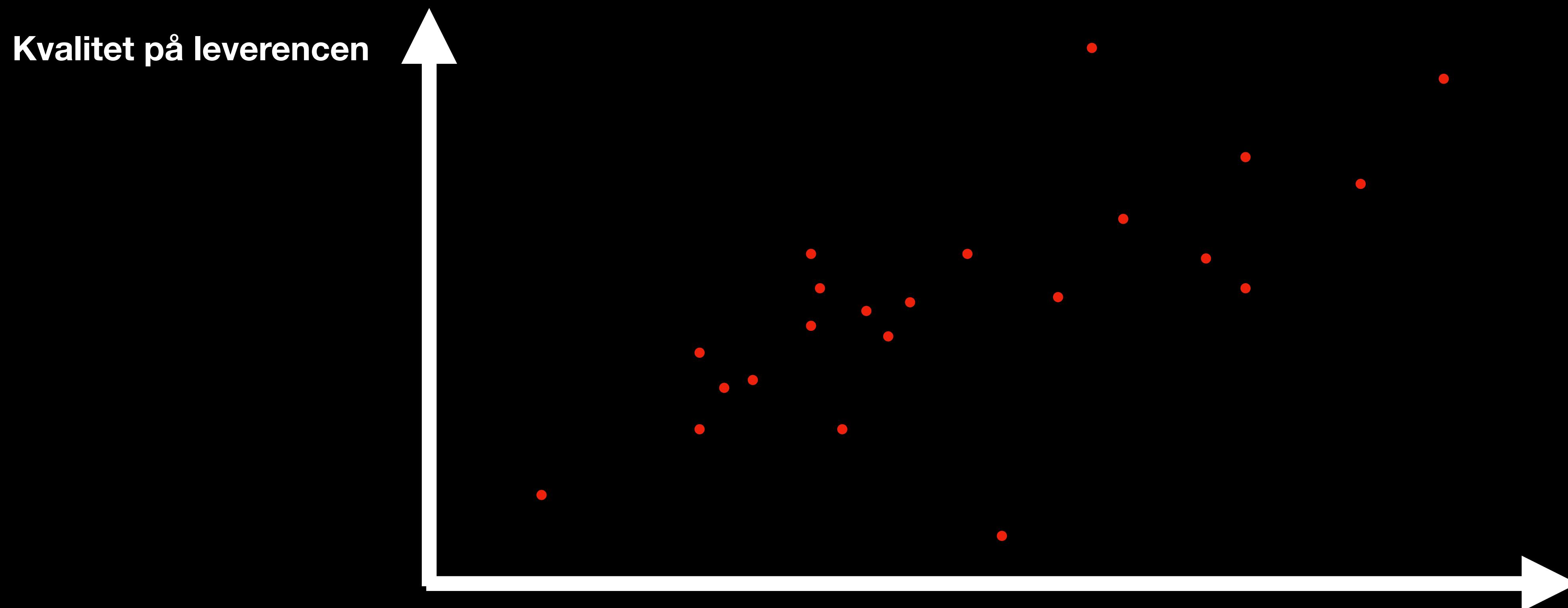


Kan kort hoppe 2 m lodret

Egenskaben ≠ signalet
Signalerings gavn er begge organismer
Signalet skal være »dyrt« (= svært at foregøgle)
men nemt at aflæse

Generativ ki er en trampolin

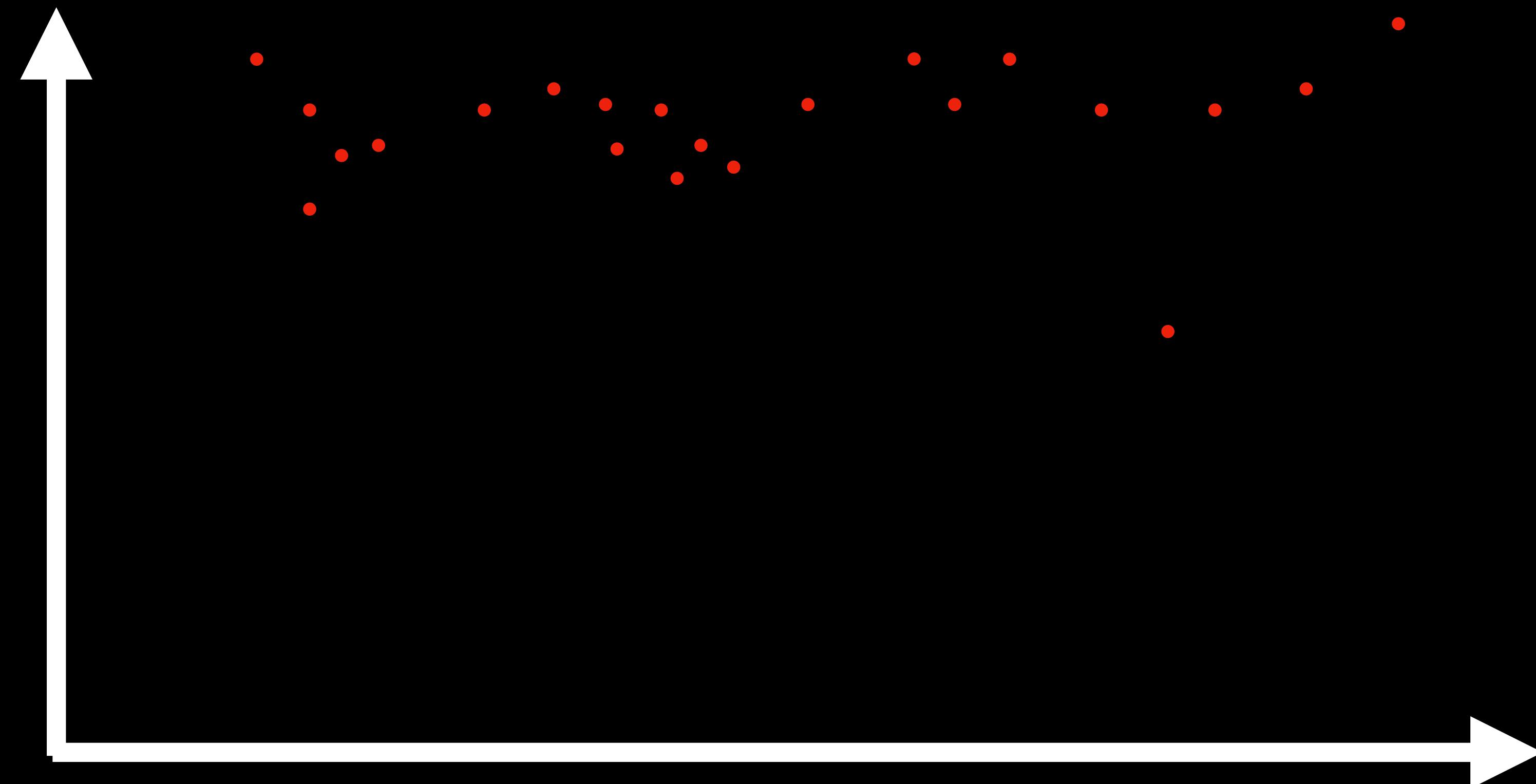




Intelligent
Flittig (arbejdsom, ordentlig)
Dygtig (opfylder læringsmål)

Social status
Rar
Social kompetent

Kvalitet på leverencen
stil,
analyse
billeder
digitalt artefakter



Skriftlig opgave uden tilsyn har nu ingen signalværdi

»Ring en ven« & uklanderlig prosa er demokratiseret

Egenskaben
intelligent
flittig
dygtig
konform
social status
rar
social kompetent

Hvad kan vi gøre

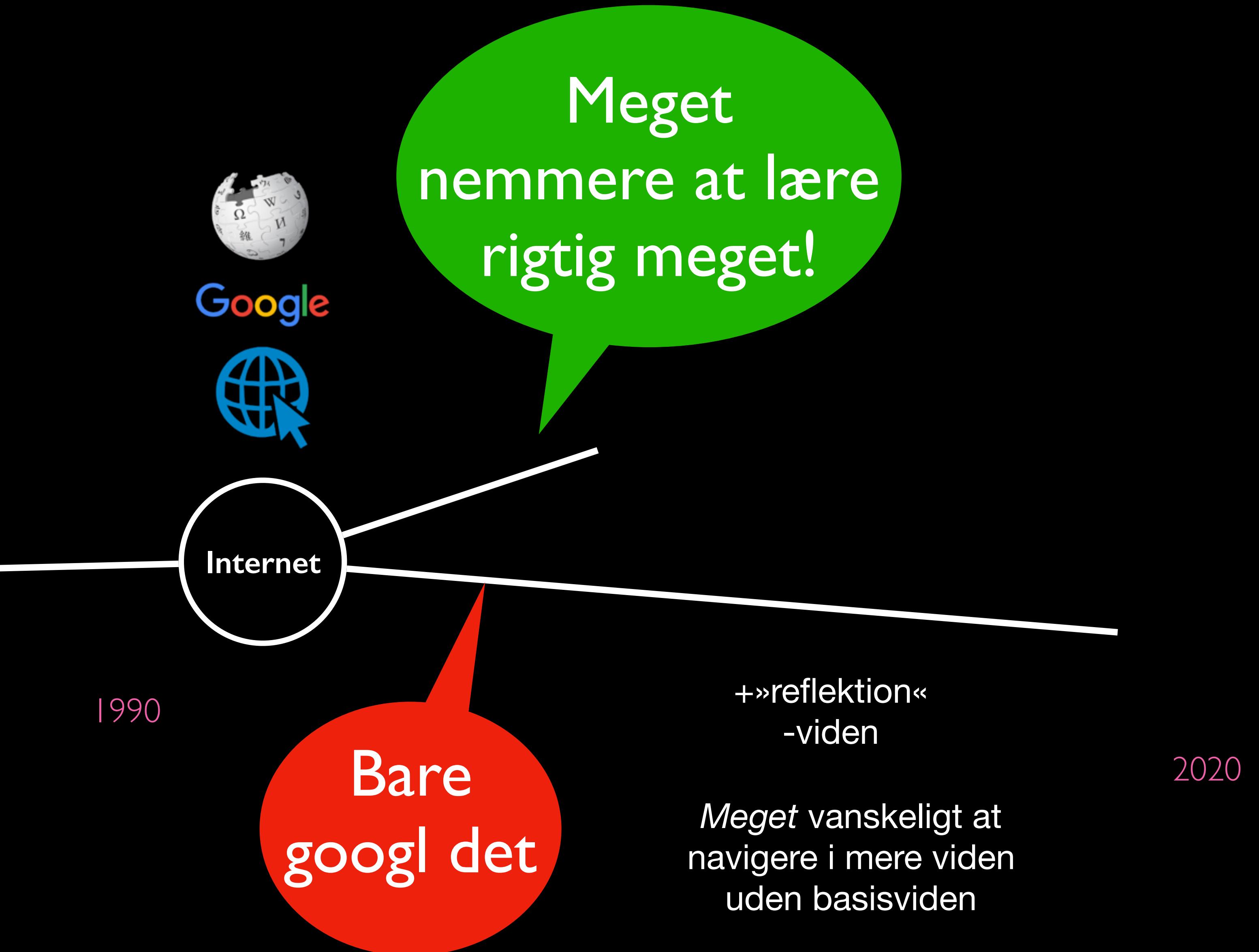
Hvad bør vi gøre

Hvad vil vi gøre?

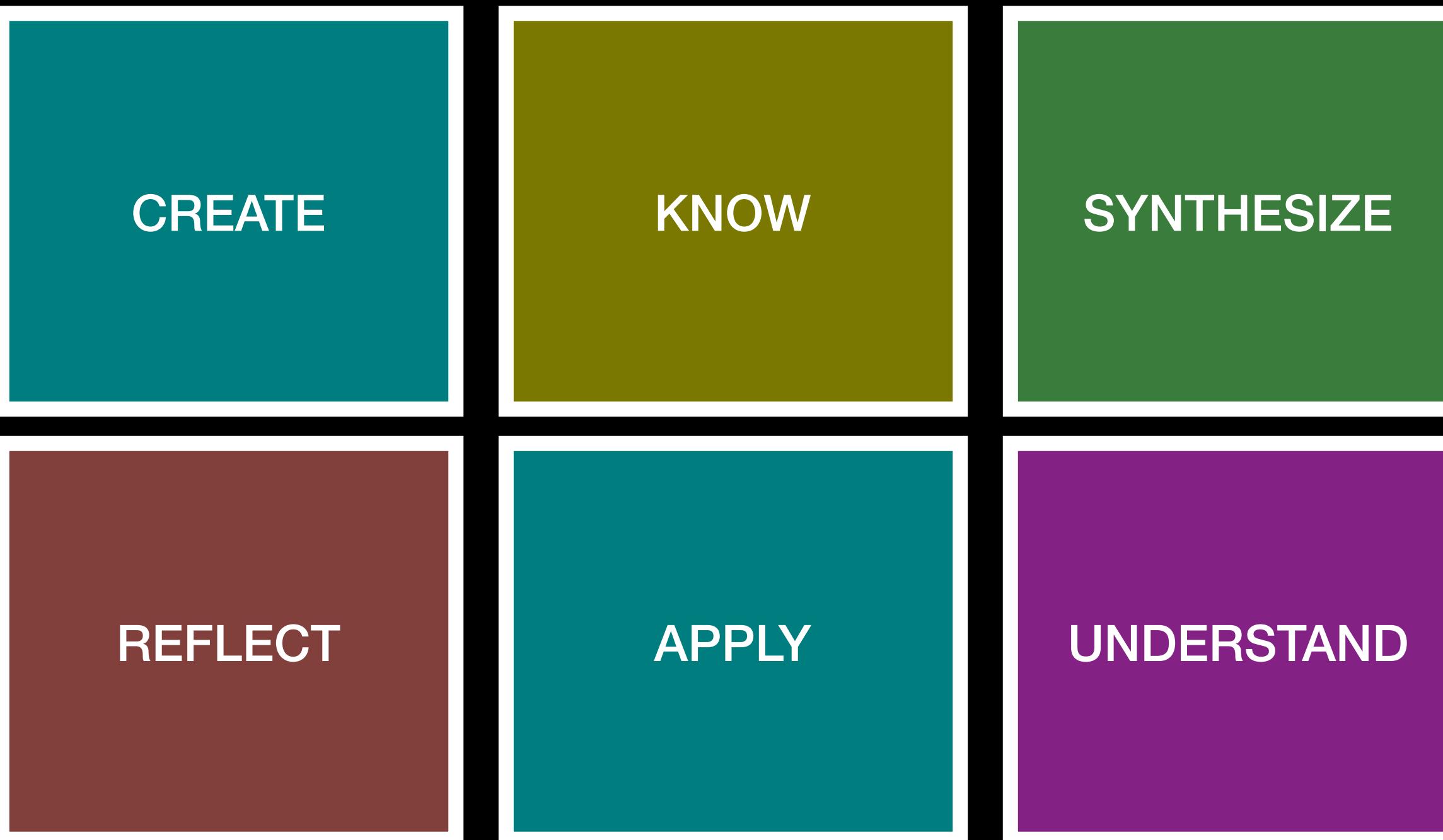
Hvad kan vi gøre

Hvad bør vi gøre

Hvad vil vi gøre?



Educational Objectives, Cognitive Domain (Bloom1956)



KNOW

UNDERSTAND

APPLY

SYNTHESIZE

REFLECT

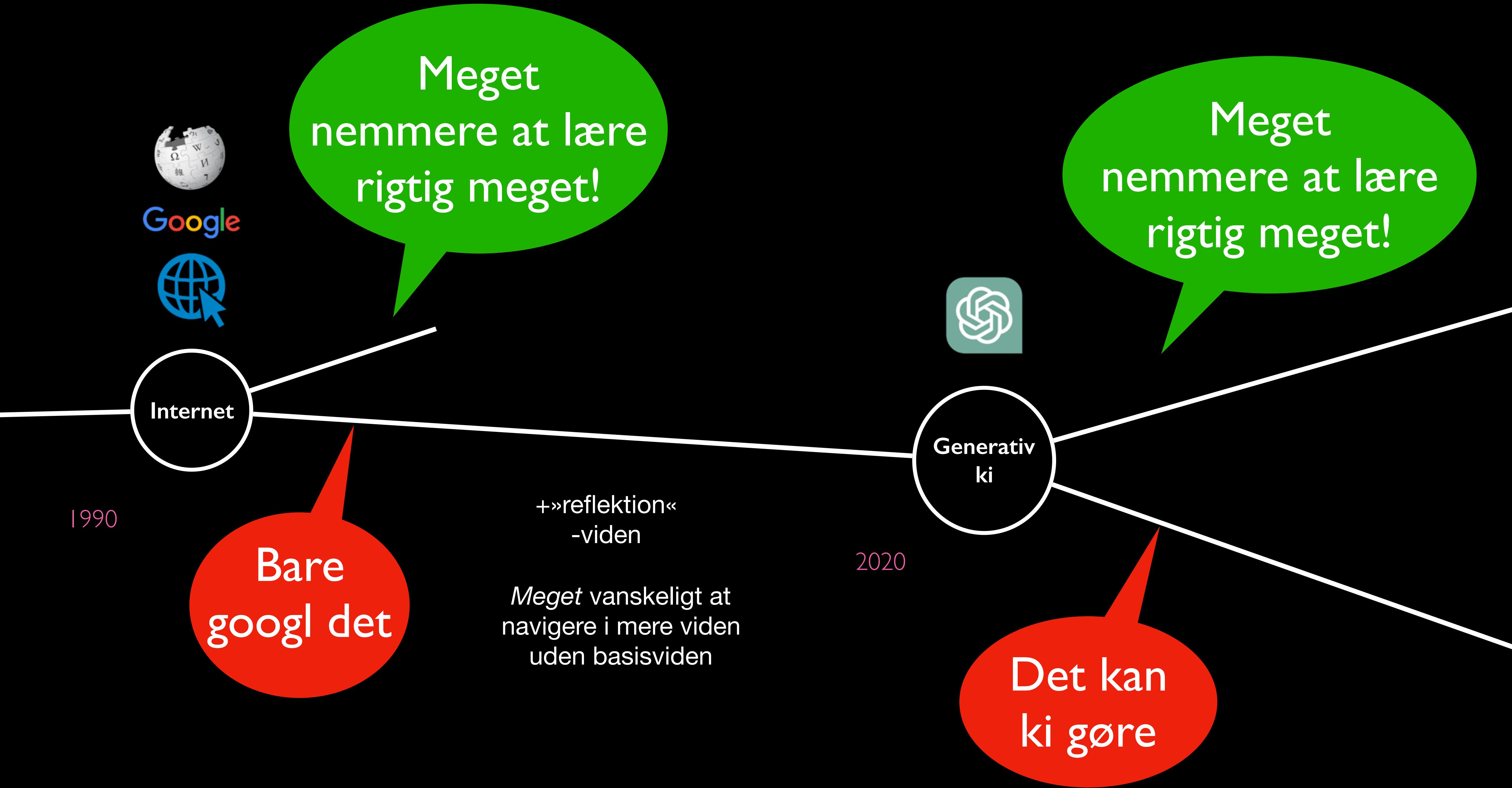
CREATE

KNOW

DERST

E

A



2020

Generativ
ki



Det kan
ki gøre

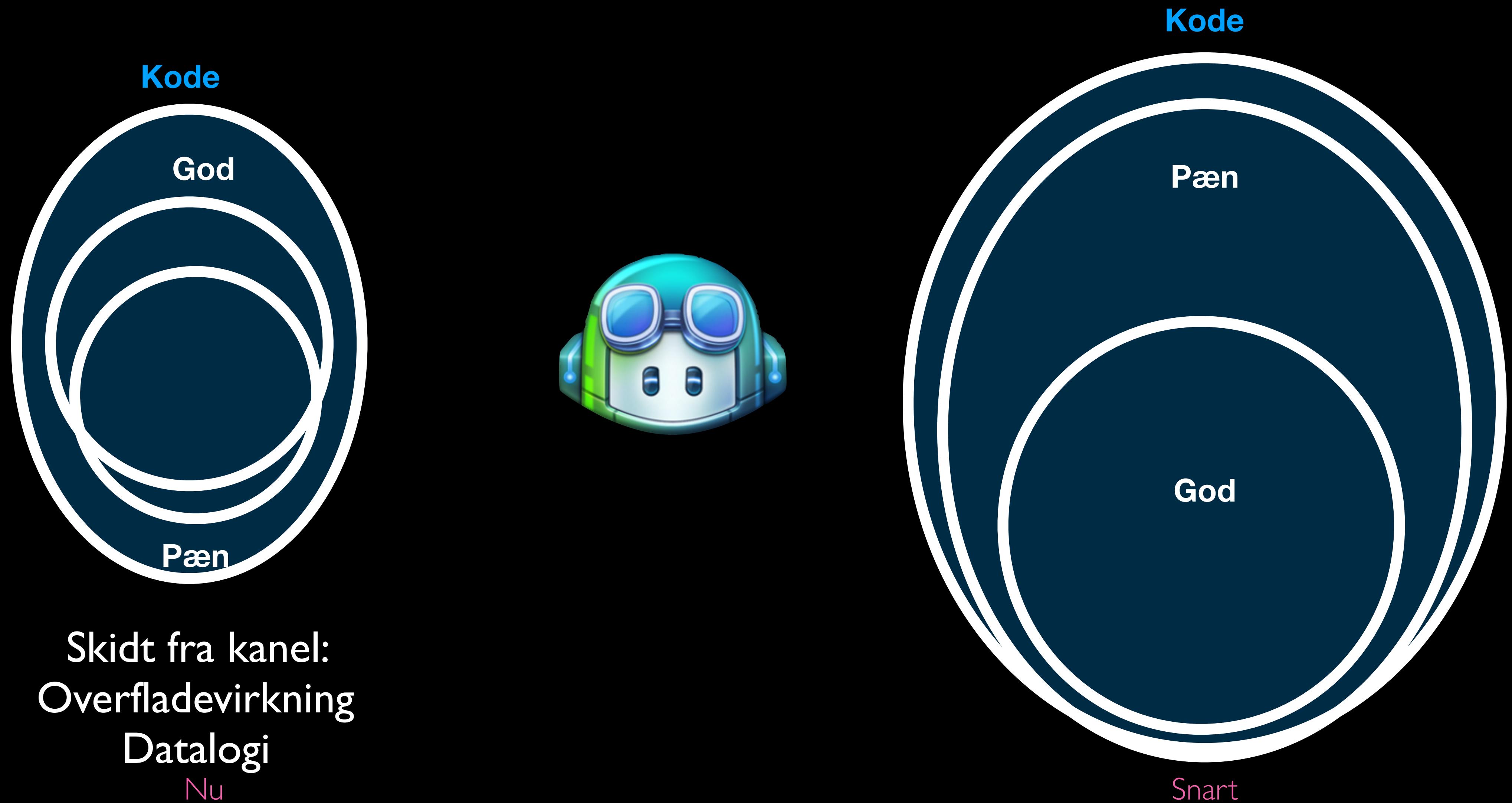
Meget
nemmere at lære
rigtig meget!



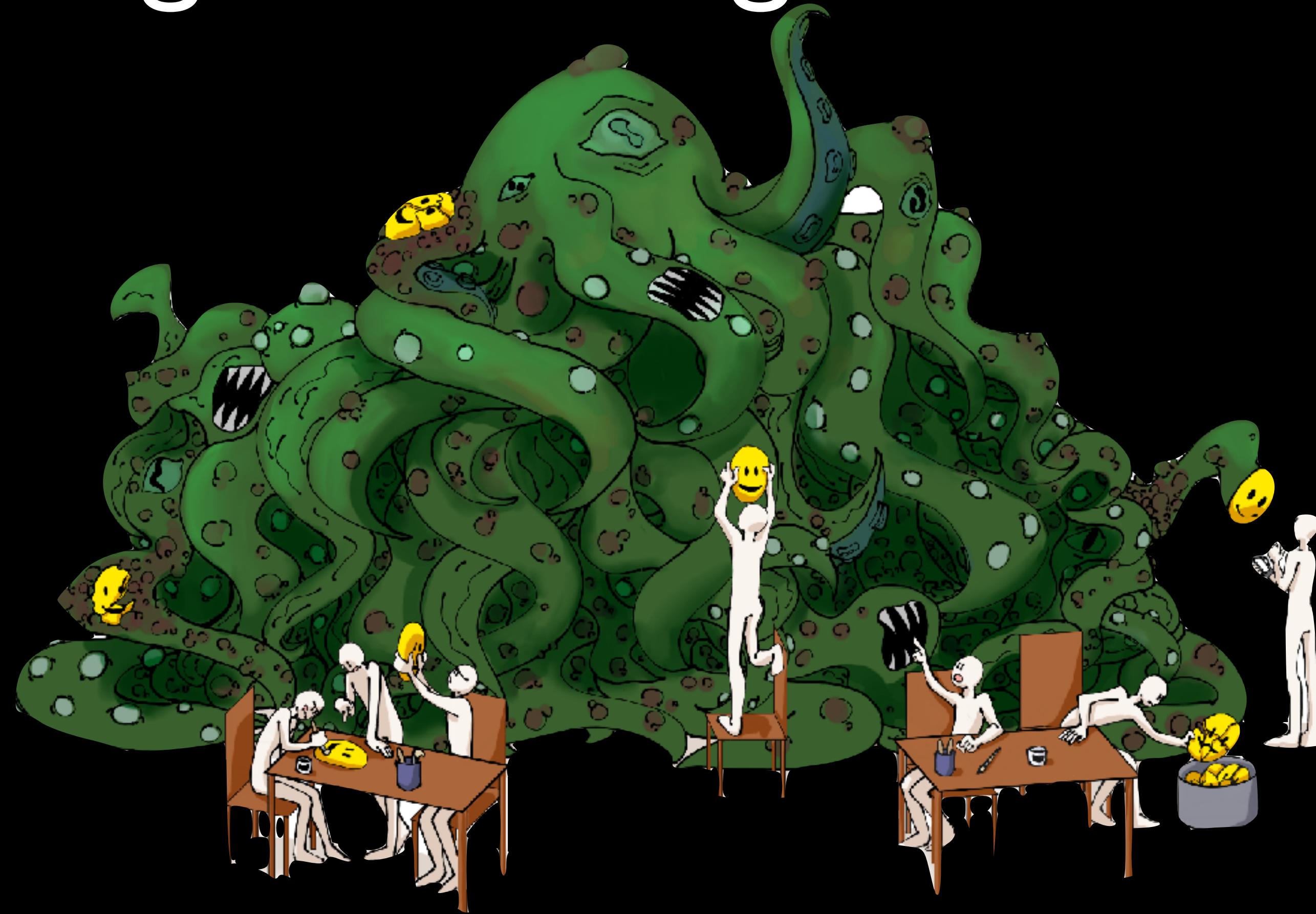
Kompetencer

Inklusion
Udfaldslighed

Spekulation: meget mere dårlig kode



Spekulation: programmeringens endeligt?



RLHF (»operant betingning ved menneskelig tilbagekobling«) > beregningstænkning?

Welcome to

EEEEEE	LL	III	ZZZZZ	AAAAA
EE	LL	II	ZZ	AA AA
EEEEEE	LL	II	ZZZ	AAAAAAA
EE	LL	II	ZZ	AA AA
EEEEEE	LLLLL	III	ZZZZZ	AA AA

Eliza is a mock Rogerian psychotherapist.

The original program was described by Joseph Weizenbaum in 1966.
This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?

YOU: Men are all alike.

ELIZA: What is the connection, do you suppose ?

YOU: They're always bugging us about something or other.

ELIZA: Can you think of a specific example ?

YOU: Well, my boyfriend made me come here.

ELIZA: Is it important to you that your boyfriend made you come here ?

YOU: He says I'm depressed much of the time.

ELIZA: I am sorry to hear that you are depressed.

YOU: It's true. I am unhappy.

ELIZA: Can you explain what made you unhappy ?

YOU:

—Feigenbaum, Eliza, 1964

Hvordan virker Eliza?

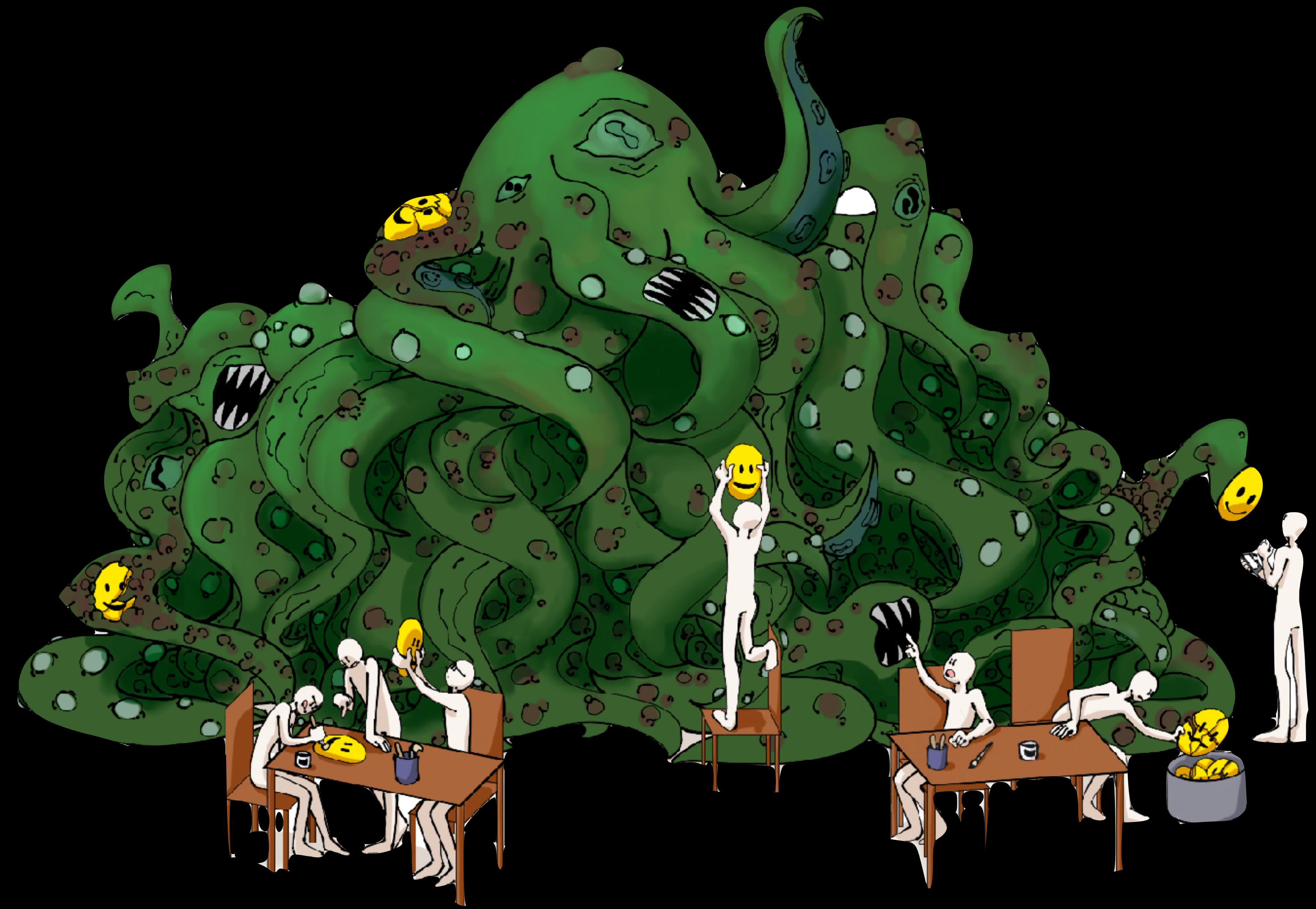
```
key: remember 5
decomp: * i remember *
reasmb: Do you often think of (2) ?
reasmb: Does thinking of (2) bring anything else to mind ?
decomp: * do you remember *
reasmb: Did you think I would forget (2) ?
reasmb: What about (2) ?
reasmb: goto what
pre: equivalent alike
synon: belief feel think believe wish
```

Hvordan virker GPT?

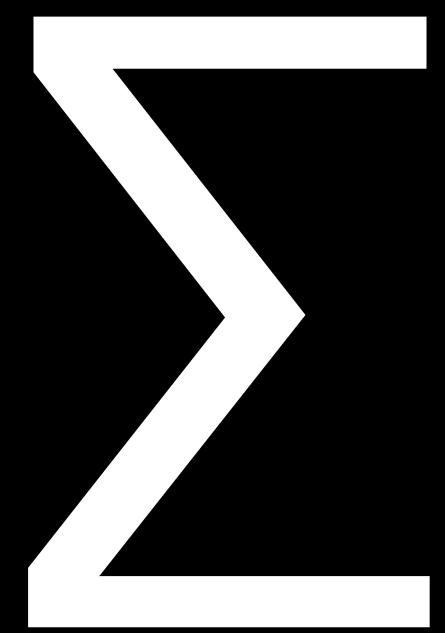
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1.0866115863623567 -1.3525763895155665 -0.017222788485716154 -1.082074672038546 0.6923335035547151
1.4178013398788807 -0.29595798268277596 -0.544592267936524 -0.19017577326656274 -0.2813609735055221
-0.2723040265202662 0.25962204968114627 -1.2075429988033952 -0.5108400786248819 -0.8949288567817734
1.4469750278986784 -0.4519338887427109 -0.6253474049220229 -0.537966358328835 -0.4212358316488312
0.5760967844824633 0.5449629371382955 0.9011203062416006 -0.6265621765392312 0.2684344330418421
-2.887992226659539 -0.1462822637393419 0.045969291467169444 -0.09973486425592275 -0.17867778278609728
-0.4236157416888609 1.4085228020673255 -1.1013963578808106 0.17934959969346864 2.046074286297879
-0.6551821095421503 0.6994695061899573 -0.9387416595827696 -2.2625240226362524 -0.5230807256771716
-2.123478197857787 -0.9273342923566504 -0.29088650082593864 -1.4325305162112967 -0.38546816994296434
1.5355530691333923 -0.2855287046699752 0.94680149592137 -1.3307109184194856 0.28074470208862534
-0.45857774621484404 -1.9101025714535596 0.21328432504620767 -2.051936800198914 -1.1084190963395992
-0.5275753910906126 -1.2477002900427032 0.4000847617328186 -1.3771985681028003 0.02125046369523839
-0.4234567973925279 0.713667086992266 -1.009517861000337 1.1406179782221022 1.0970378217142316
0.5587415149893091 -0.14406015597100483 -0.8808988611306637 0.5702251960491618 1.4483531109927847
-1.4376959096669846 -1.1340869441063395 2.4783796369270013 -1.4900277542070737 0.21456868410574265
0.2929399158382123 -0.005231681361731191 -1.7676678642887482 -1.1042828927488735 0.09815597801639207
-0.7754785573097438 0.6971238560131782 0.20647923846502714 -1.4961792454391944 0.46906247439949555
1.161246501025446 1.5098193008695369 -2.1901430694361657 -0.4933564597214423 0.7588881193329783
0.380386677099361 -0.5731819212045001 -0.05513272936032314 -0.3883000502404011 -0.11195880155285792
0.12831619992457183 -1.4554829628284214 2.4018014772005203 0.2223068309562163 -0.08195266667928601
0.053679607902617714 0.23737060303637775 0.03248053414892346 -0.45253838841220023 -1.351993934947922
-0.19479620508451762 0.34429597873673506 -2.978462589584215 0.802254598096871 1.4608713597984502
-1.206947119755617 0.9305255631636172 -0.8033499668337178 -0.07438474560367545 1.4682040141385
0.04536974837828212 0.7494592151079184 0.6099883897663217 0.06480457088633015 -1.524645647211468
-0.9832016200364718 1.1545130730581195 1.2332657501758435 0.25860998346291036 0.6305748074473086
0.7790157792688545 -0.23017226039410554 1.659460780487888 -0.46859866892092766 -0.056288007003880244
1.5499329922924656 -0.09094510130406454 0.9746177567519314 -0.7299257493157898 -0.9204718199740698

We use the same model and architecture as GPT-2, including the modified initialization, pre-normalization, and reversible tokenization described therein, with the exception that we use alternating dense and locally banded sparse attention patterns in the layers of the transformer, similar to the Sparse Transformer. To study the dependence of ML performance on model size, we train eight different sizes of model, ranging over three orders of magnitude from 125 million parameters to 175 billion parameters, with the last being the model we call GPT-3. Previous work suggests that with enough training data, scaling of validation loss should be approximately a smooth power law as a function of size; training models of many different sizes allows us to test this hypothesis both for validation loss and for downstream language tasks.

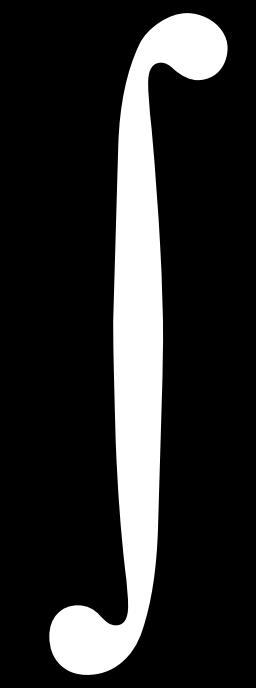
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Spekulation: analysens hævn



Logik
Kombinatorik
Algebra
Diskret sandsynlighedsteori
Talteori

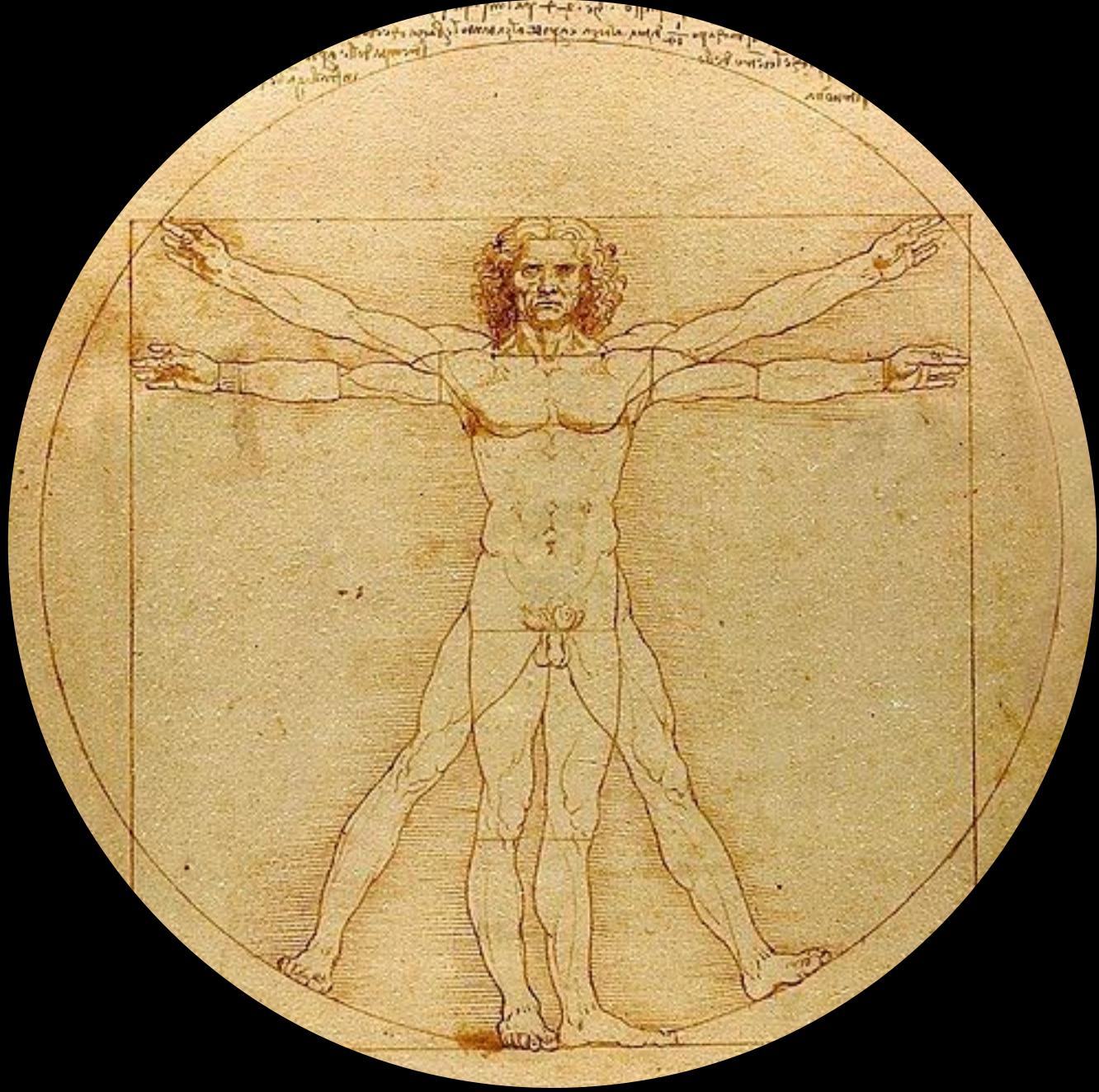


Flervariabelanalyse
Statistik
Differentialregning

Før

Snart

Spekulation: oplysningens endeligt



Forklaring og
konstruktion går
hånd i hånd

Før

Største
ingeniørsproblem
nogensinde løst
uden at forstå,
hvad der foregår

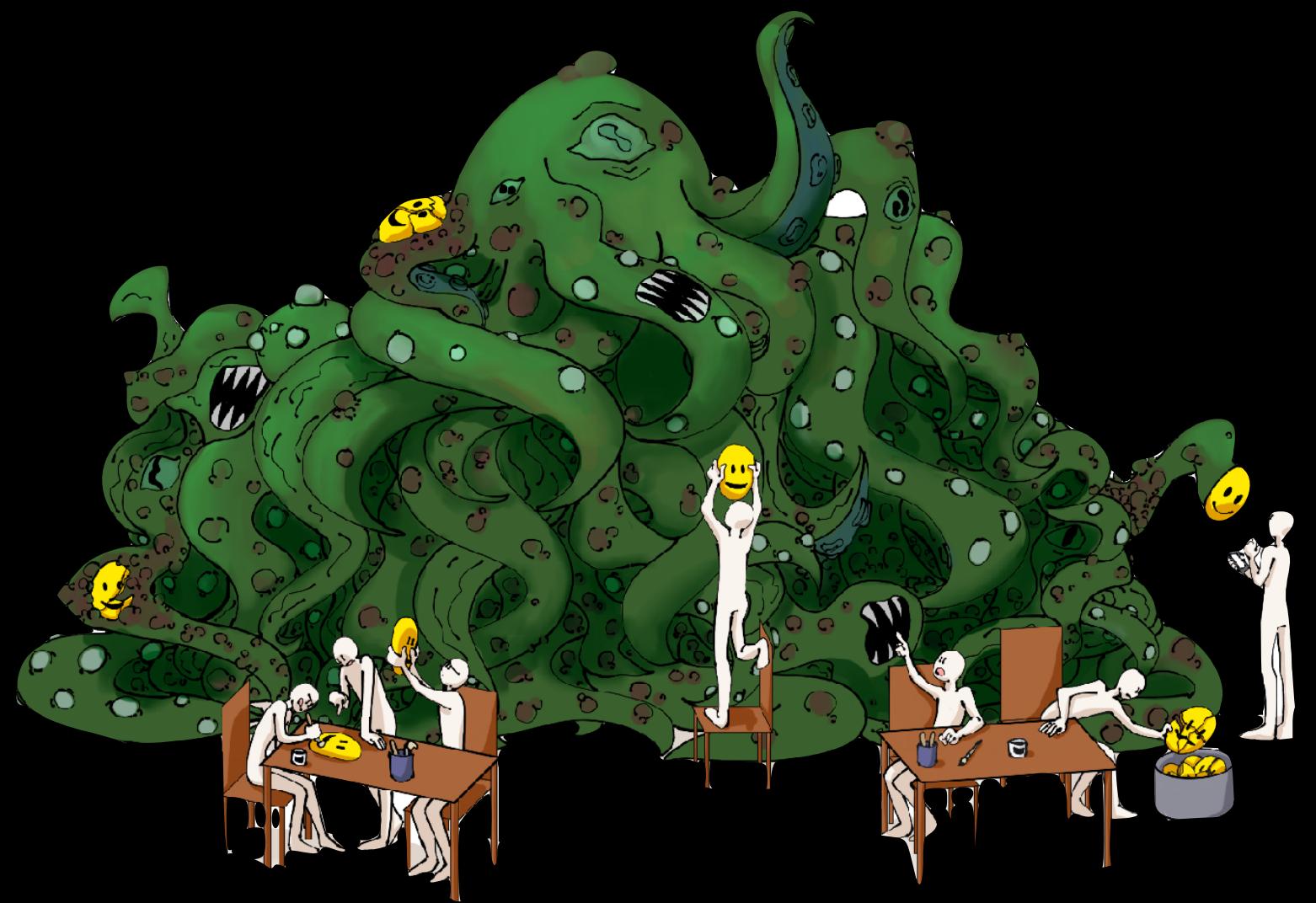


Fremskridt
uden forklaring

Store sprogmodeller

Snart

Tak



+

