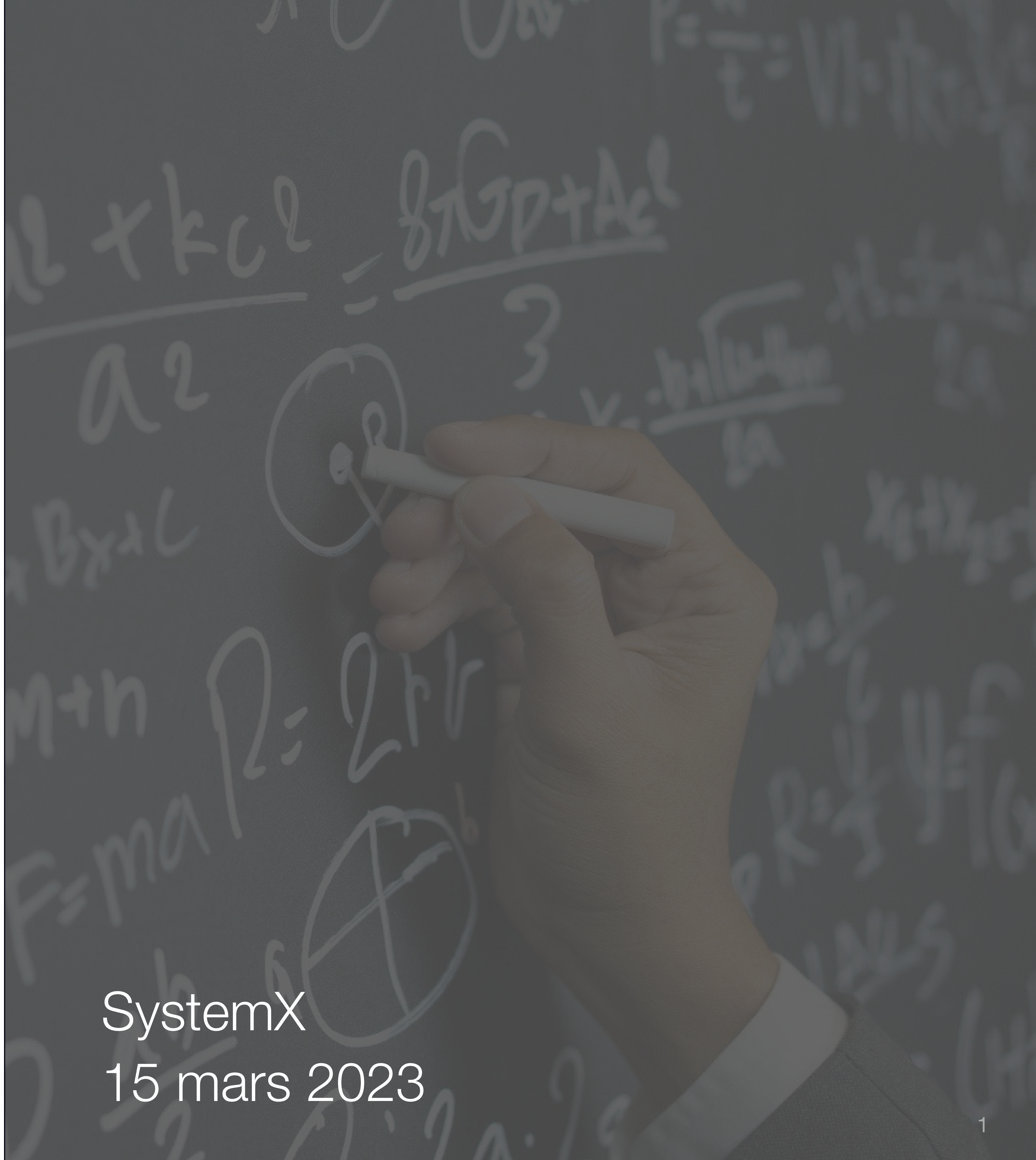
Information theory meets human-computer interaction

Michel Beaudouin-Lafon
Université Paris-Saclay

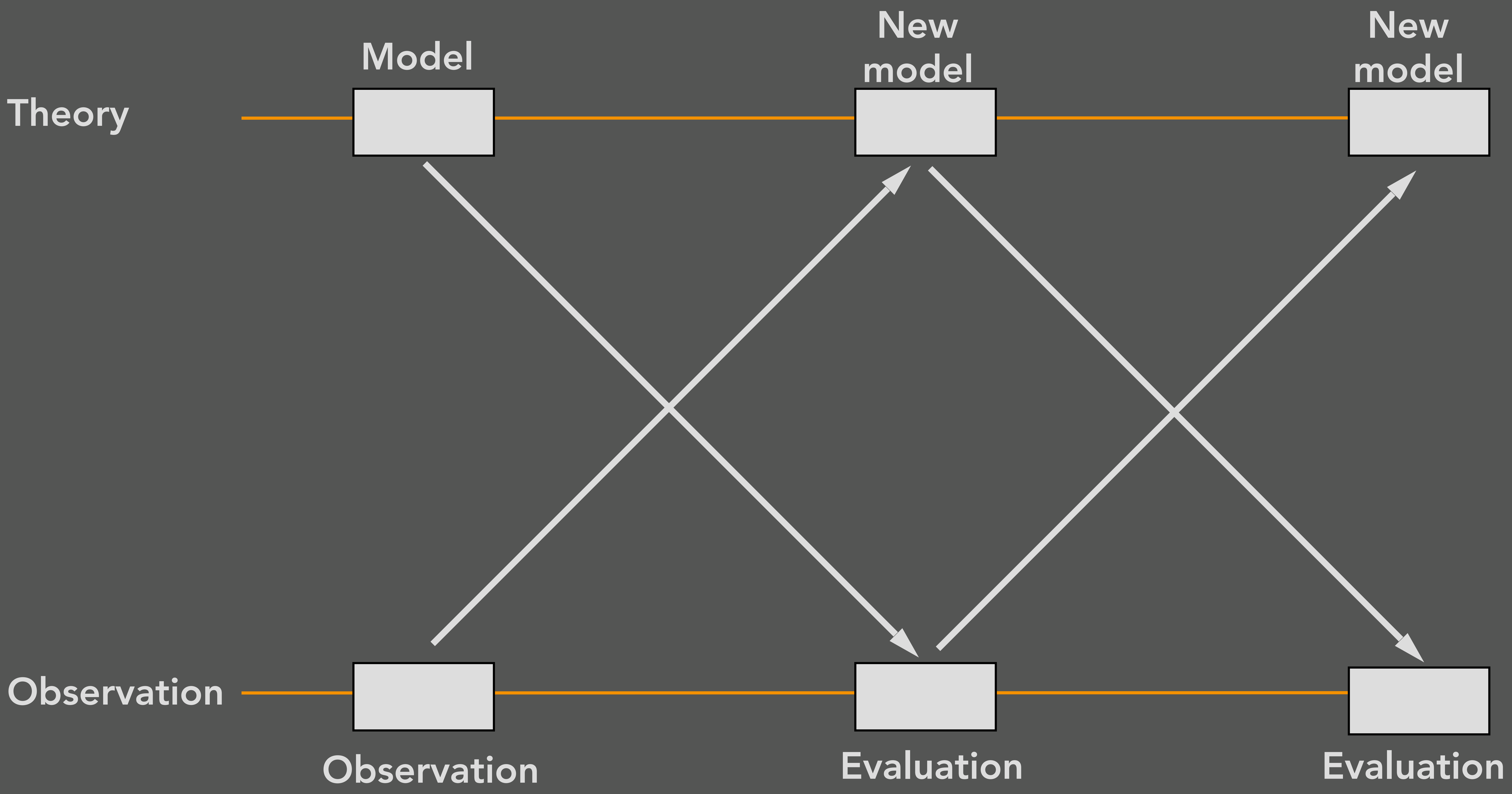


SystemX
15 mars 2023

Theory in Human-Computer Interaction

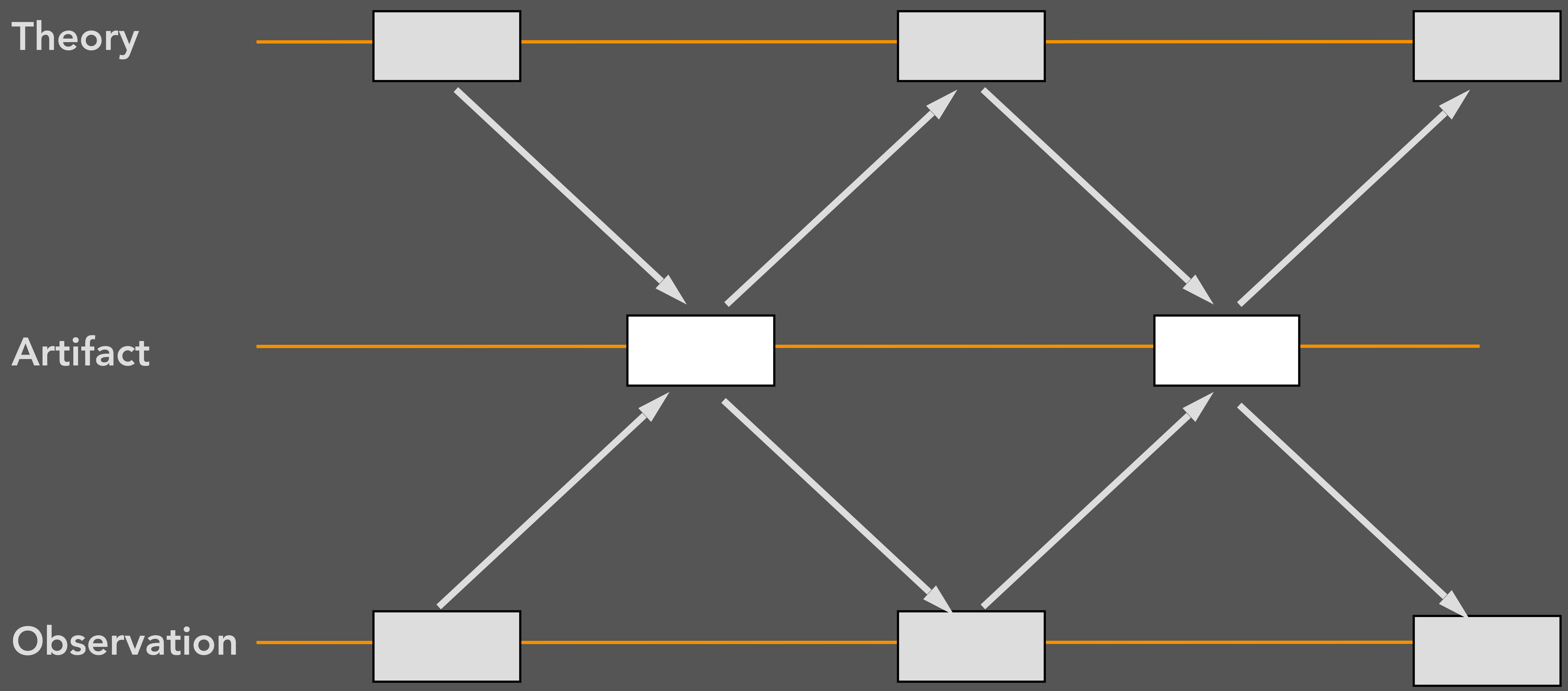
Theory in Natural Sciences

Mackay & Fayard, 1997



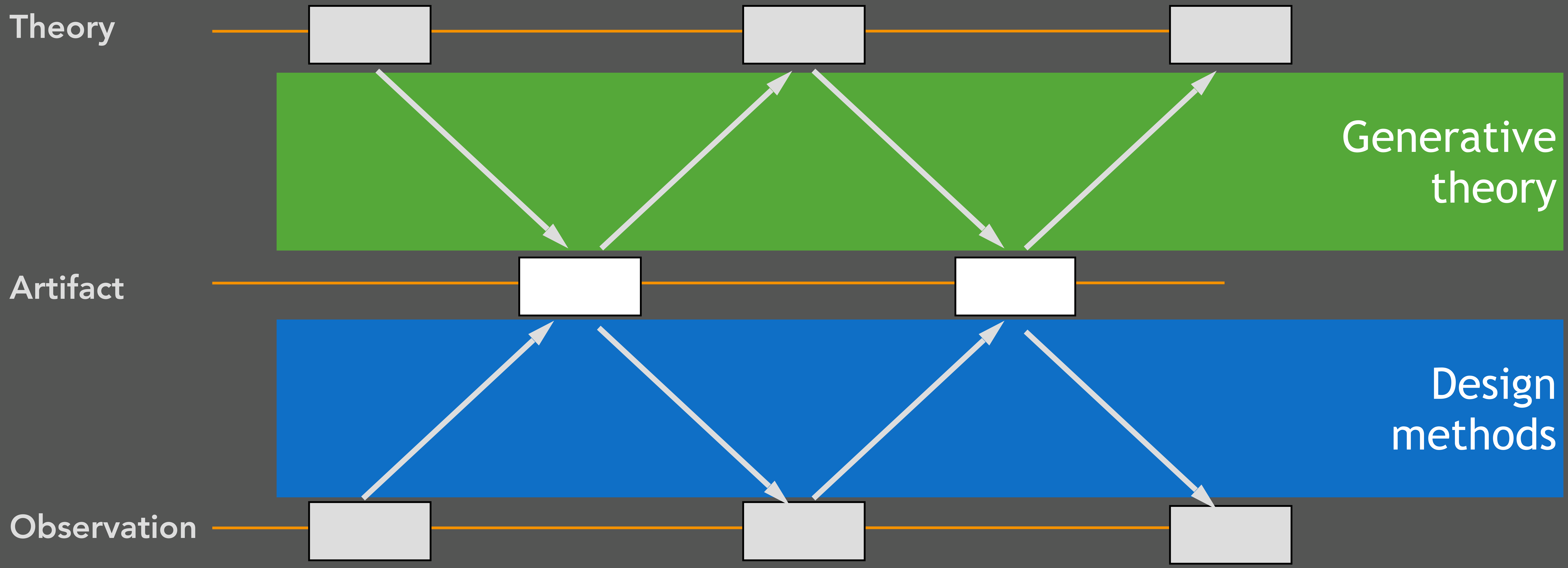
Theory and HCI

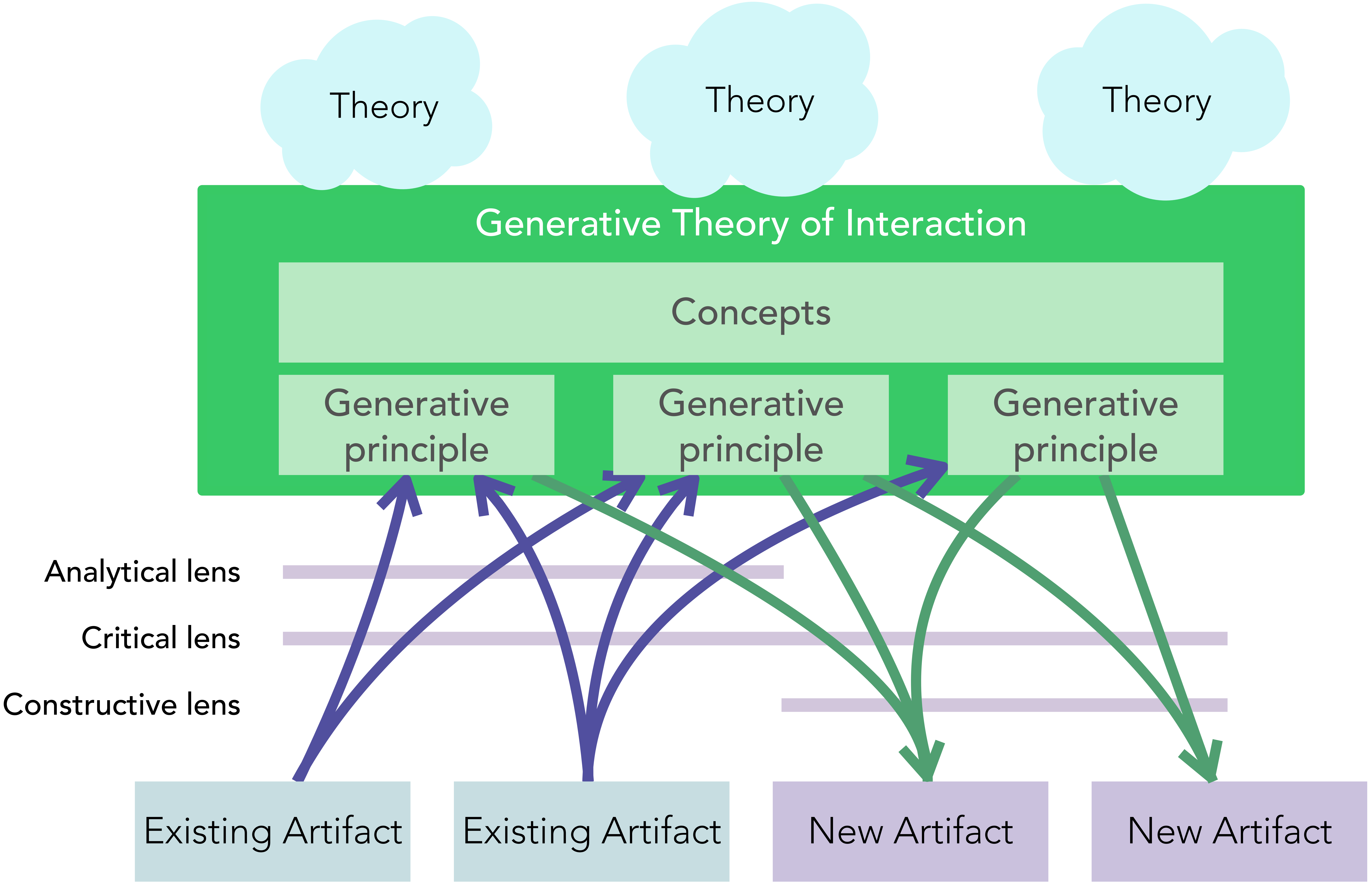
Mackay & Fayard, 1997



Theory and HCI

Beaudouin-Lafon, Bødker & Mackay, 2021

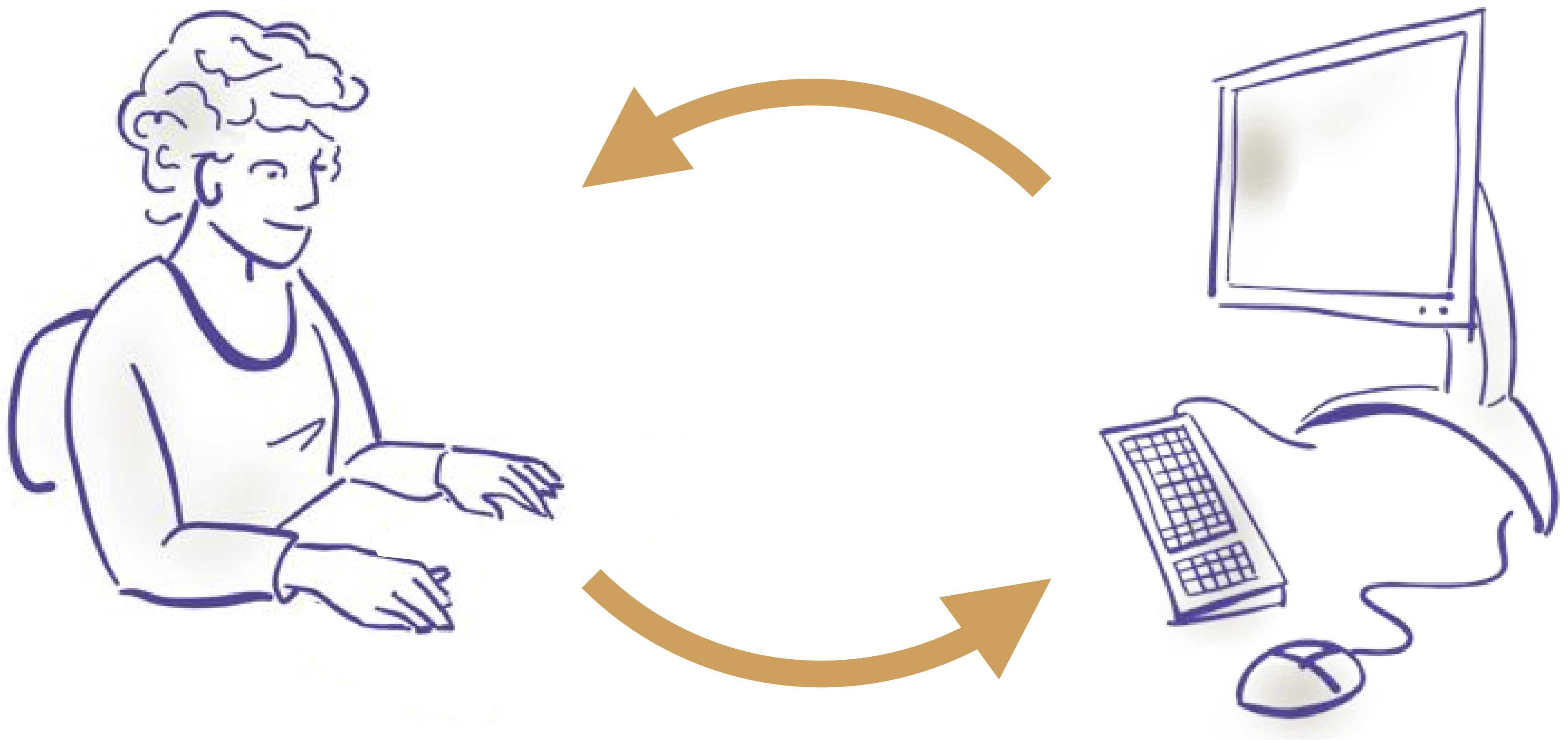




Theory
Theory
Theory
Generative Theory of Interaction
Concepts
Generative principle
Generative principle
Generative principle
Analytical lens
Critical lens
Constructive lens
Existing Artifact
Existing Artifact
New Artifact
New Artifact

Information

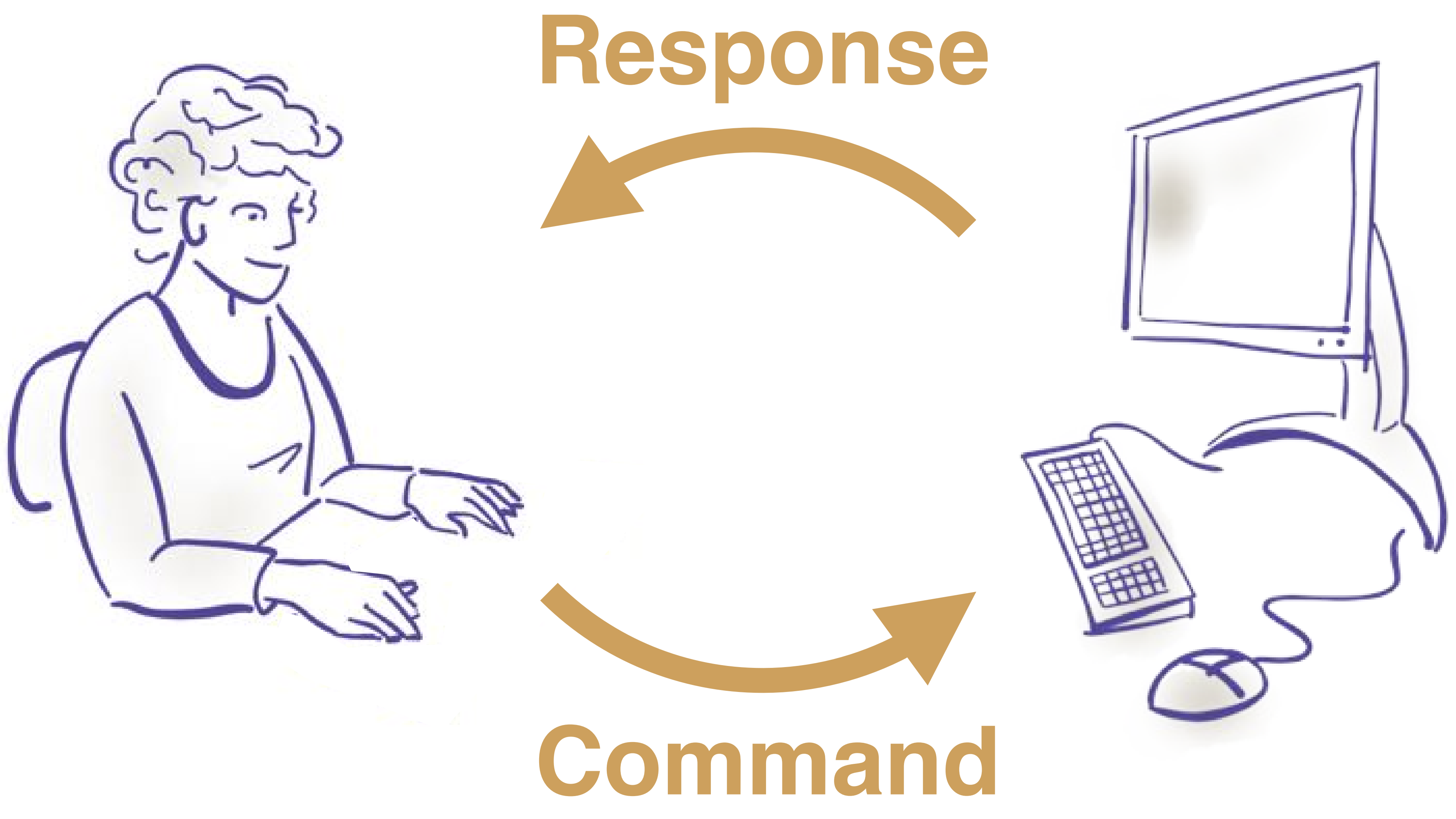
Interaction as a phenomenon



What is sent by the user to the computer?

What is sent by the computer to the user?

Interaction as a phenomenon



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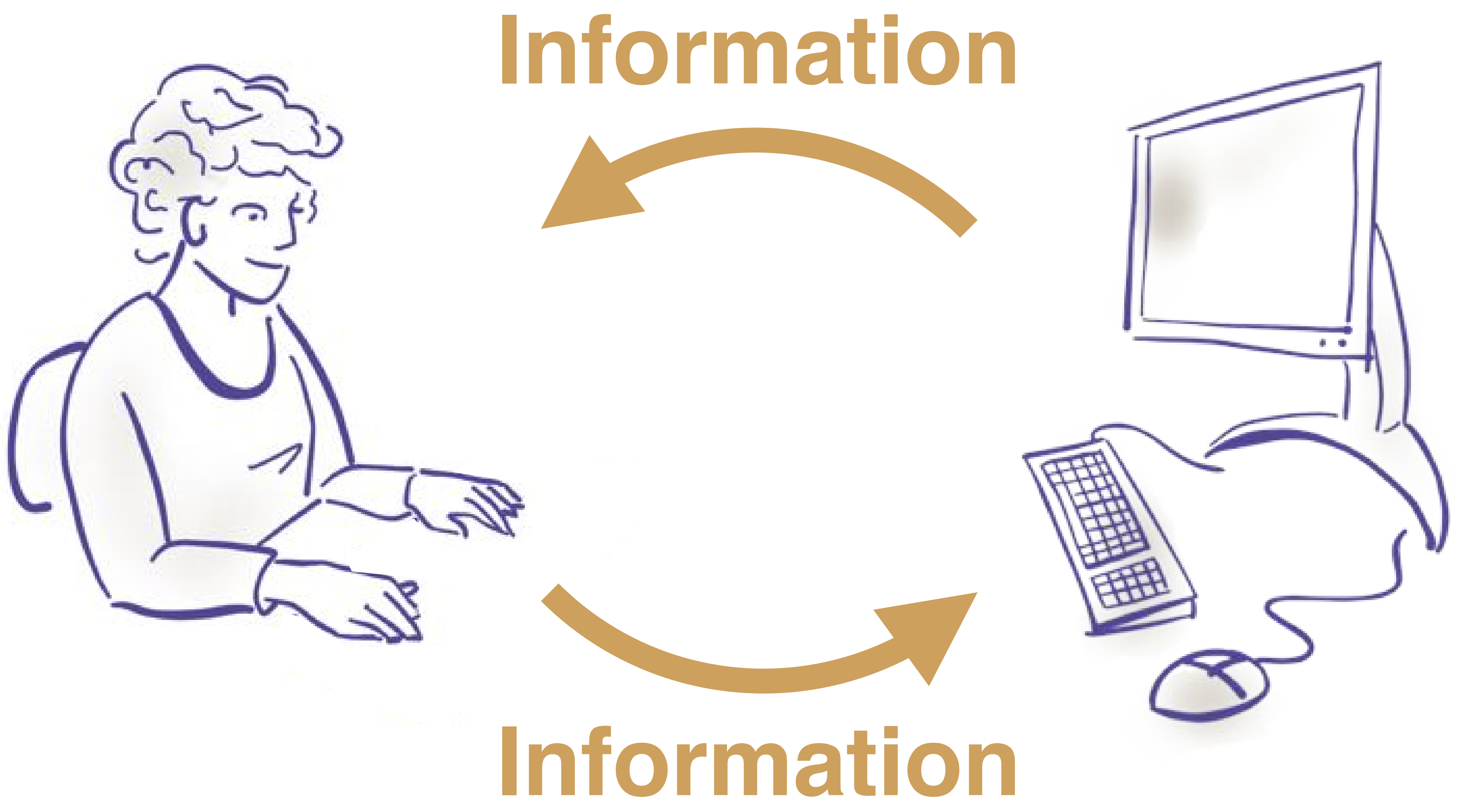
Interaction as a phenomenon



What is sent by the user to the computer?

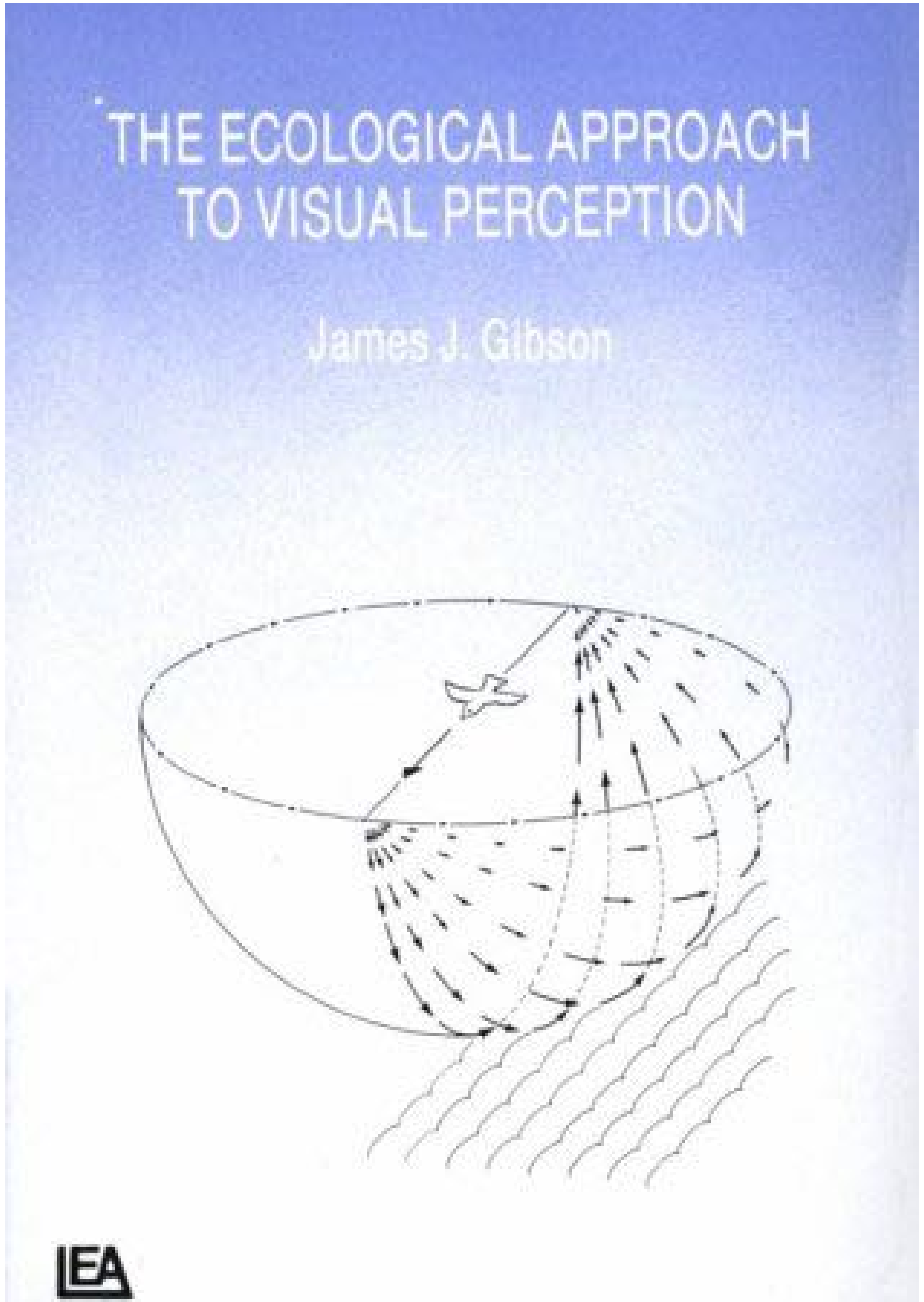
What is sent by the computer to the user?

Interaction as information communication

James Gibson

Ecological perception (1979)

Known in HCI for
the notion of “affordance”

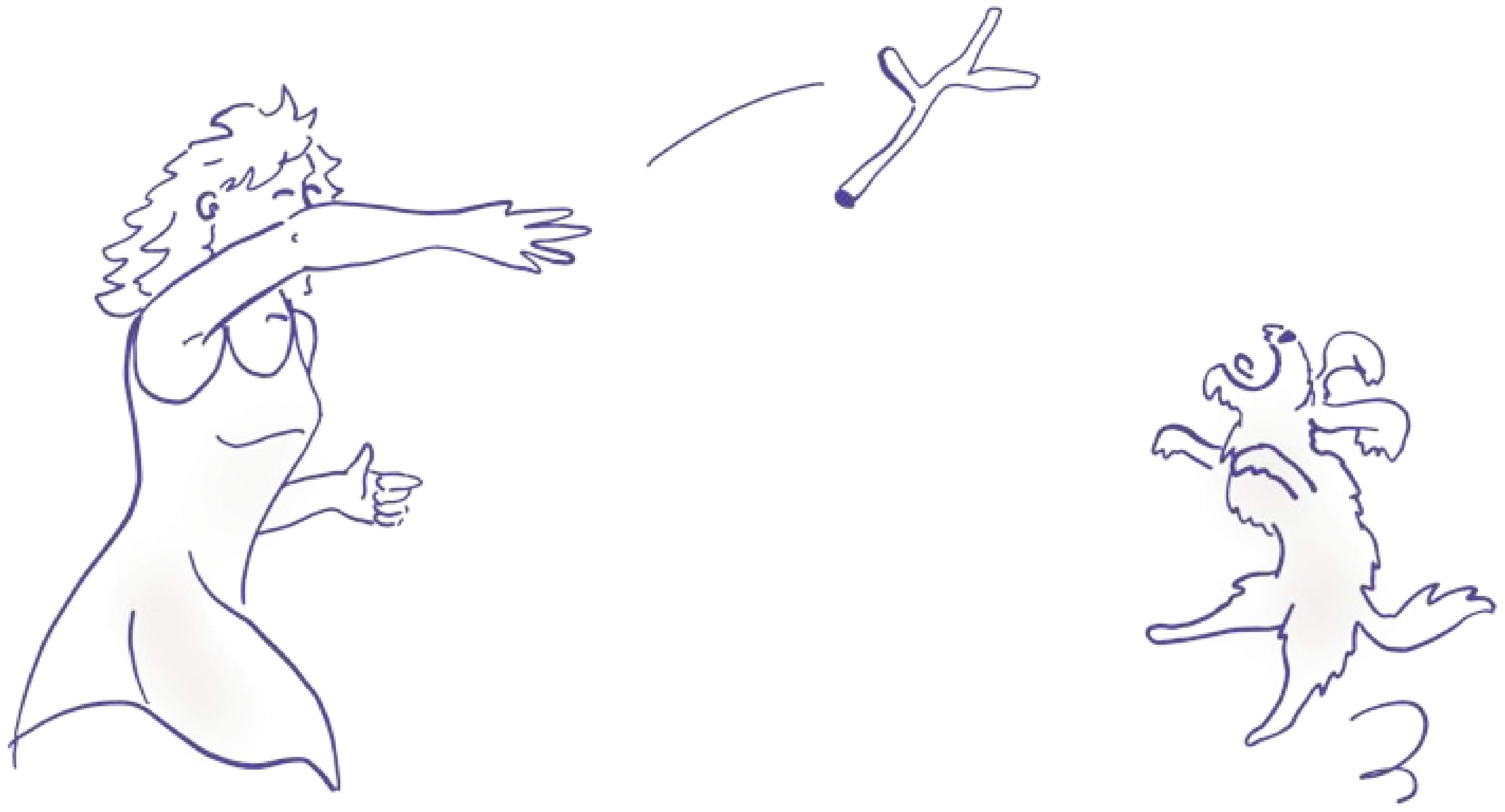


Co-evolution between organism and its environment

“Elegant” perceptual processes

Information is in the optical array and the optical flow

“Information pickup”



The organism is equipped to extract invariants

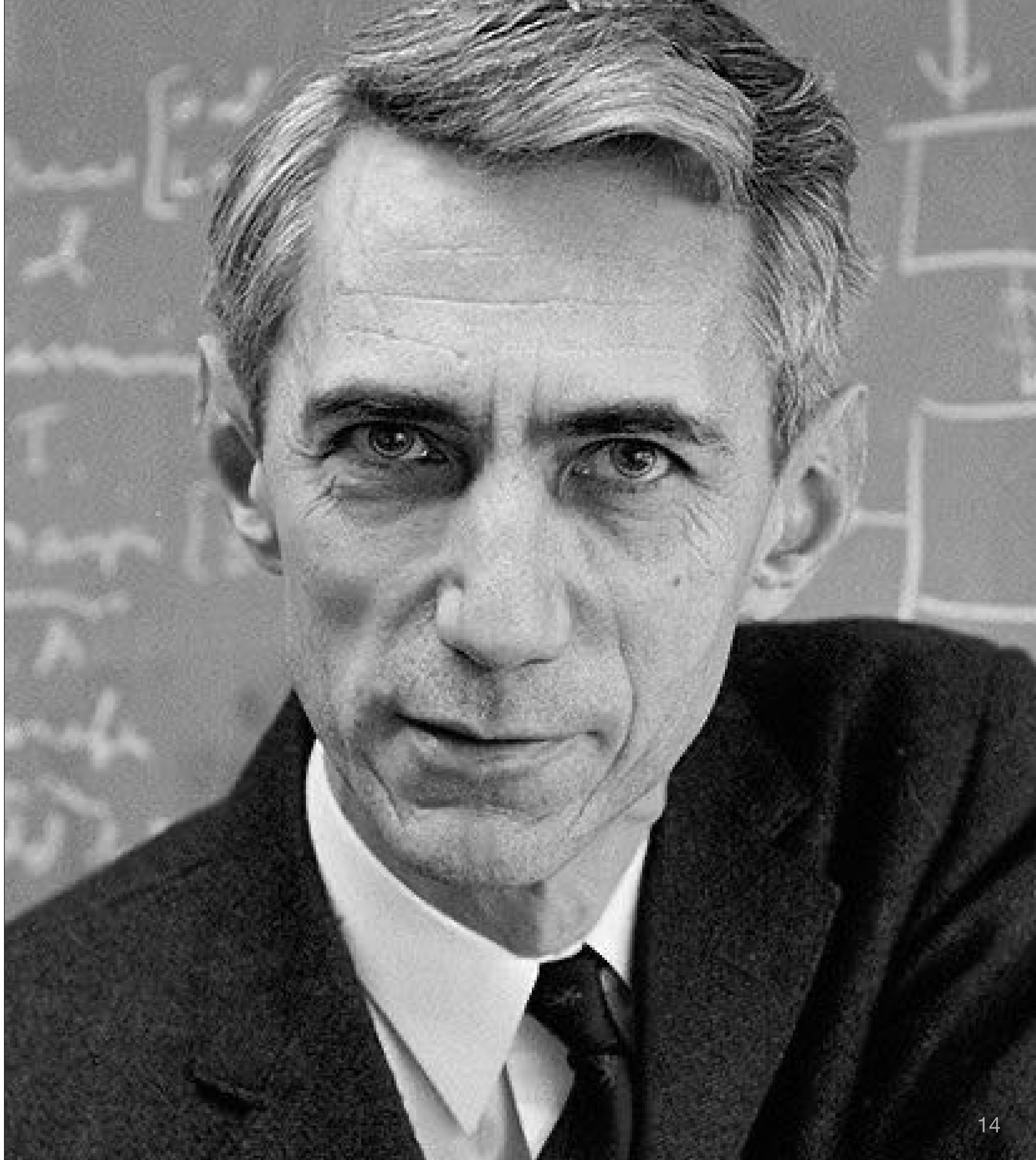
Action-perception coupling

act to perceive

perceive to act

Claude Shannon

Theory of information (1948)



Concept of information

Information reduces uncertainty

Information carried by an event *x* of probability *p(x)*:

$$h(x) = \log_2(1/p(x)) = -\log_2(p(x))$$

Draw a coin: h(heads) = 1 bit
Draw a dice: h(3) = 2.58 bits

Concept of entropy

A measure of uncertainty

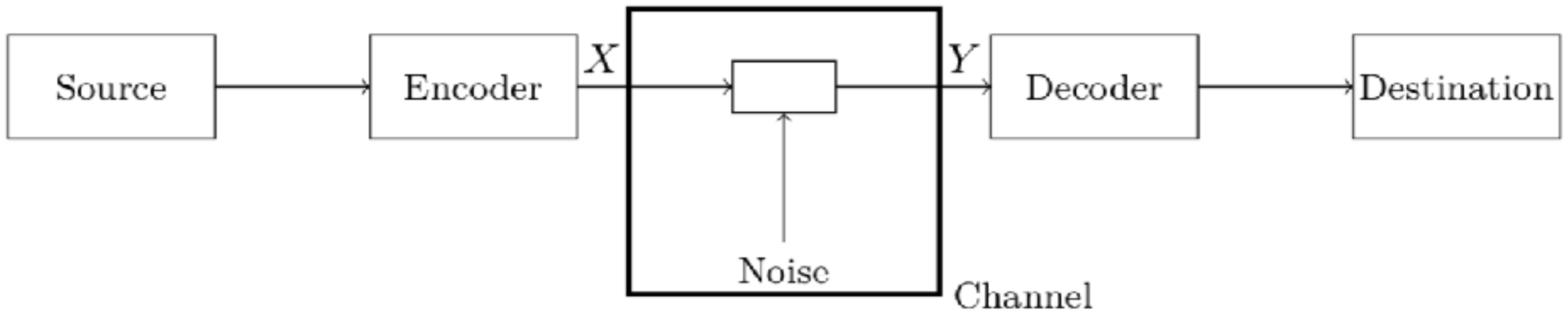
Entropy of a random variable:

$$H(X) = -\sum_{x} p(x) \log_2 p(x)$$

Entropy is maximal when the distribution p(X) is uniform

English text: entropy between 0.6 and 1.3 bits per character

Information transmission



Entropy of a random variable:

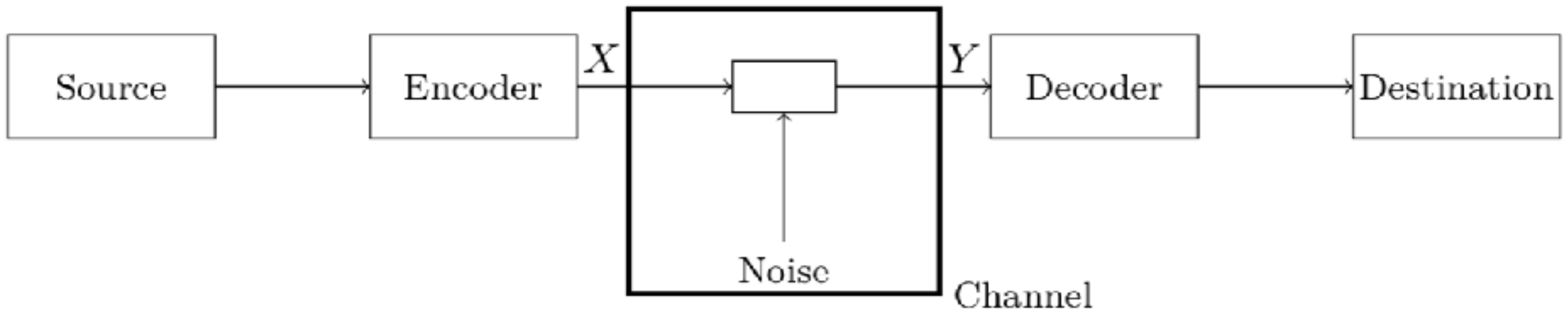
$$H(X) = -\sum_{x} p(x)\log_2 p(x)$$

Transmitted information:

$$I(X;Y) = H(Y) - H(Y|X)$$

some information is lost

Shannon's theorem 17



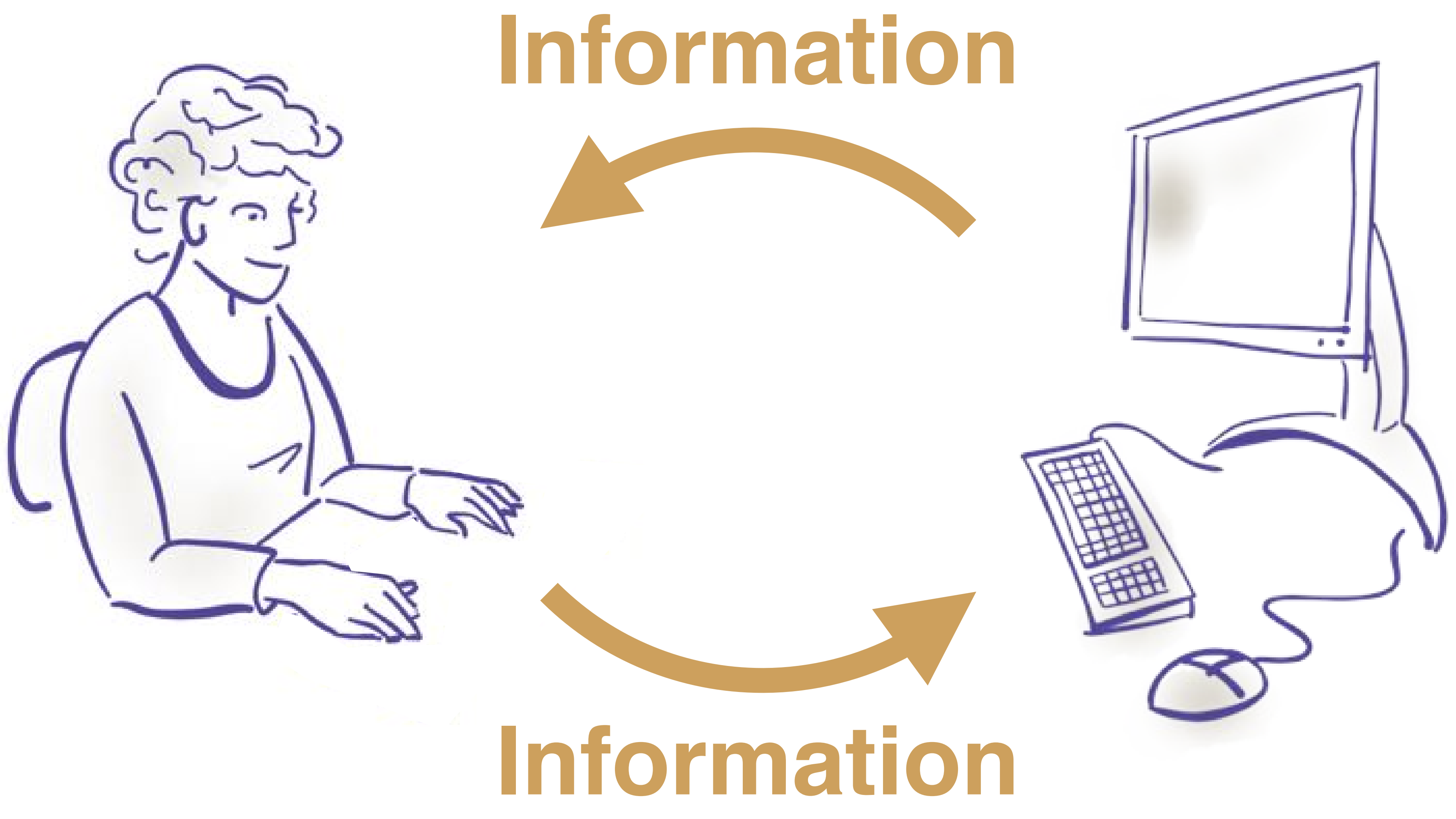
Capacity of a channel subject to Gaussian noise:

$$C = B_W \log_2 \left(1 + \frac{P}{N} \right)$$

C is measured in bits/second

Maximum transmitted information

What information?



User -> computer
message (commands)
-> Shannon

Computer -> User
view
-> Gibson

Pointing

Pointing

The most frequent task in GUIs

Many targets, some very small

Trade-off between speed
and precision

Cost of error can be high

Pointing

If the computer knew where I want to point, it could do it for me

Pointing performance is limited by human capabilities

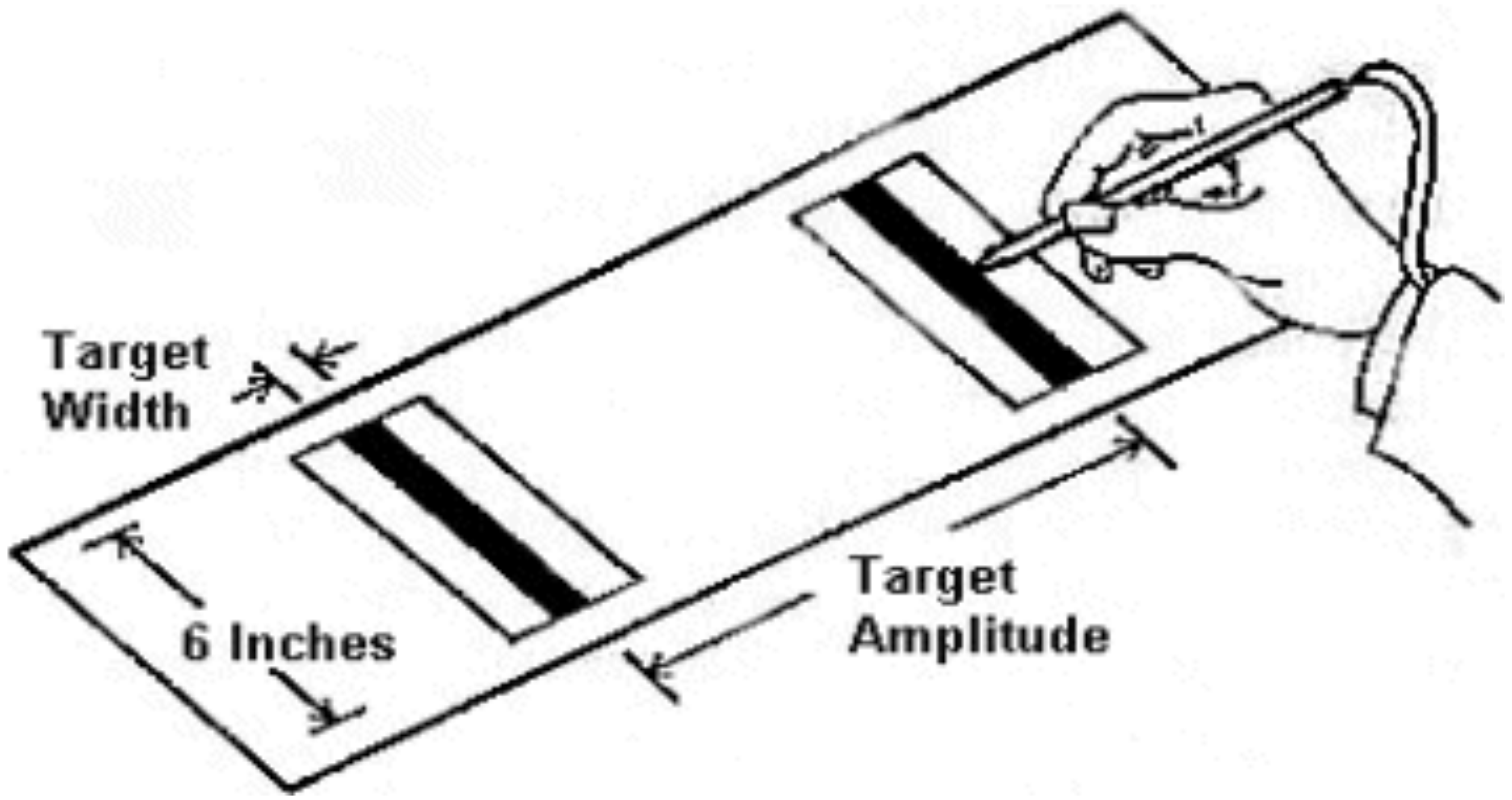
Paul Fitts

Psychologist

Also a pioneer in aviation safety

HAGA-MAGA list

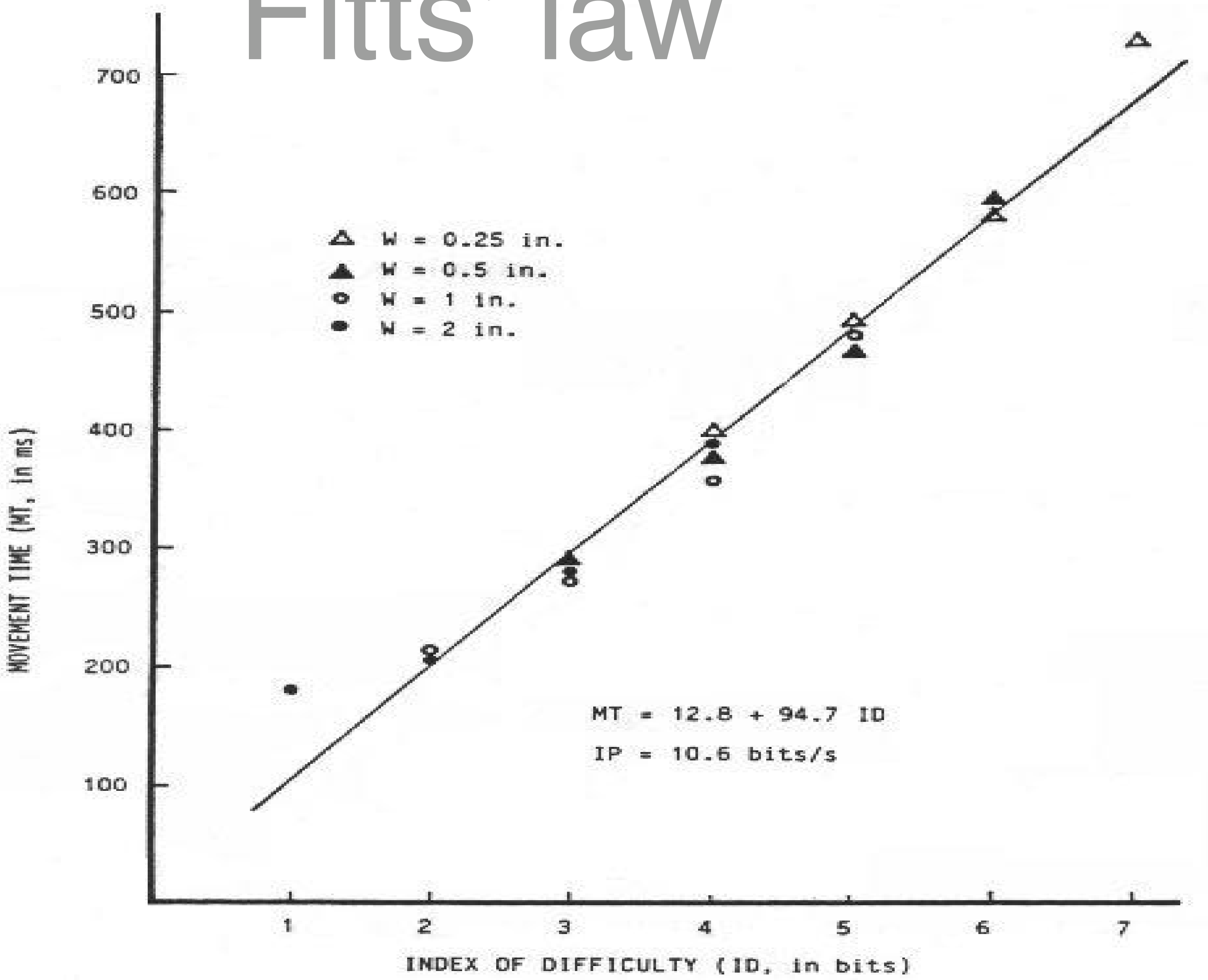
Fitts' law (1954)



Speed-precision trade-off in aimed movements

D = distance to target
W = target width

Fitts' law



Speed-precision trade-off
in aimed movements

D = distance to target
W = target width

MT = k x ID movement time
ID = log(1 + D/W) index of difficulty

Fitts' law

A tool to compare pointing devices or pointing techniques

Speed-precision trade-off in aimed movements

D = distance to target
W = target width

MT = k x ID movement time
ID = log(1 + D/W) index of difficulty

Shannon meets Fitts

Parallel between

$$MT = k \log_2\left(1 + \frac{D}{W}\right)$$

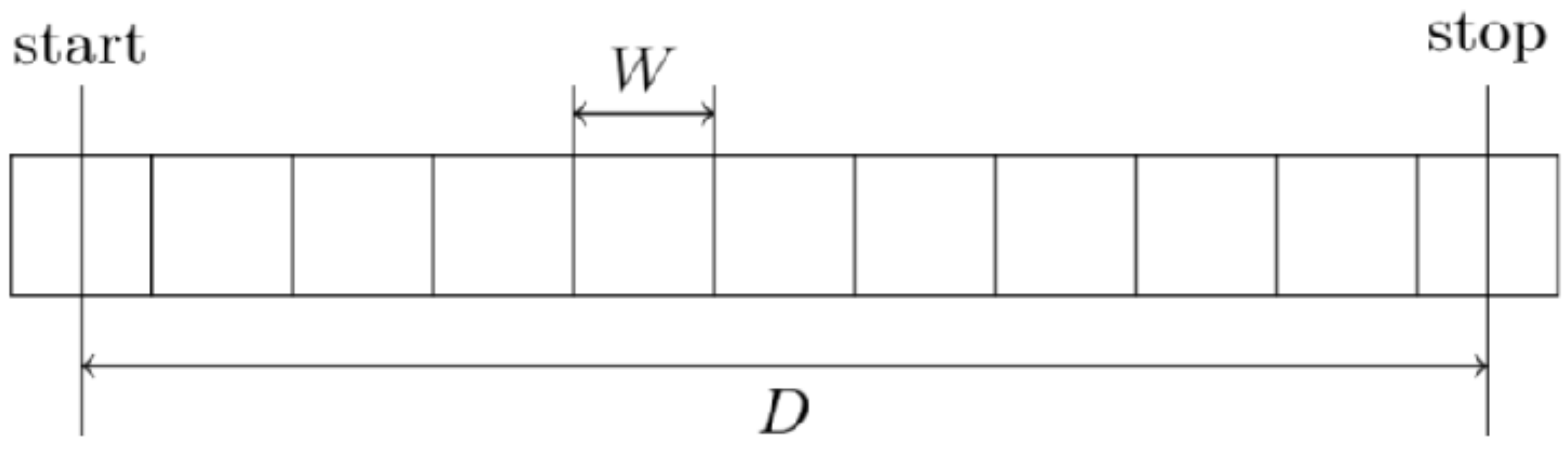
and

$$C = B_W \log_2\left(1 + \frac{P}{N}\right)$$

Distance = Signal

Width (tolerance) = Noise

Shannon meets Fitts



Aiming is choosing

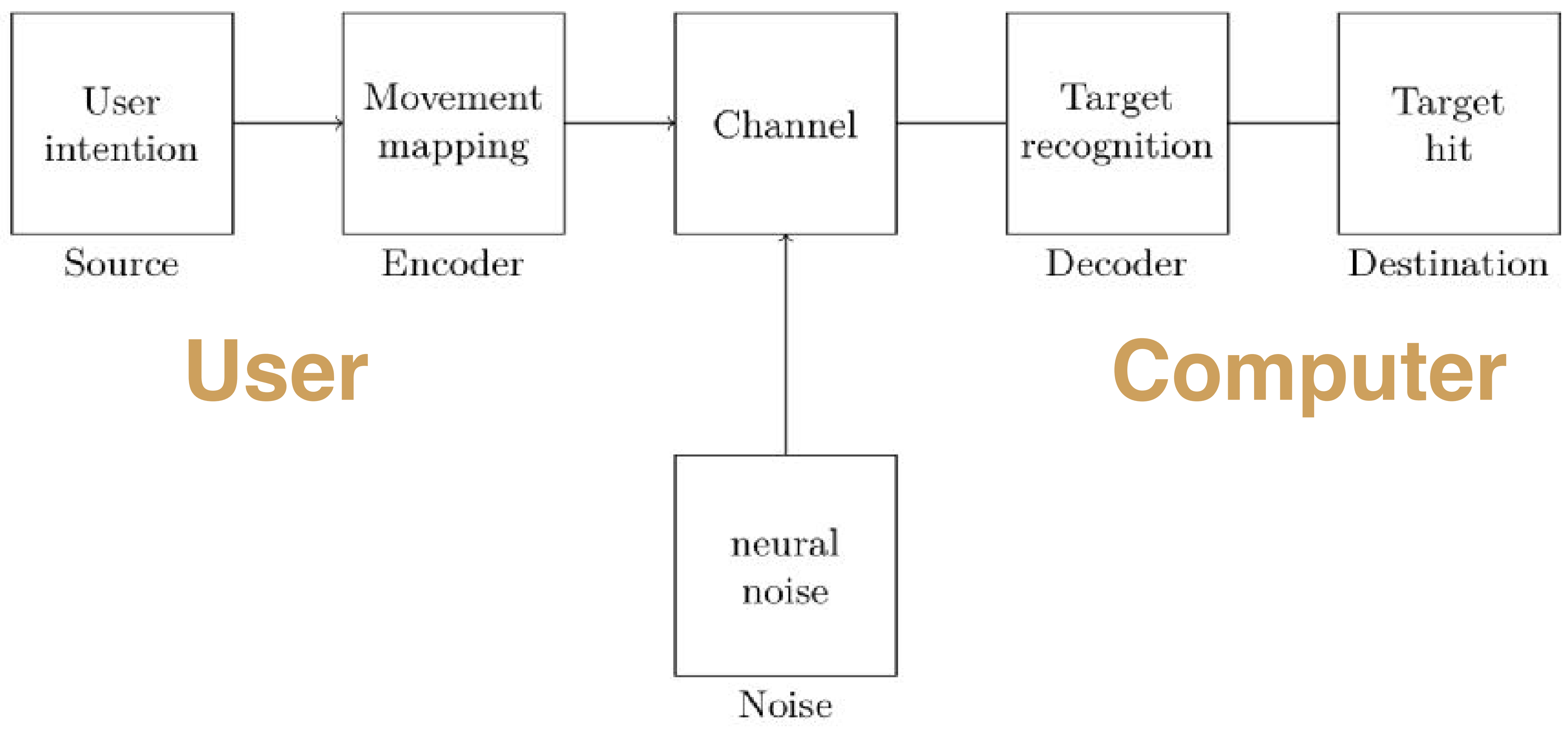
$$X = -\frac{D}{2}, -\frac{D}{2} + W, \ldots, \frac{D}{2} - W, \frac{D}{2}$$

$$H = \log_2\left(1 + \frac{D}{W}\right) = ID$$

Index of difficulty = source entropy

No transmission!

Shannon meets Fitts



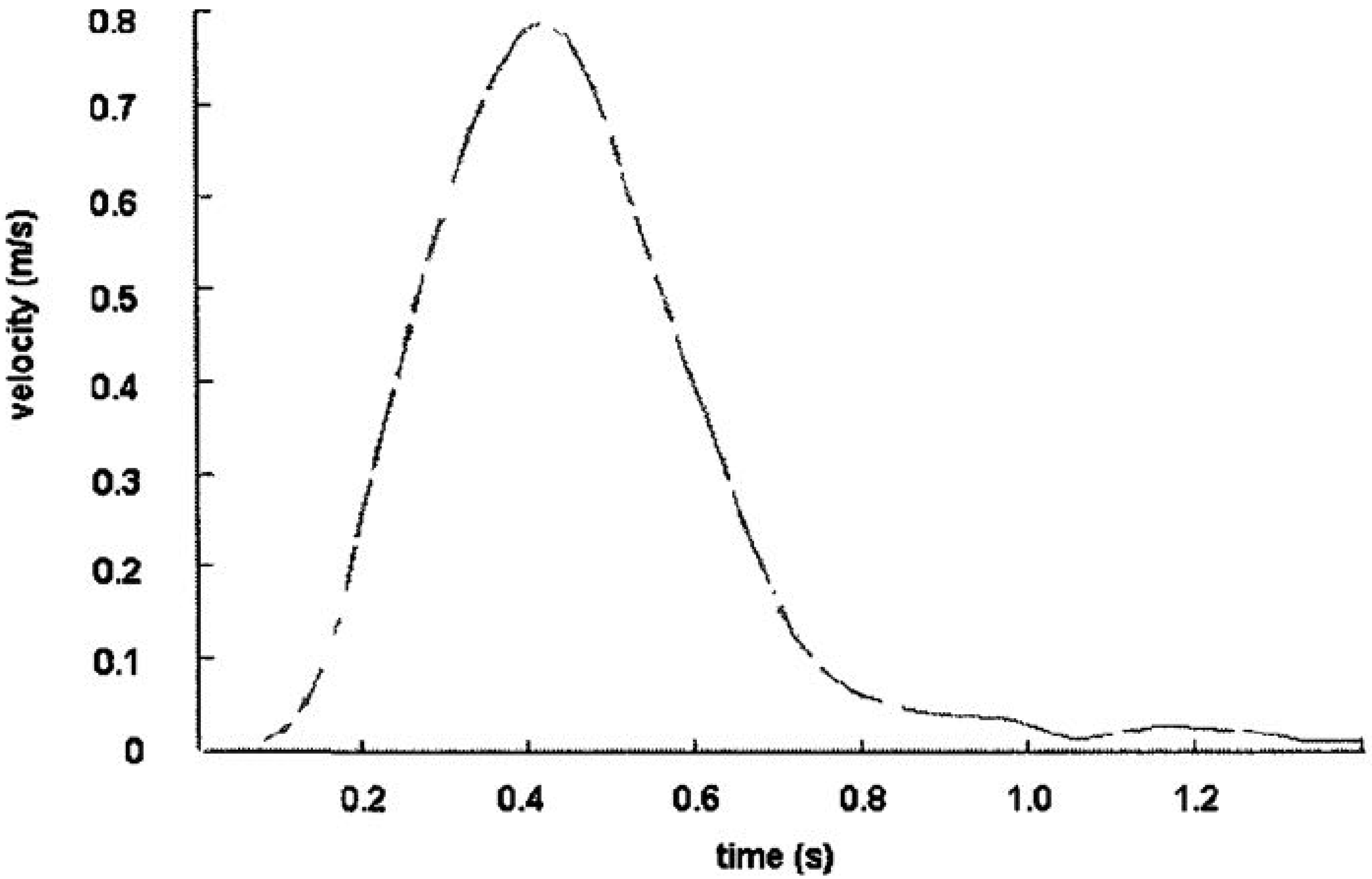
Gori, Rioul & Guiard, 2018

Modeling the motor system as the (noisy) channel

If *e* is the error rate

$$C = (1 - e)\log_2\left(1 + \frac{D}{W}\right)$$

Limits of Fitts' law



First, ballistic movement,
followed by corrective movements

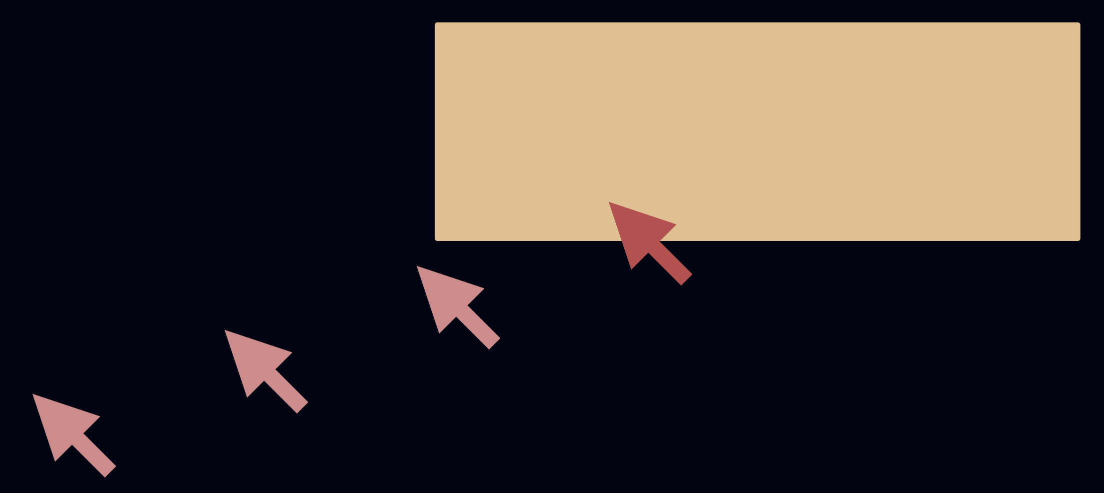
Validity of the law

Distance < amplitude of the arm
Target size > motor tremor

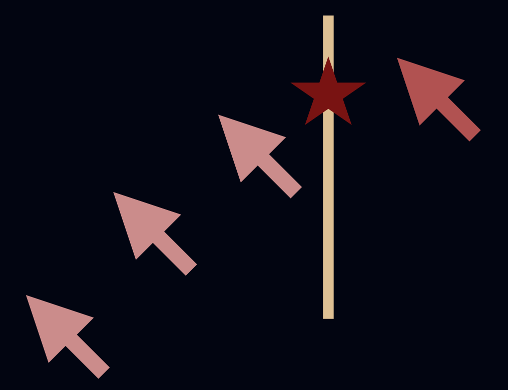
Distance < ~1m
Target size > ~0.5mm
ID < ~11 bits

Other laws of movement

Fitts' law in 2D



Goal passing / crossing (Accot & Zhai)



The Steering law (Accot)

“Beating” Fitts’ Law

How can the system
help the user
reach the target faster?

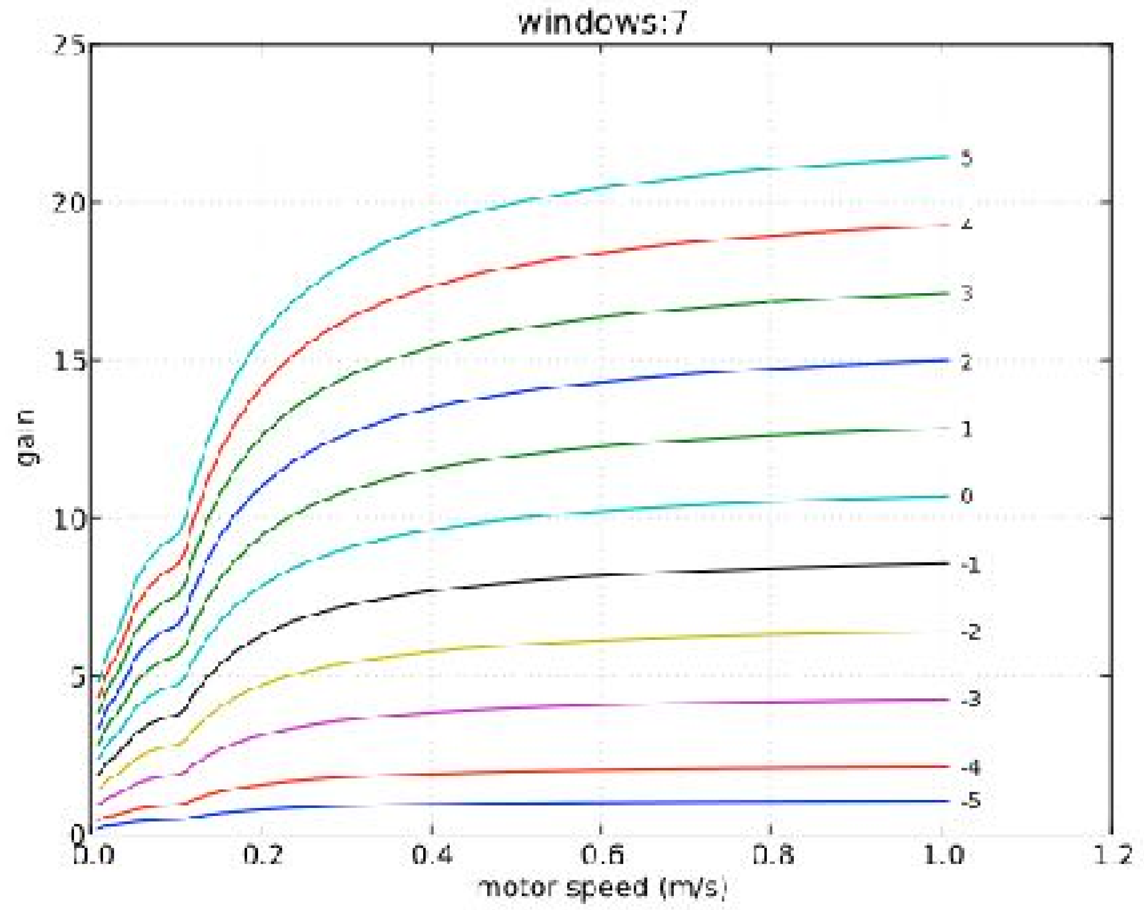
Pointing as
human-computer partnership

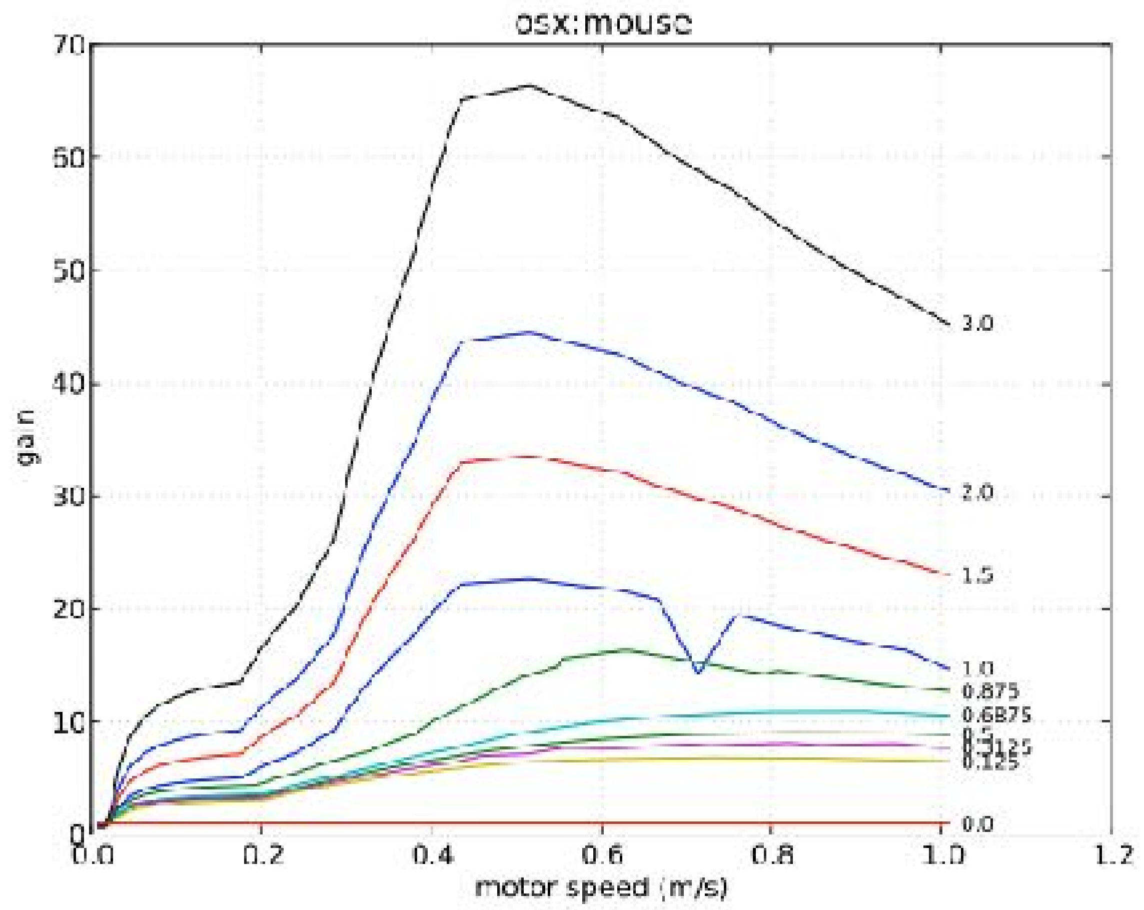
“Beating” Fitts’ Law

How can the system
help the user
reach the target faster?

1. Extract user intention

Pointer acceleration
Transfer function

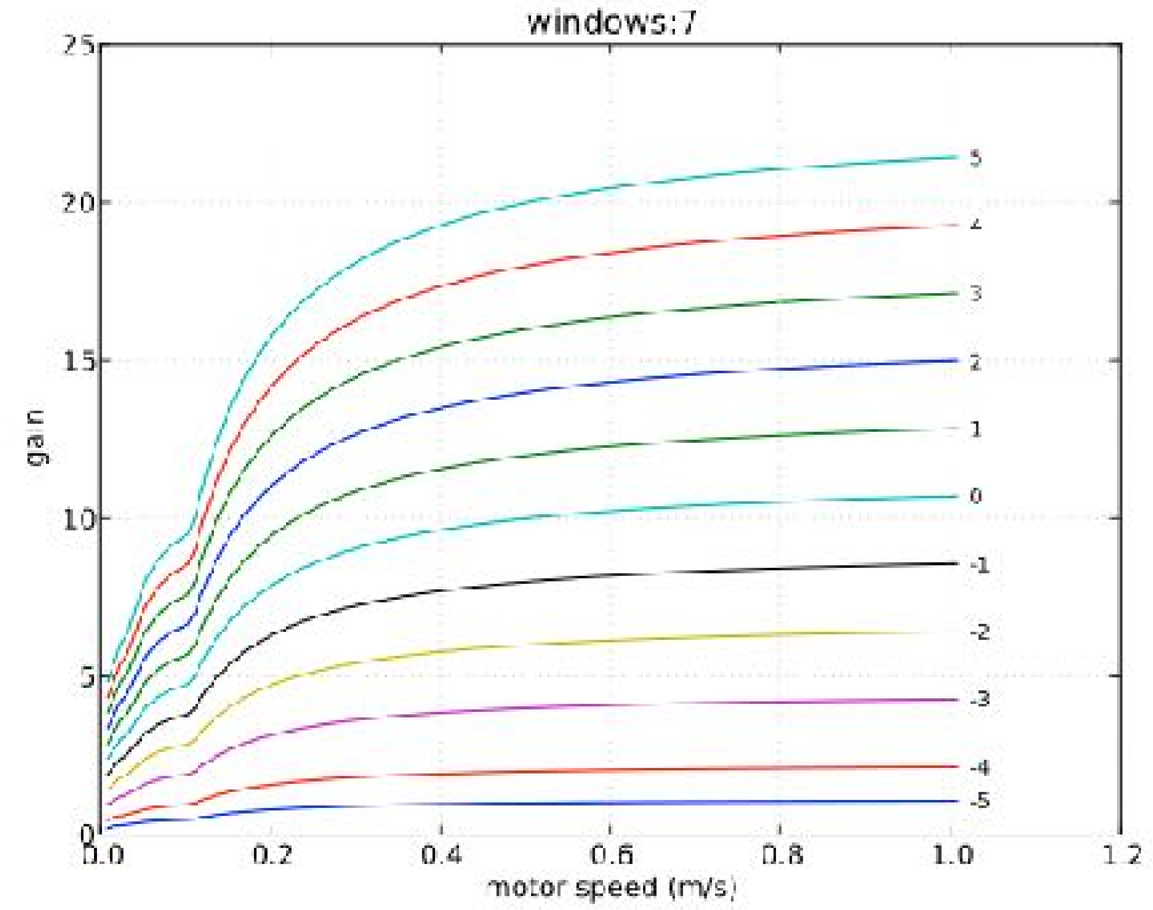


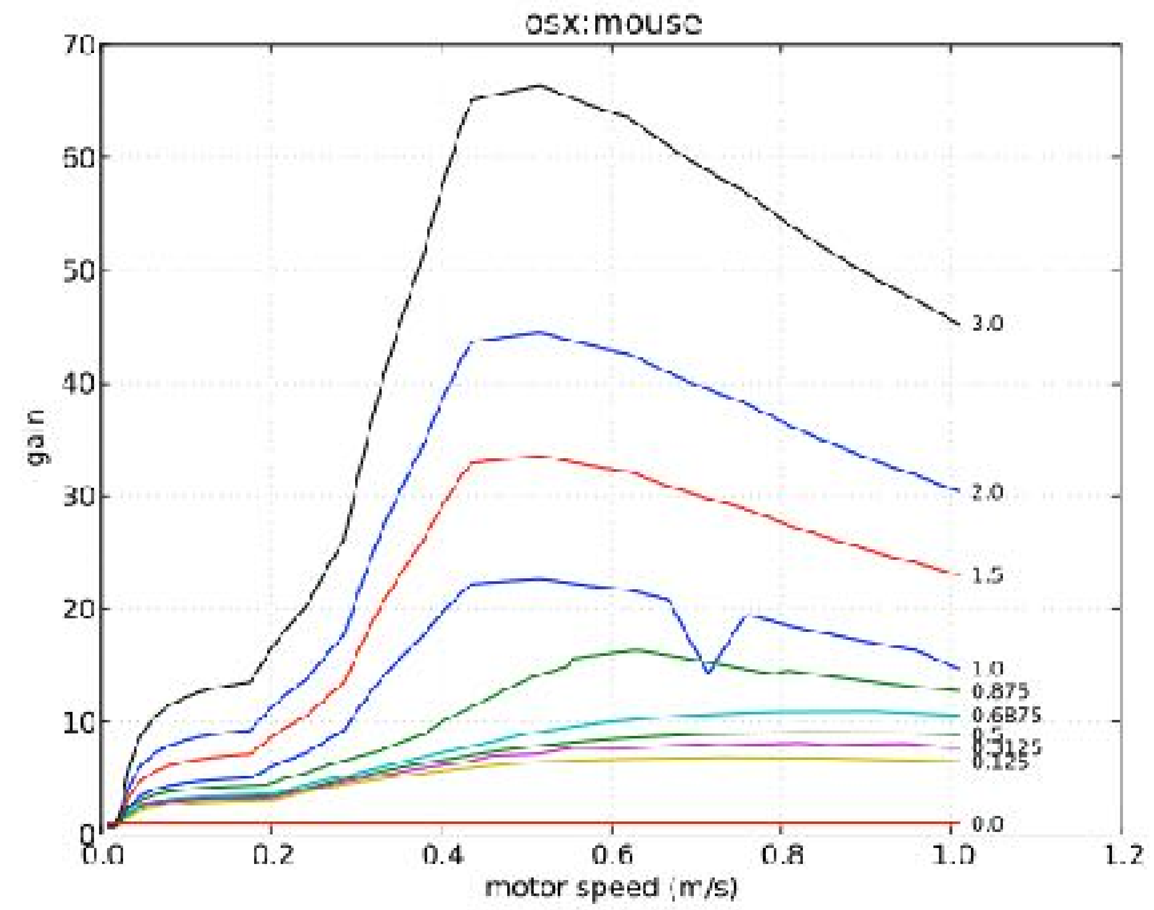


Move the cursor proportionally faster when the mouse moves faster:
moving fast means wanting to go further away

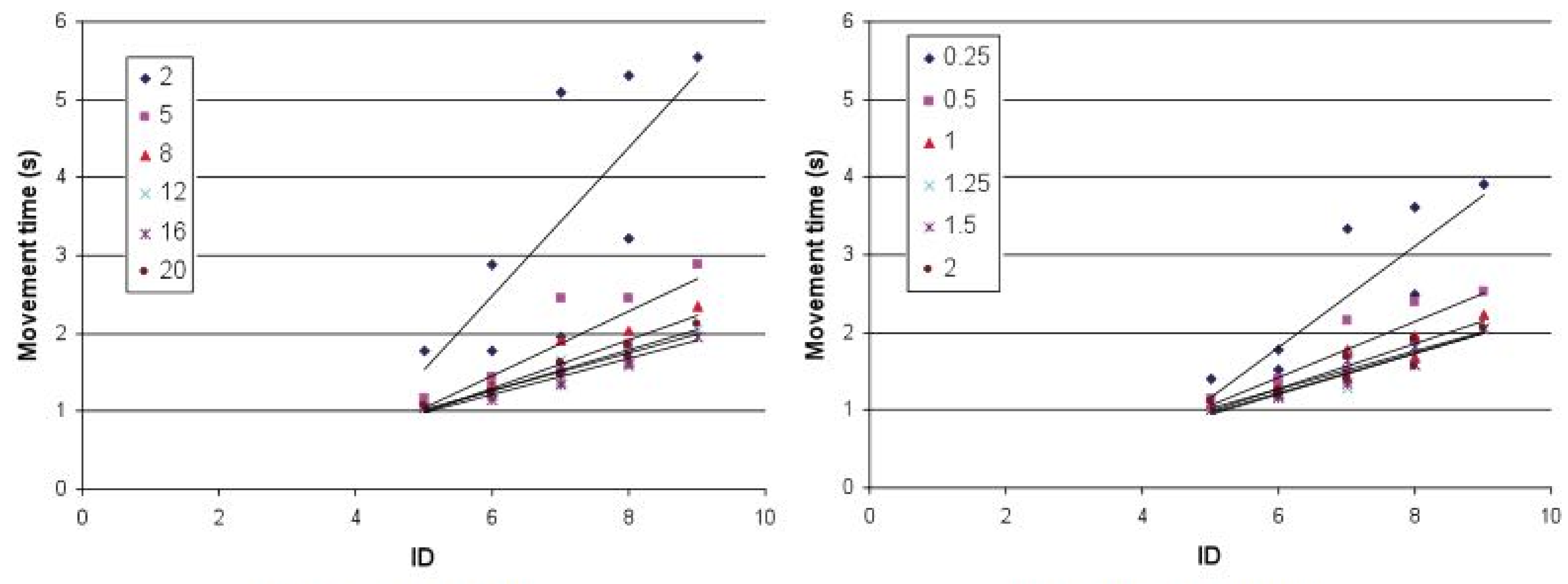
Casiez et al., 2008

Pointer acceleration Transfer function





Real but moderate effect on performance



(a) Constant Gain

(b) Pointer Acceleration

Gliding cursor

Beaudouin-Lafon et al., 2014

Cursor with inertia

Similar to scrolling a list
on a smartphone

Does not improve pointing time
BUT
user controls the cursor only
part of the time

“Beating” Fitts’ Law

How can the system
help the user
reach the target faster?

1. Extract user intention
2. Use information about targets

Semantic pointing

Adapt the transfer function to the “landscape” of targets: higher gain in the space between targets

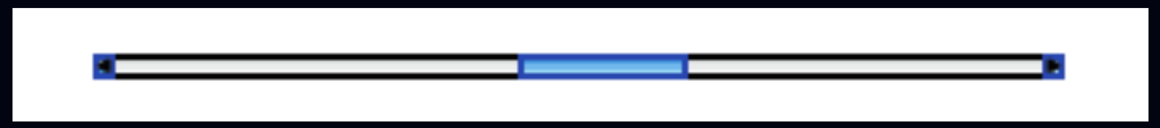
Blanch et al., 2004

Semantic pointing

Blanch et al., 2004

Adapt the transfer function to the “landscape” of targets: higher gain in the space between targets

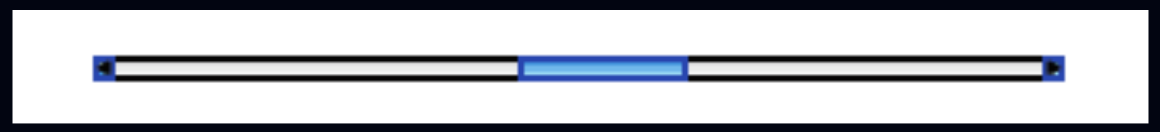
Visual space



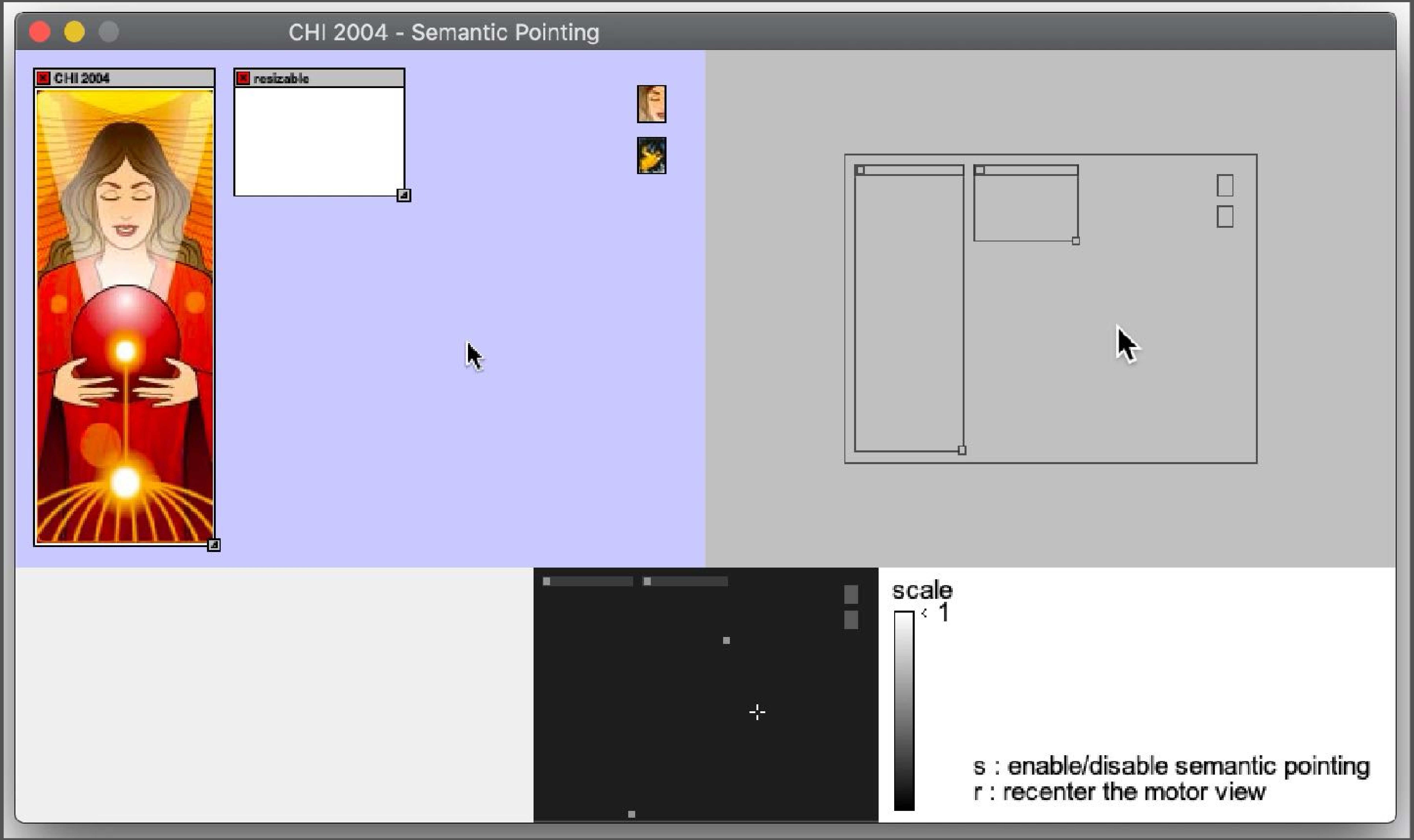
Semantic pointing

Blanch et al., 2004

Adapt the transfer function to the "landscape" of targets: higher gain in the space between targets

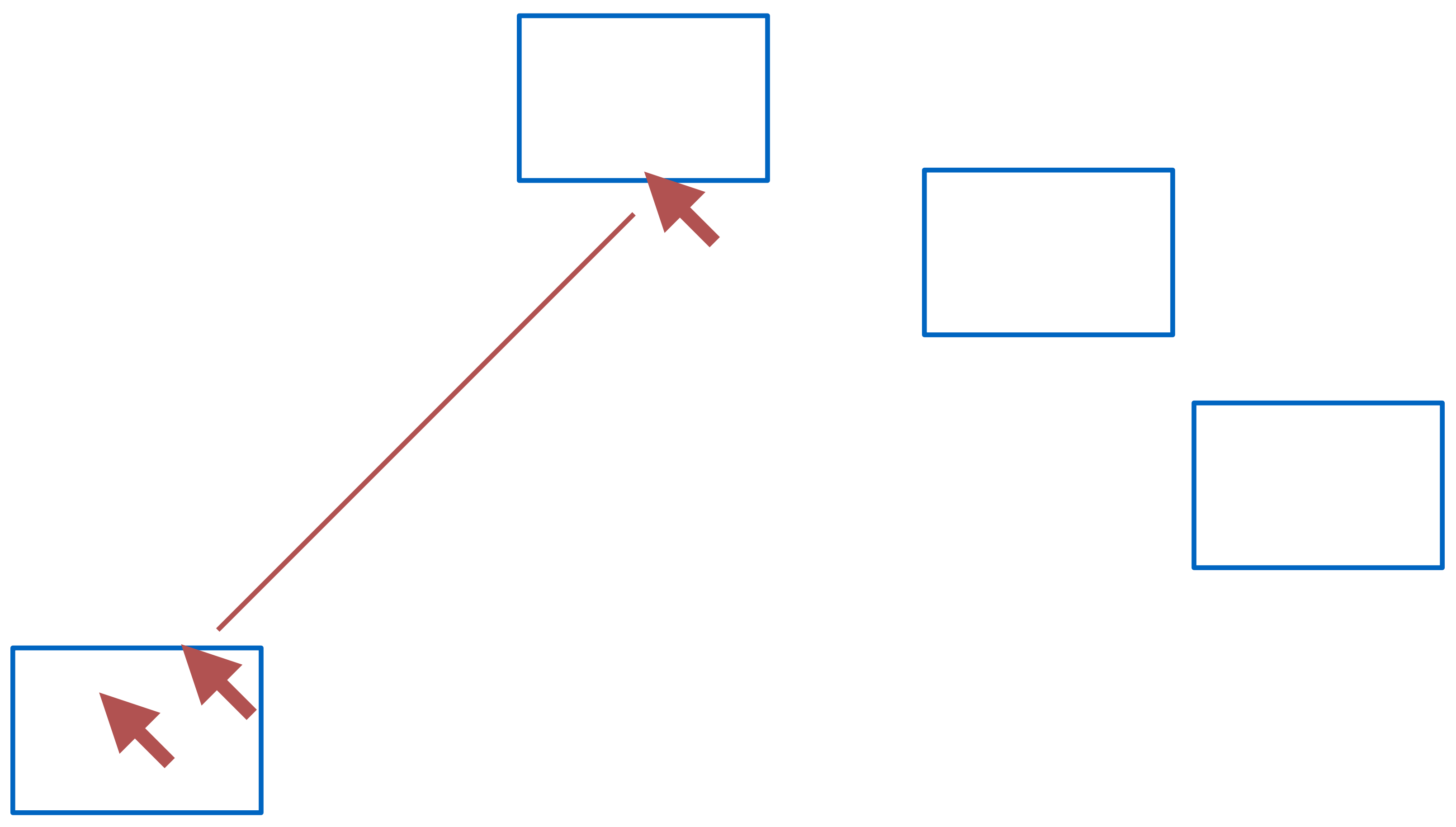
Visual space 

vs. Motor space 



Semantic Pointing - Guiard, Blanch & Beaudouin-Lafon, 2004

Object pointing

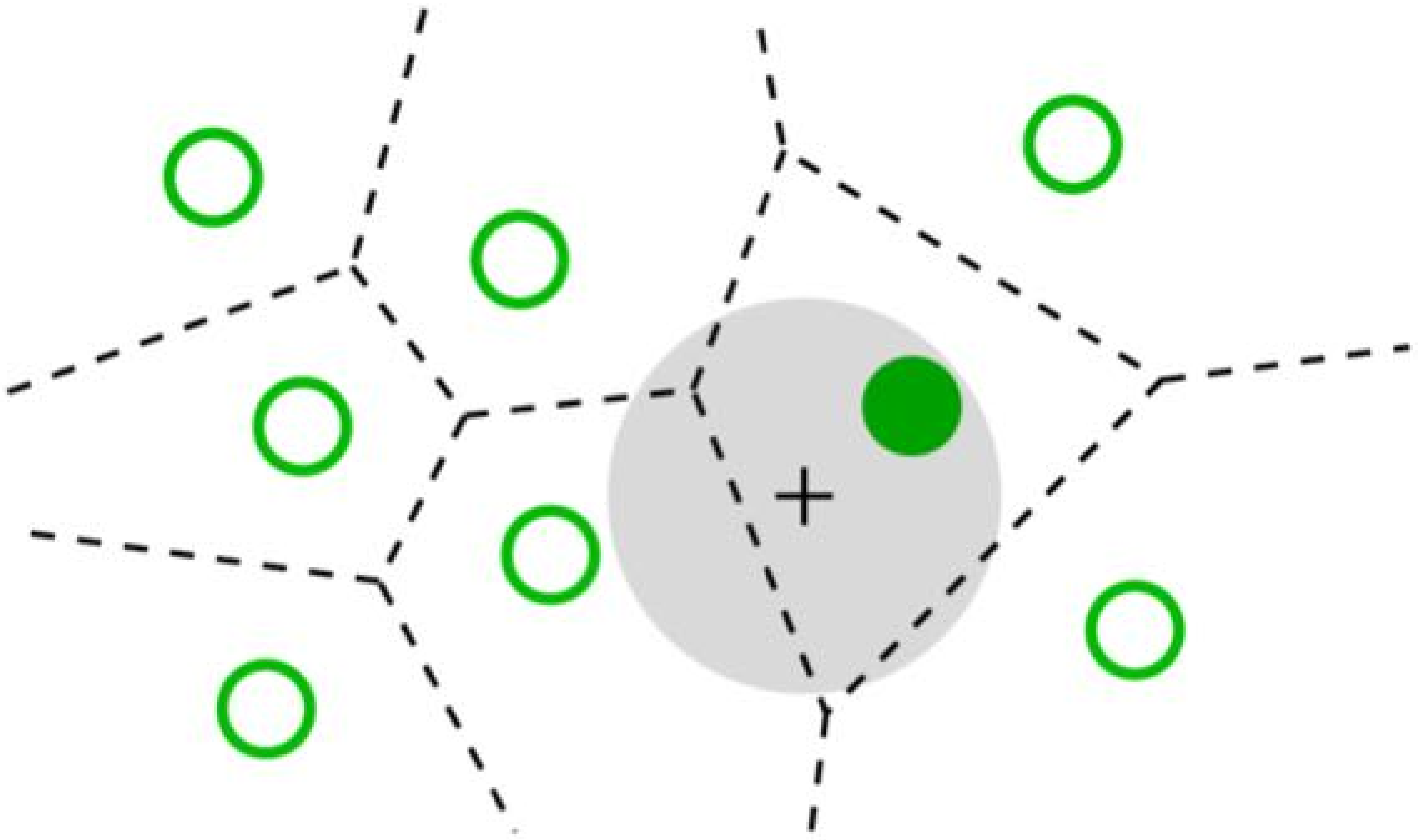


Guiard et al., 2004

Extreme version of Semantic Pointing: the cursor ignores empty space and jumps from one target to the next

Problem:
error correction is costly

Bubble pointer



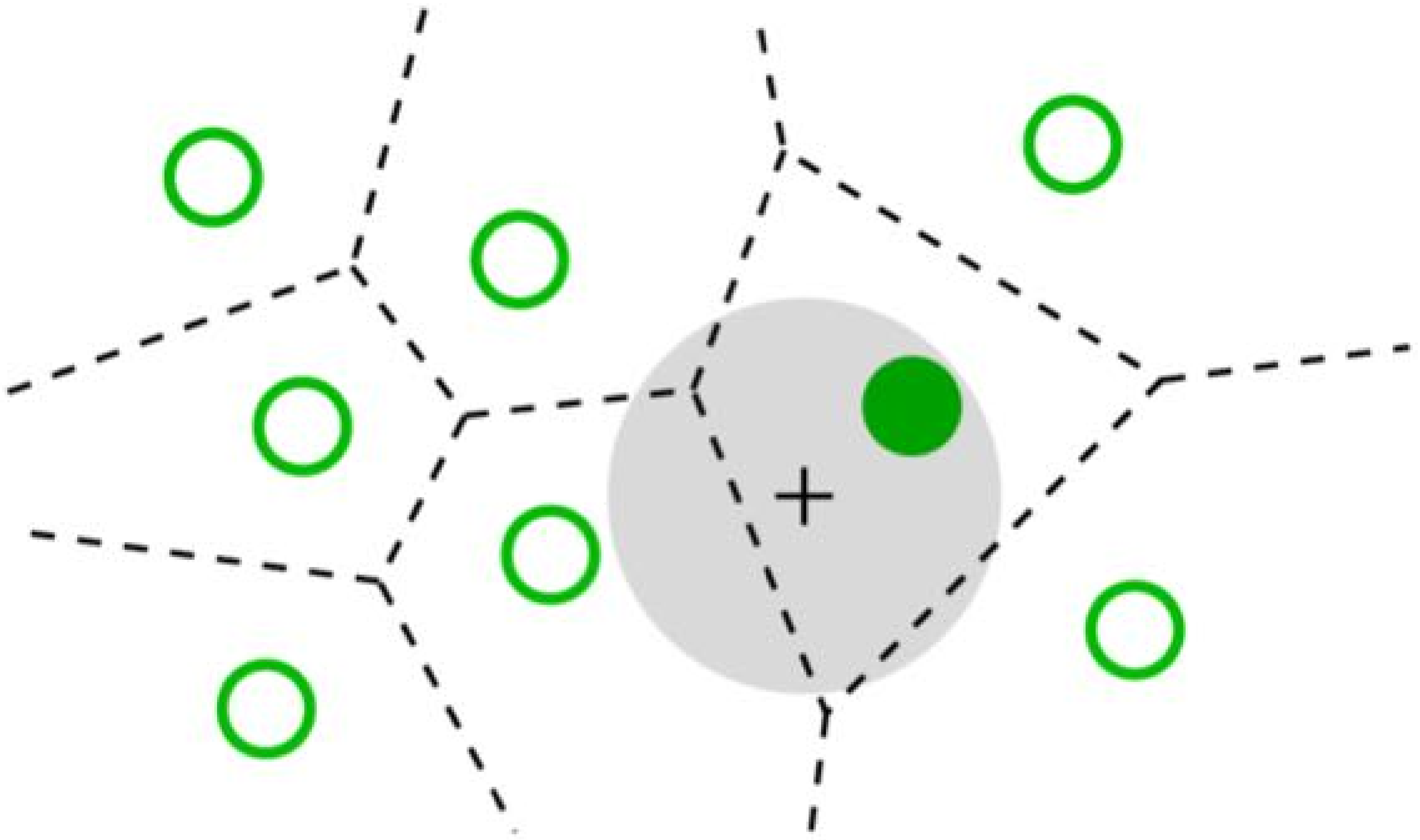
Grossman & Balakrishnan, 2005

Similar idea to Object Pointing:
eliminate empty space

Any click is a click
on the nearest target

Based on the Voronoi diagram
of target positions:
targets are effectively
as big as possible

Bubble pointer



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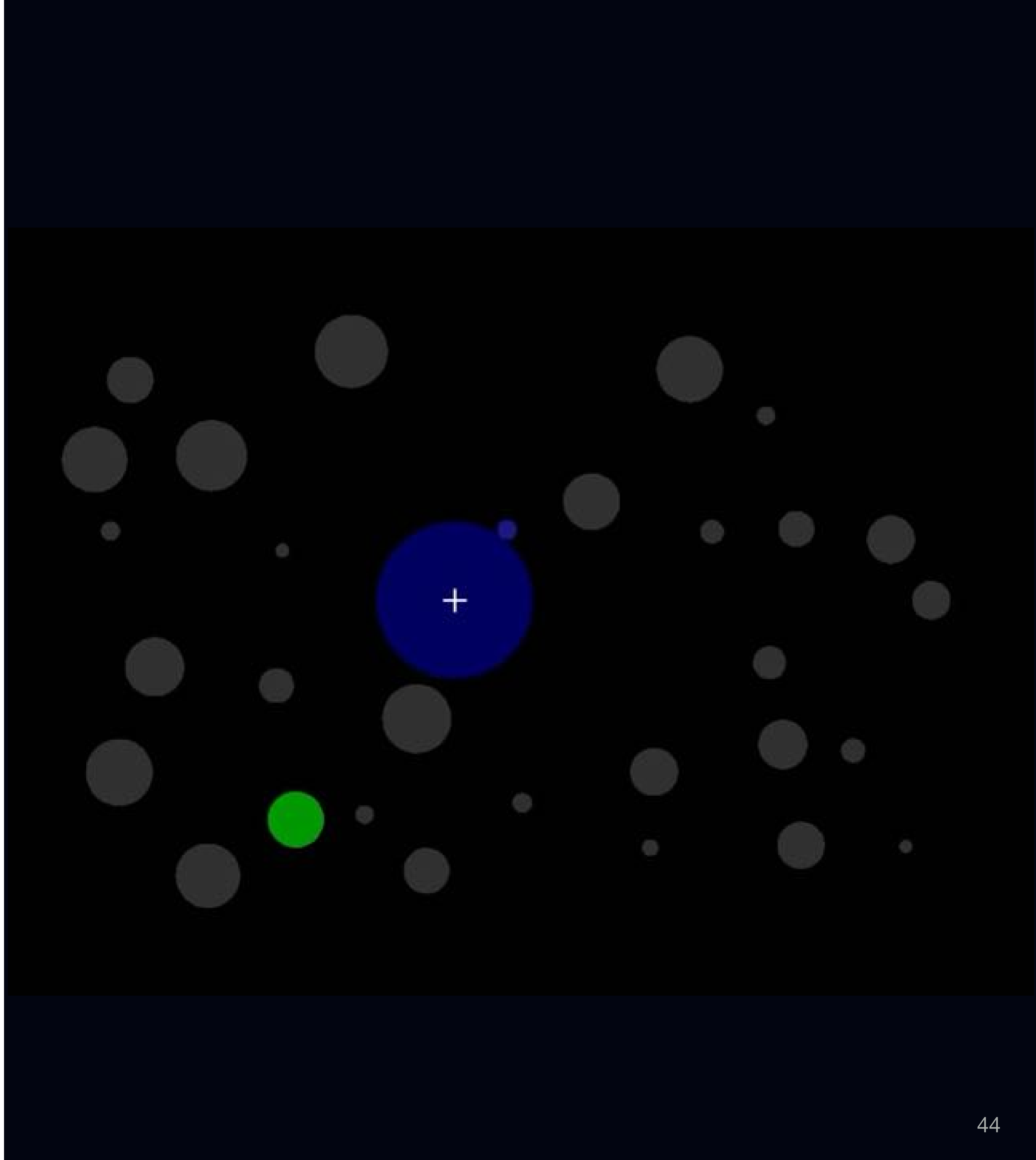

Expanding targets

McGuffin & Balakrishnan, 2002
Zhai et al., 2003

Targets grow
when close to cursor

Pointing time predicted
by expanded target size

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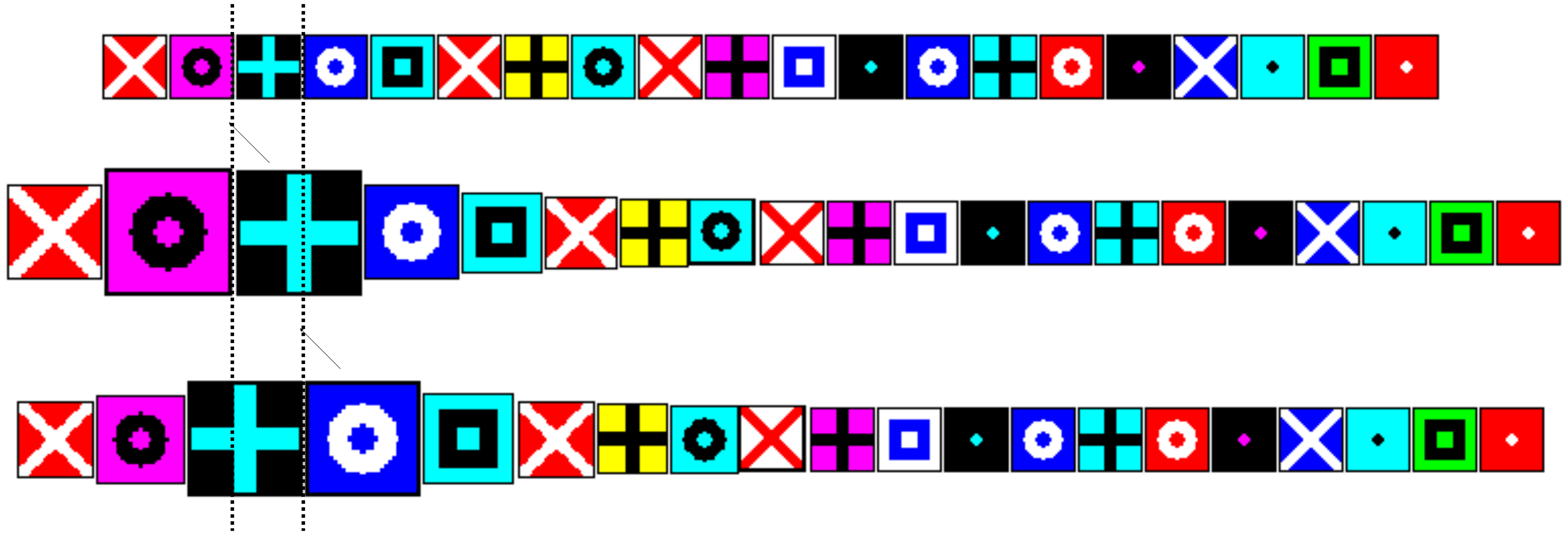
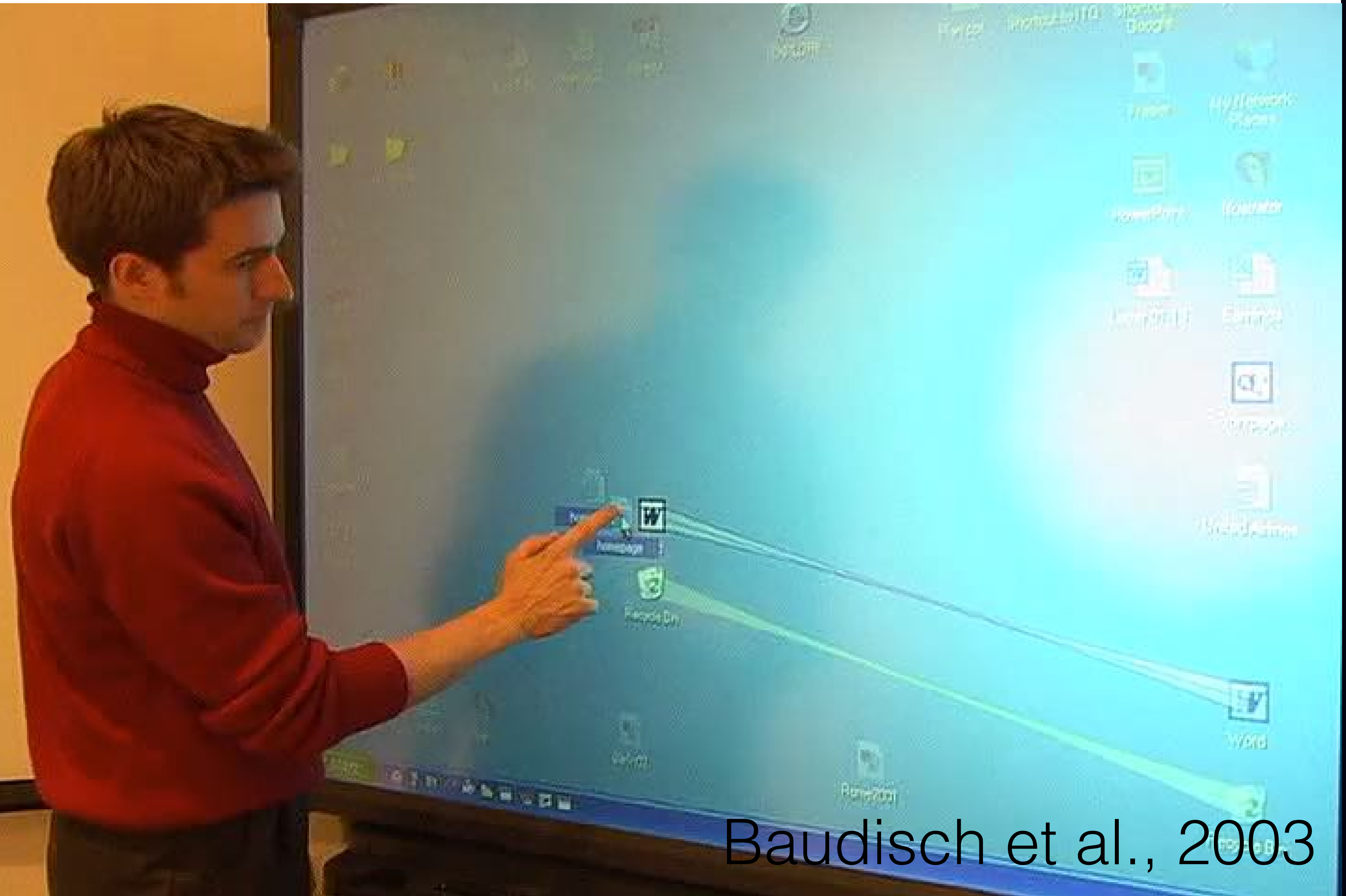


Targets grow
when close to cursor

Pointing time predicted
by expanded target size

But does not work
with dense targets
(example: MacOS dock)

Drag-n-pop



Baudisch et al., 2003

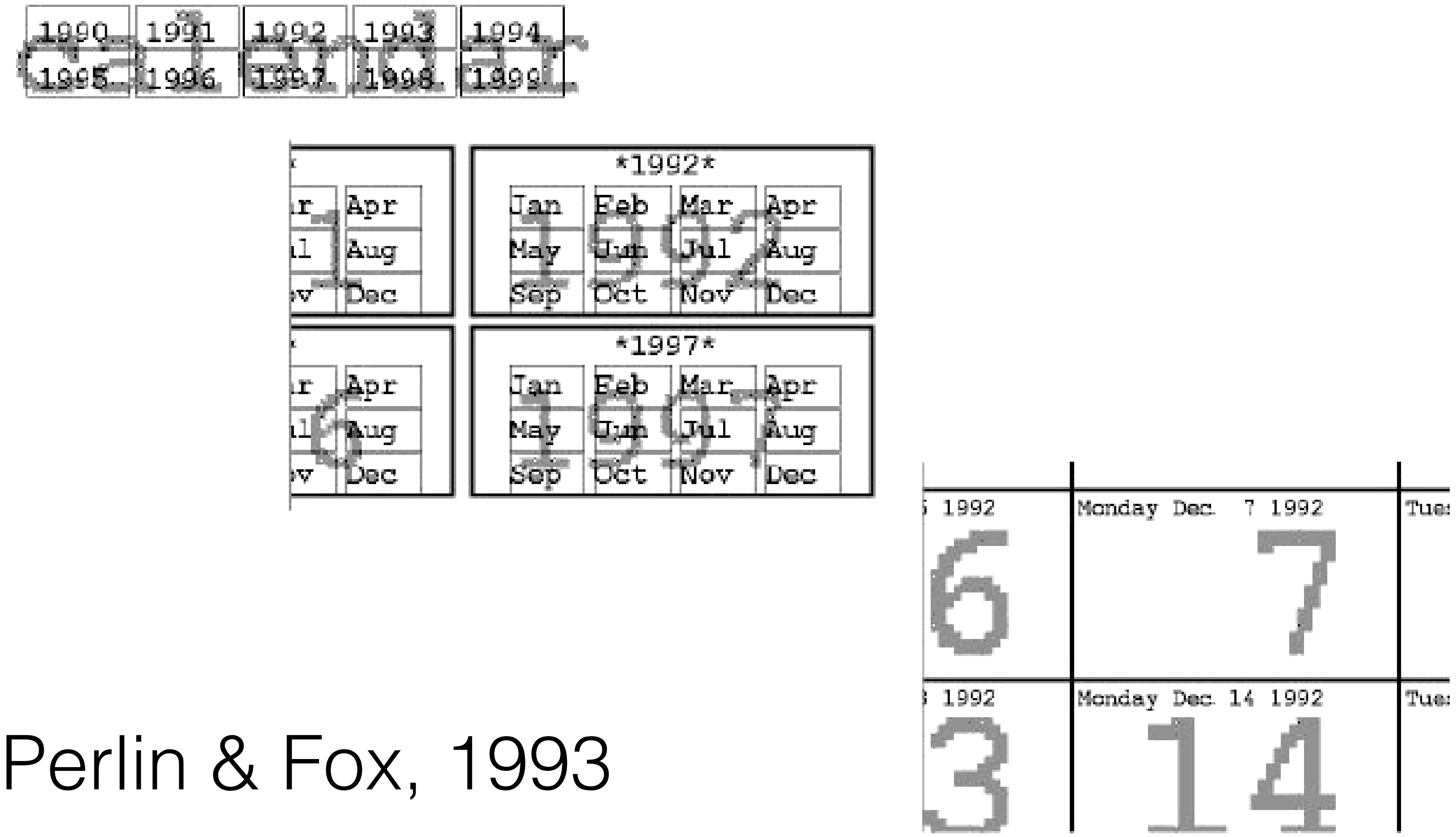
Reducing target distance during drag-and-drop by having target icons “fly” towards the cursor

“Beating” Fitts’ Law

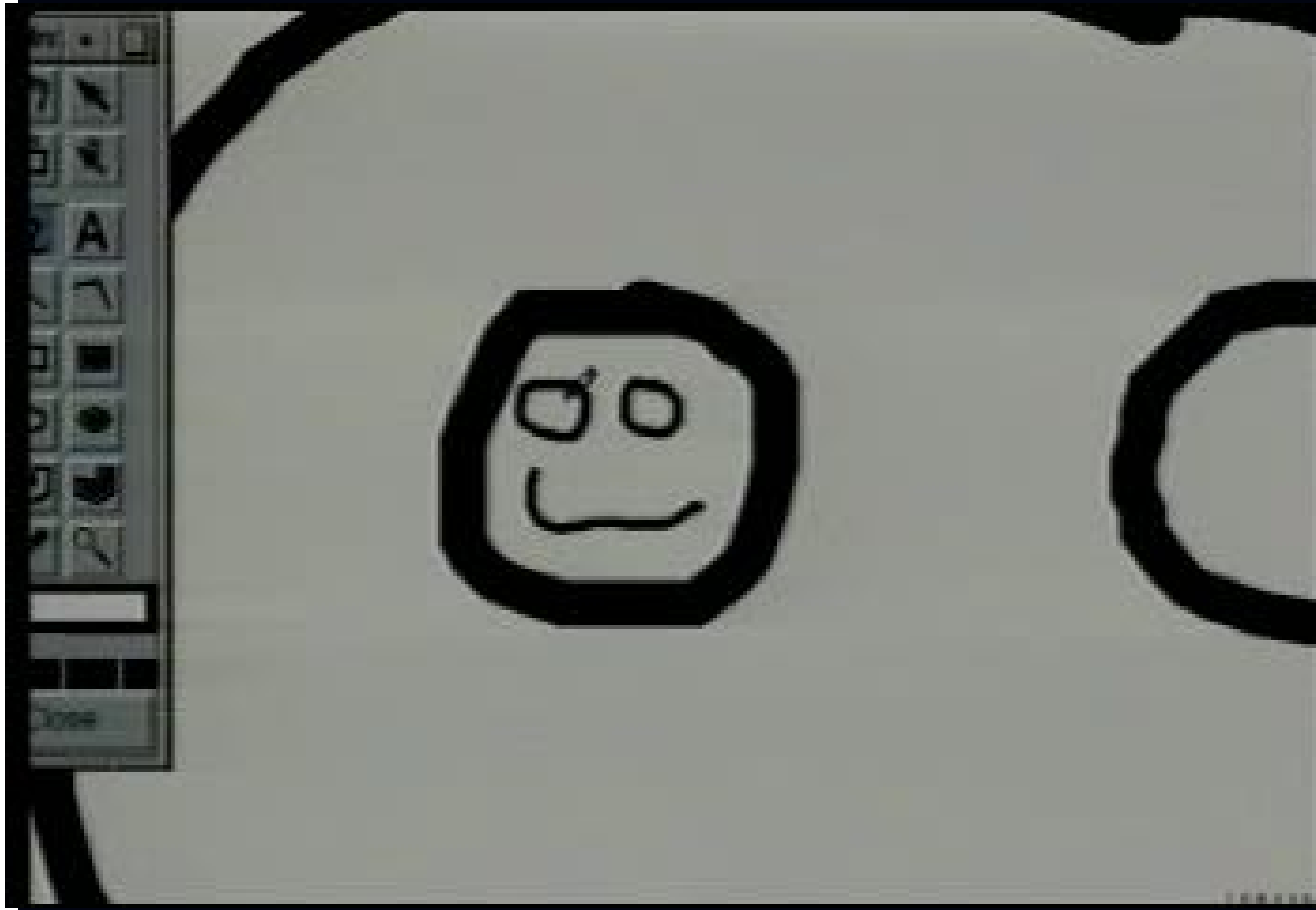
How can the system
help the user
reach the target faster?

1. Extract user intention
2. Use information about targets
3. Breaking the limits

Zoomable user interface (ZUI)

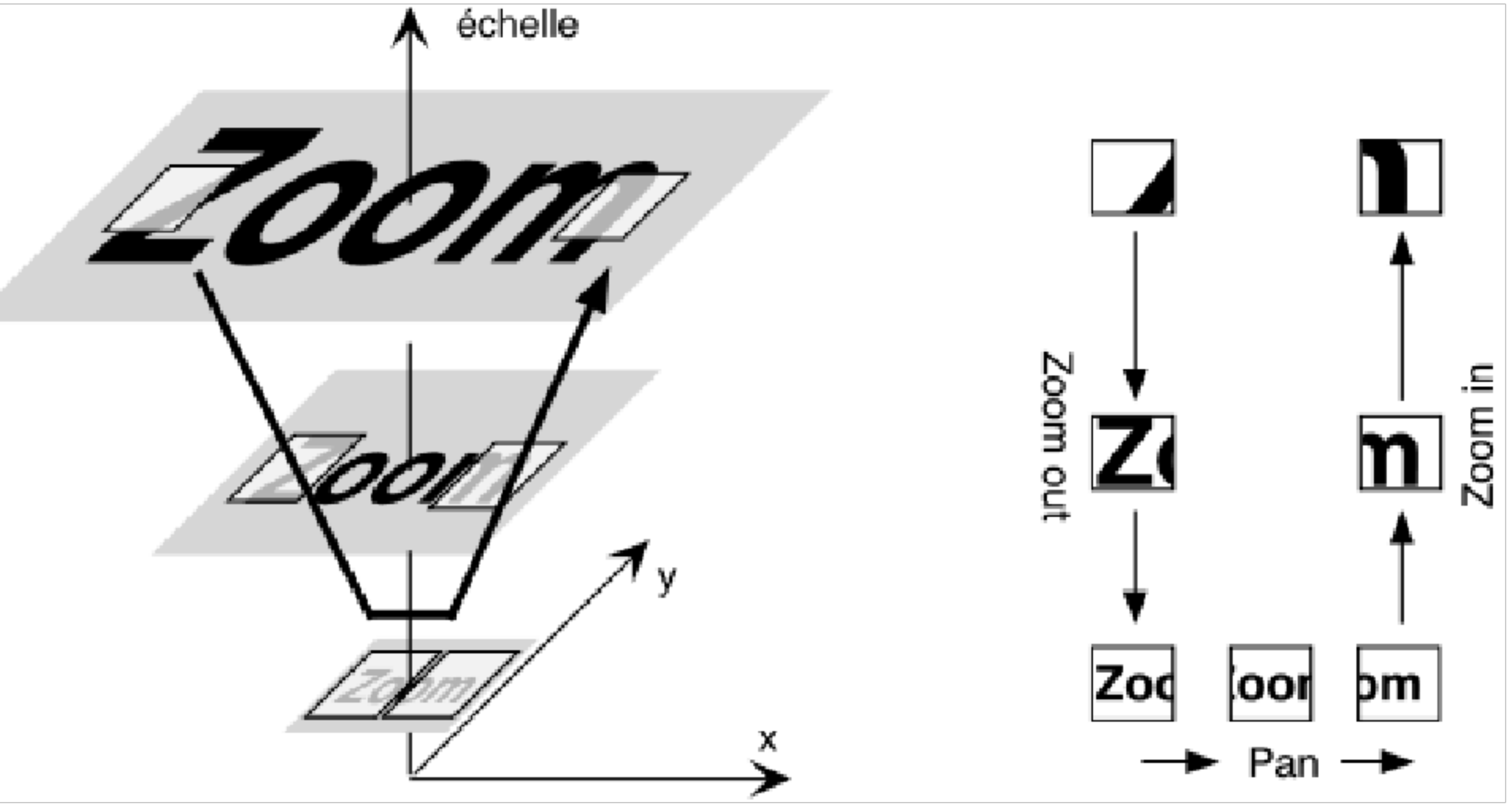


Perlin & Fox, 1993



Bederson & Hollan, 1994

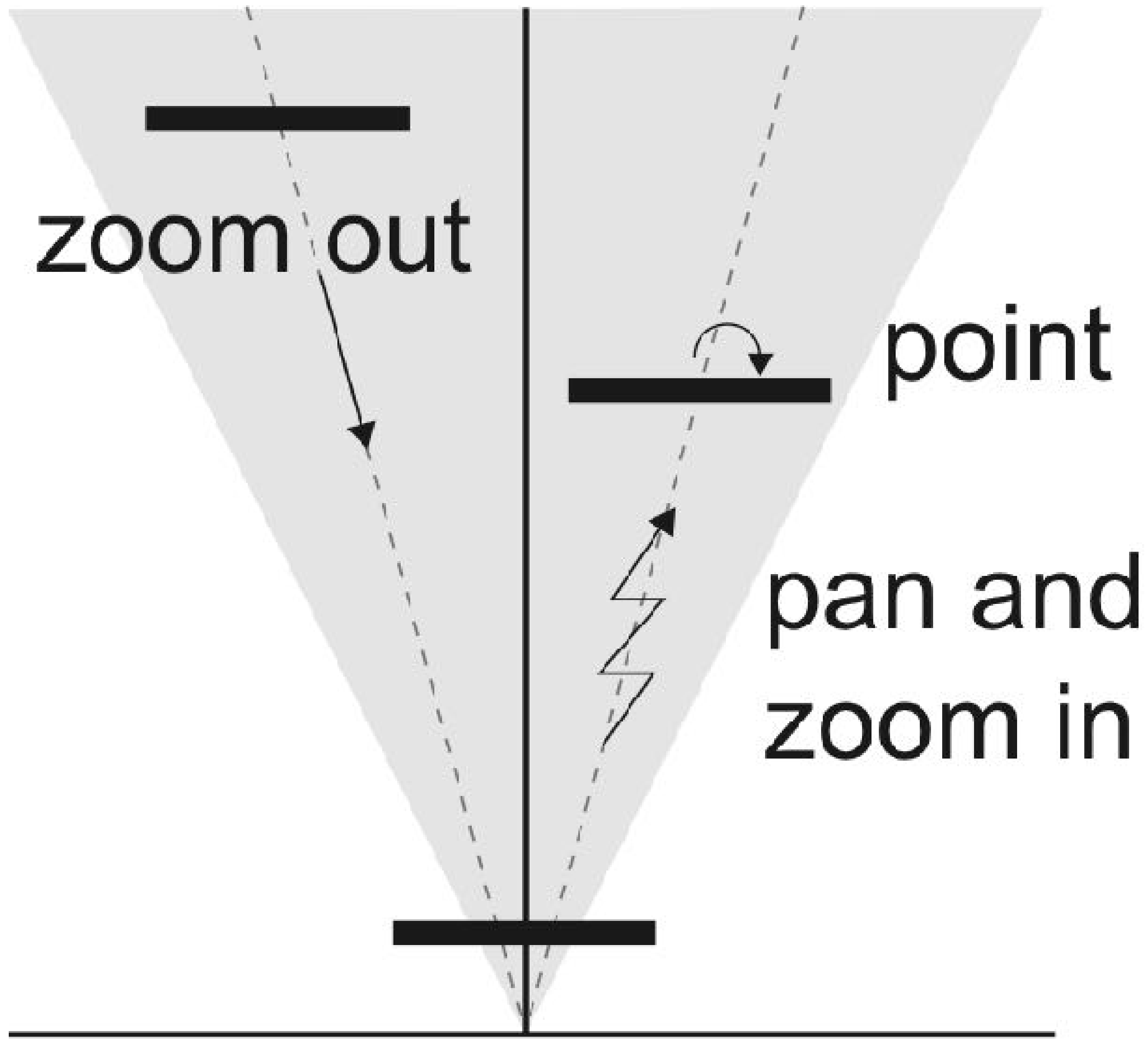
Multiscale pointing



Very different from
“normal” pointing

Zoom out to see the target
Pan and zoom in towards it

Multiscale pointing



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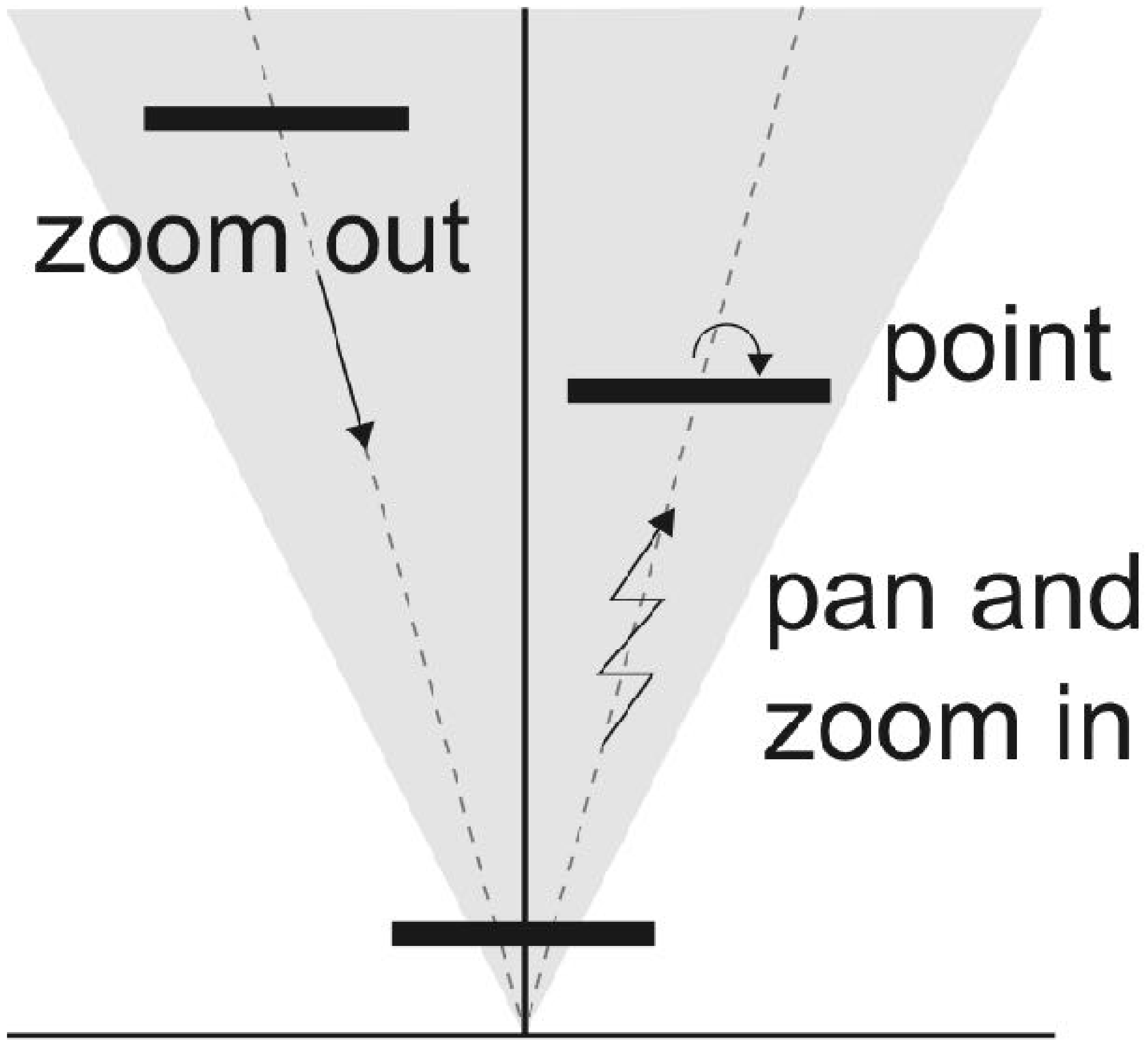
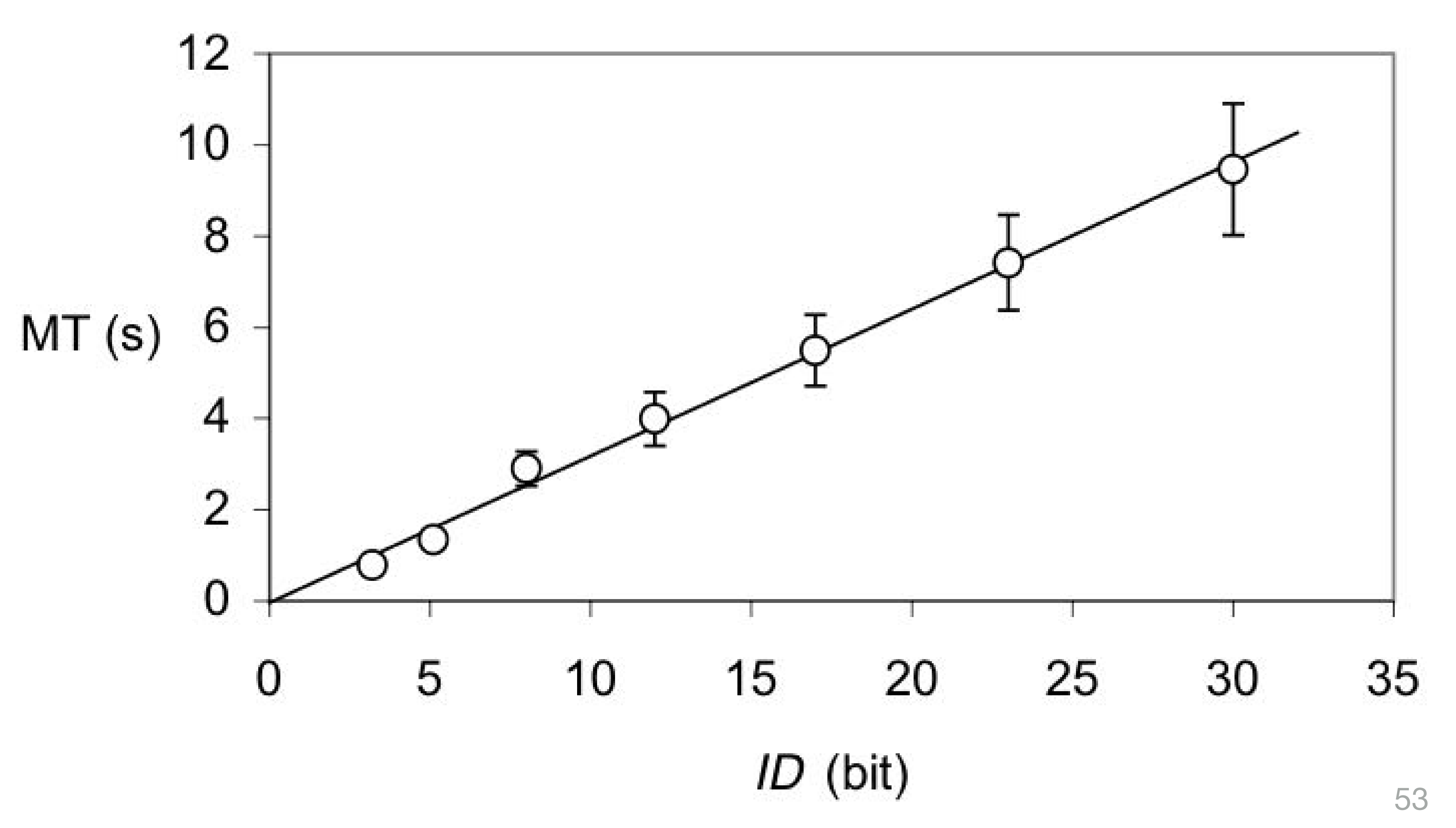
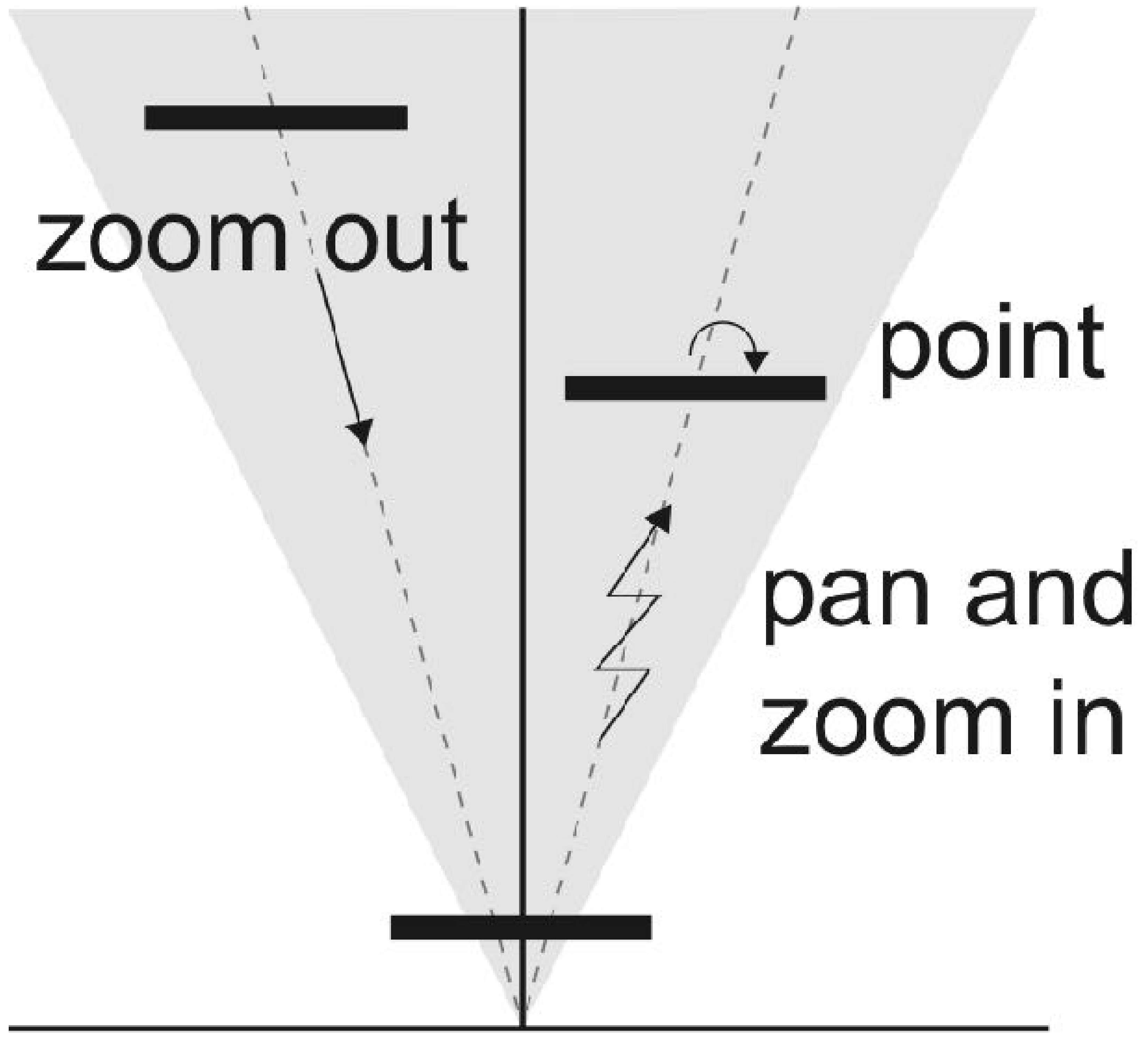


Guiard & Beaudouin-Lafon, 2004

Pointing time predicted by Fitts' law up to ID = 30+



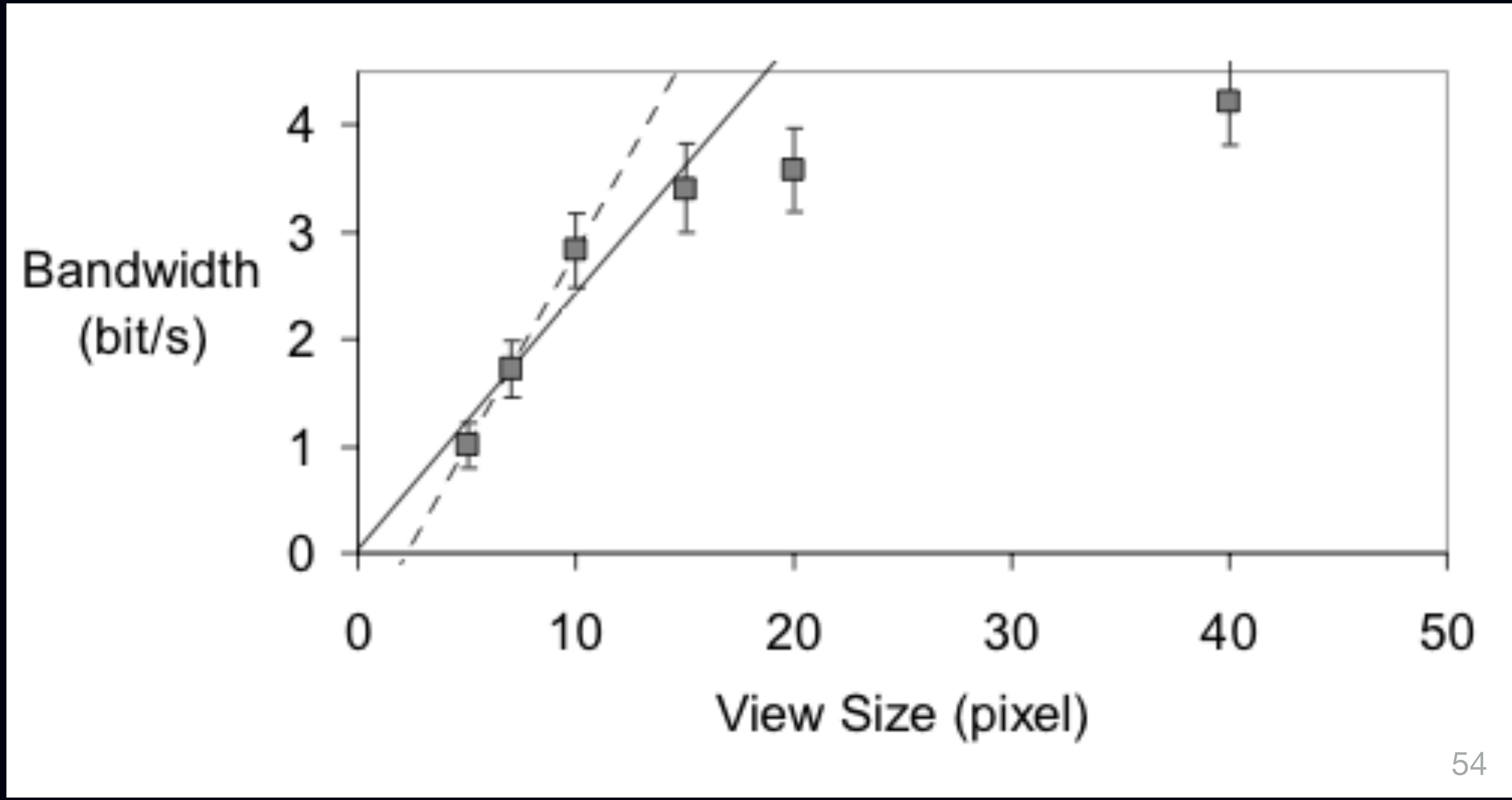
Multiscale pointing



Guiard et al., 2004

Effect of view size

For small views: MT = k ID / V



Orthozoom

(a) (b)

Appert & Fekete, 2006

Extend a scrollbar to
pan and zoom a 1D document

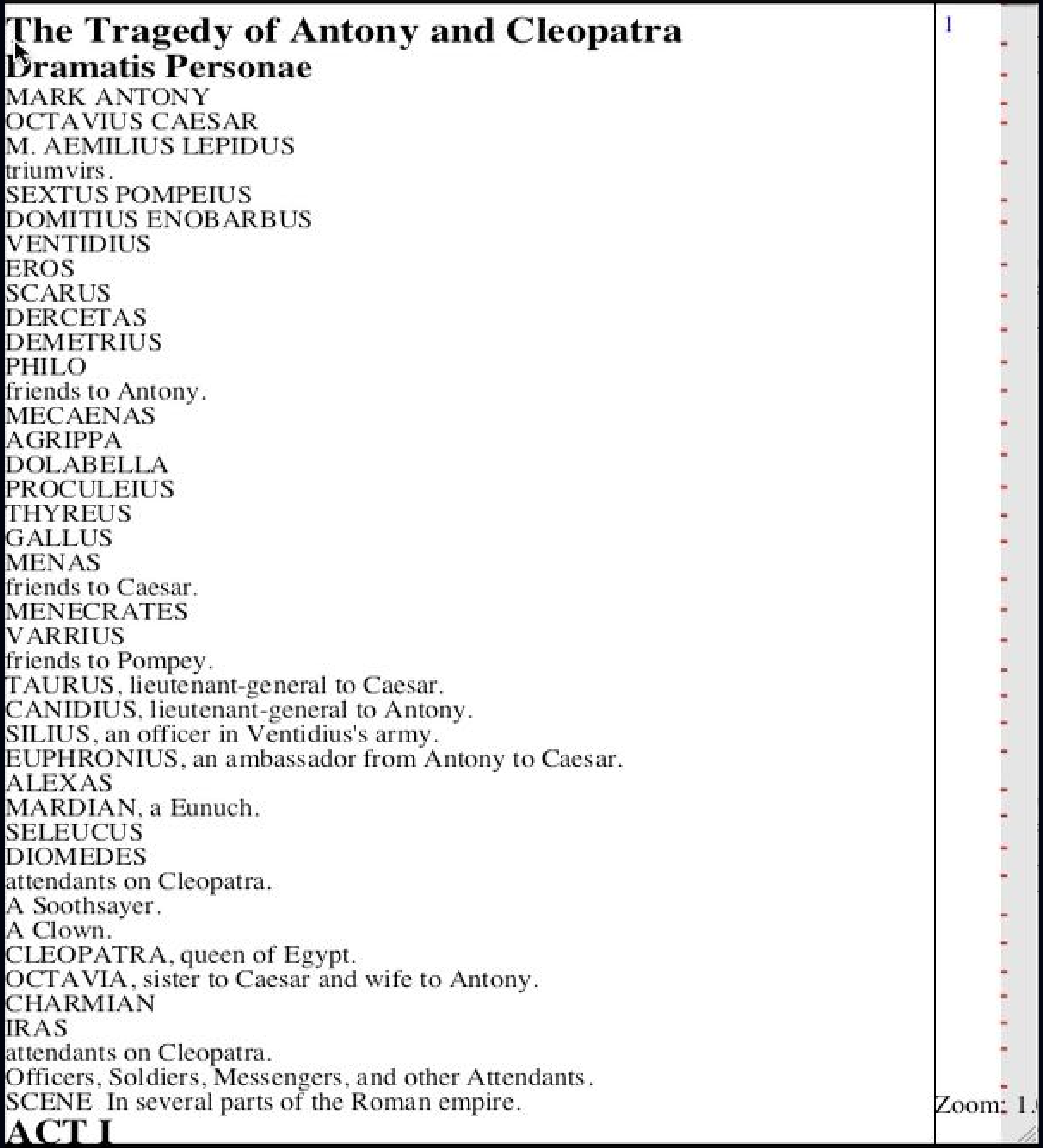
Use orthogonal dimension to zoom

Twice as fast
as the best known technique

Orthozoom


(a) (b)

Appert & Fekete, 2006



“Beating” Fitts’ Law

How can the system
help the user
reach the target faster?

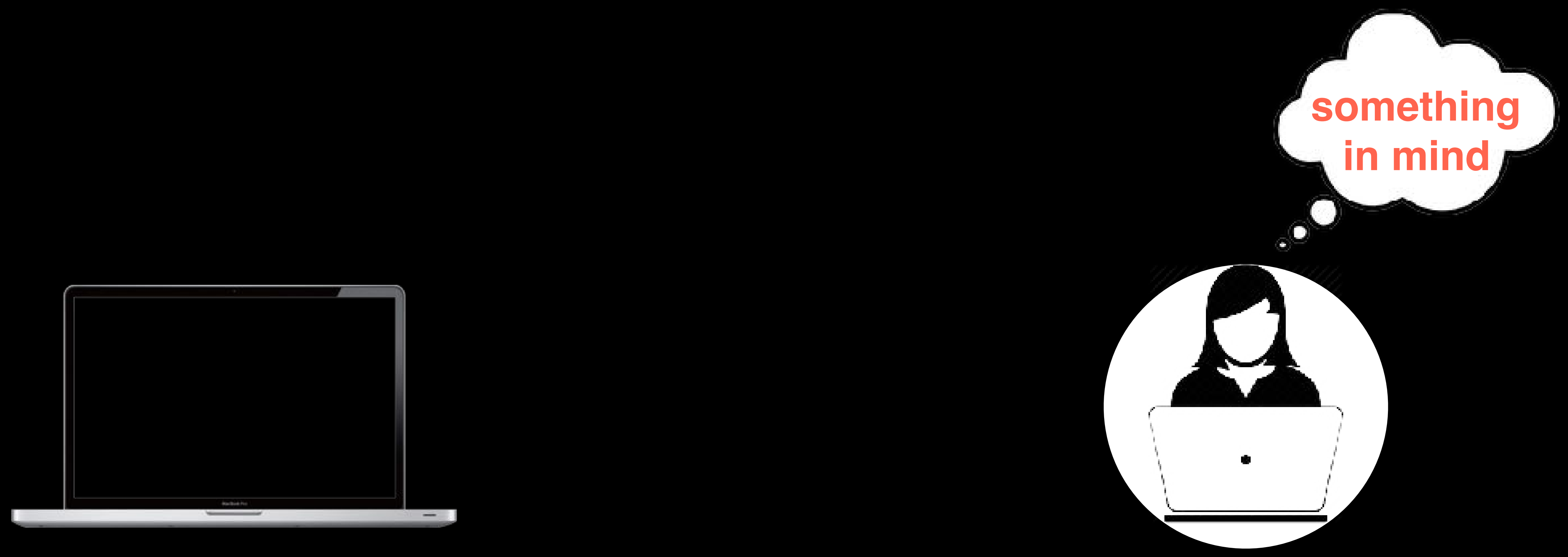
1. Extract user intention
2. Use information about targets
3. Breaking the limits
4. Challenge the user

BIG: Bayesian Information Gain

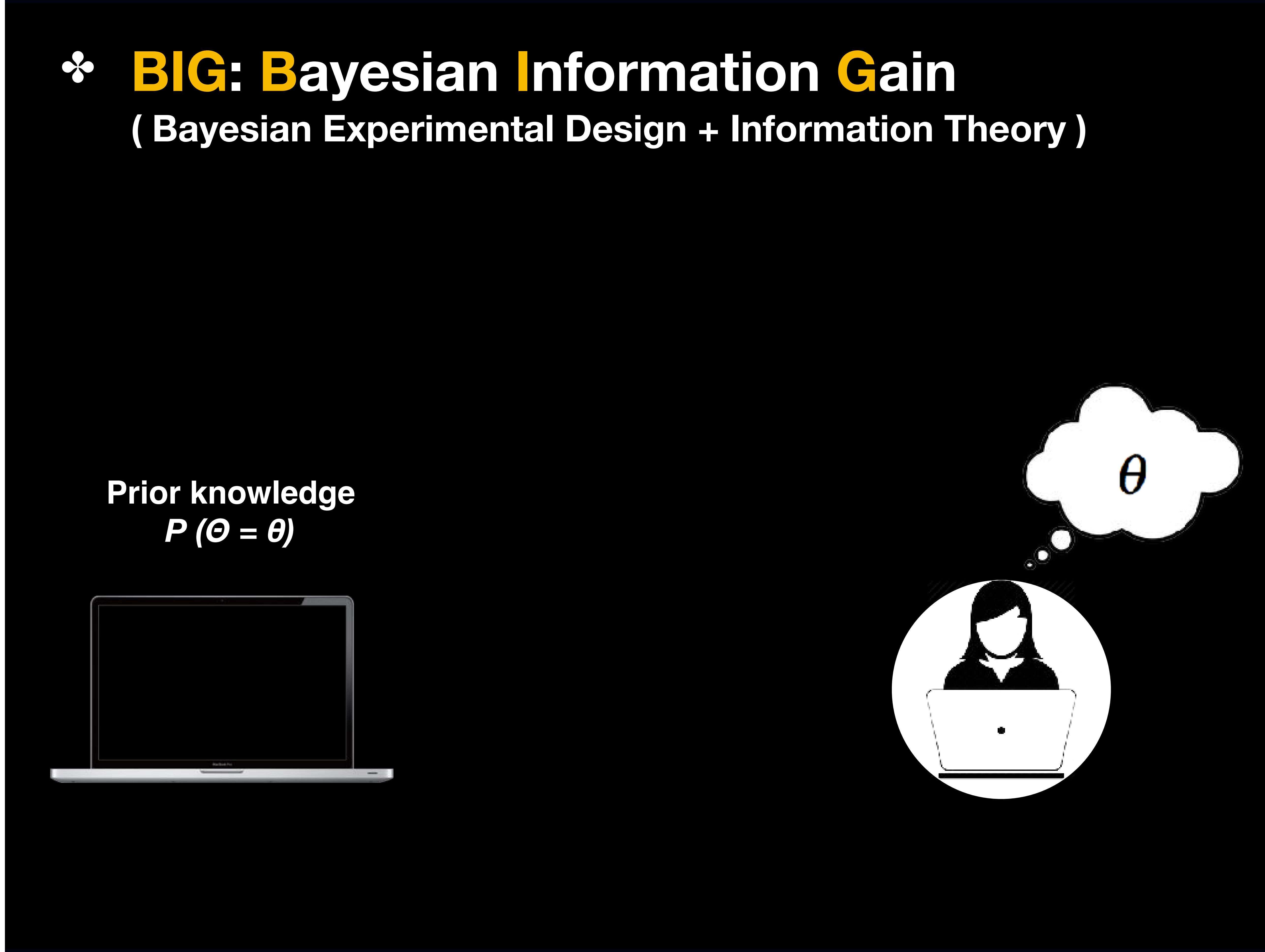
Liu, D’Oliveira, Rioul, Beaudouin-Lafon, 2017

BIG: Bayesian Information Gain

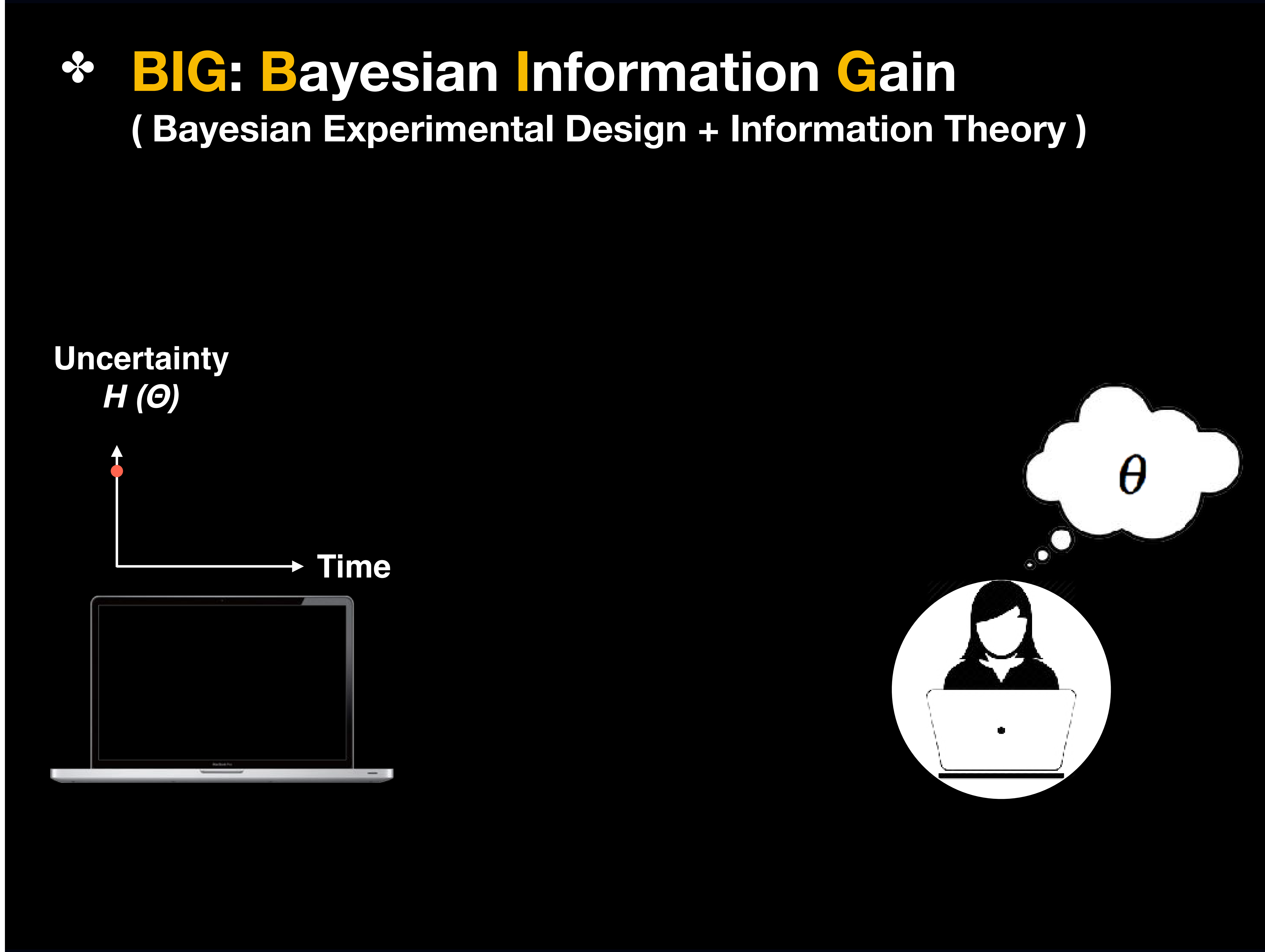
✤ **BIG: Bayesian Information Gain**
(Bayesian Experimental Design + Information Theory)



BIG: Bayesian Information Gain



BIG: Bayesian Information Gain



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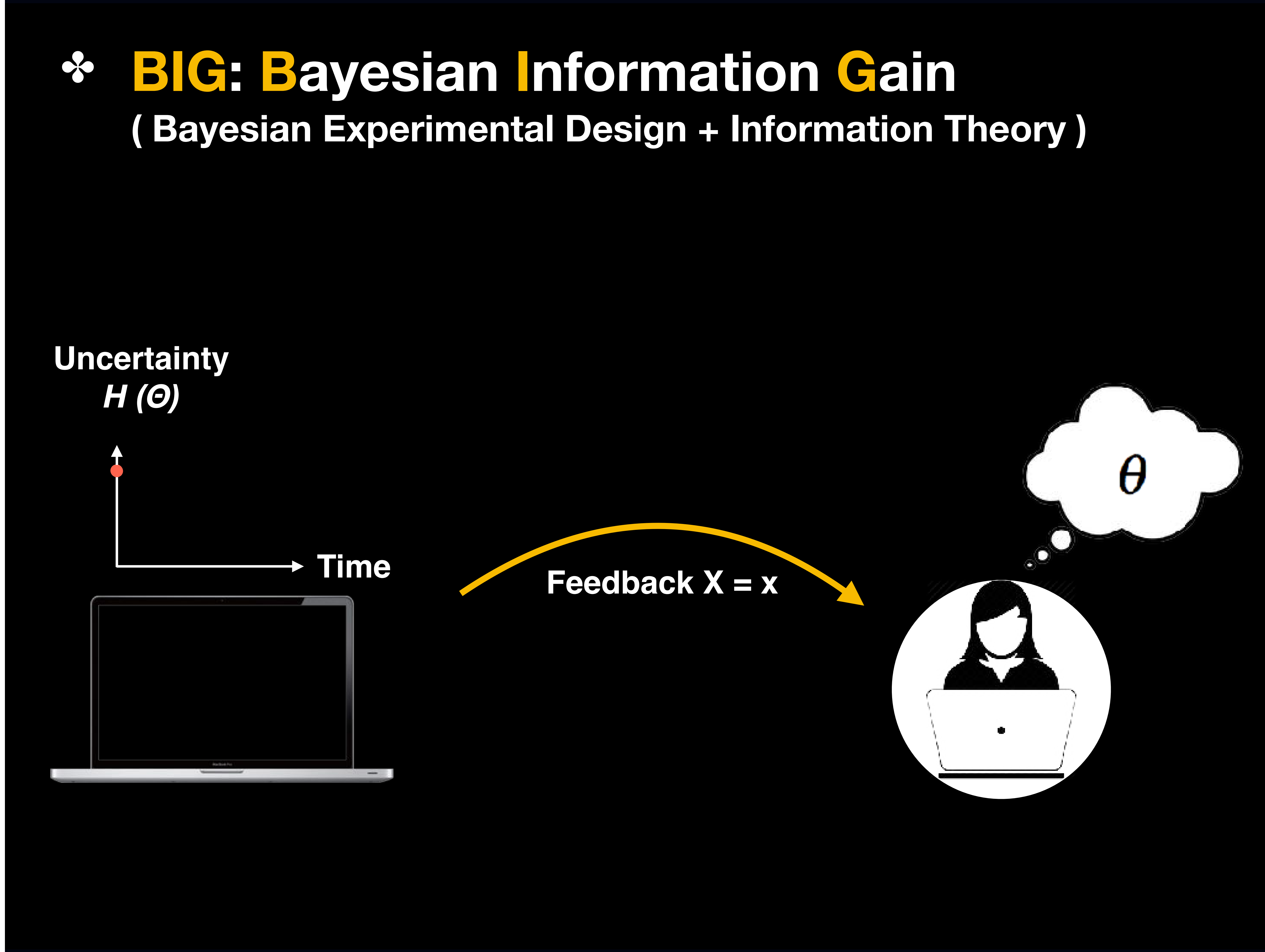

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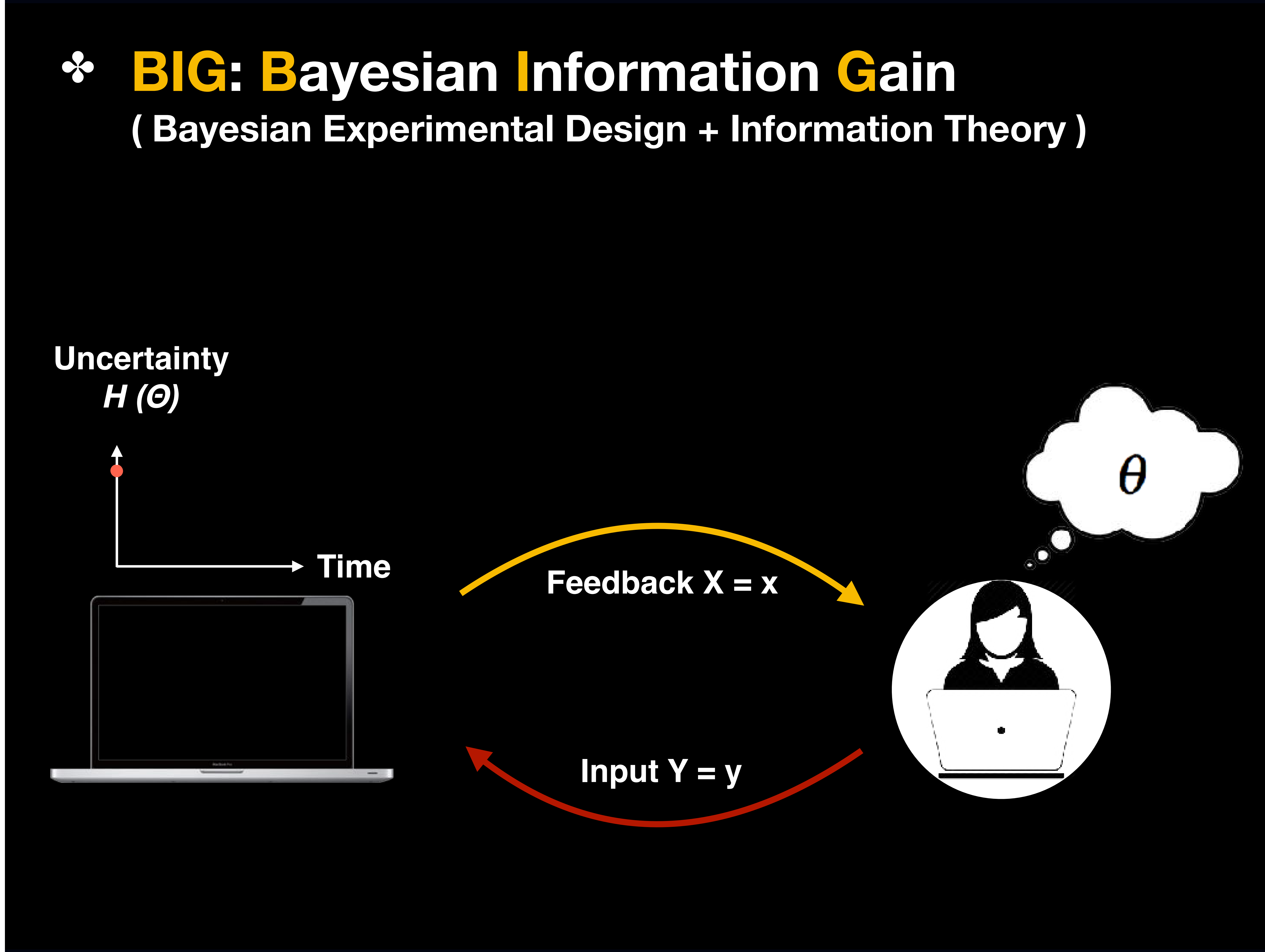

BIG: Bayesian Information Gain

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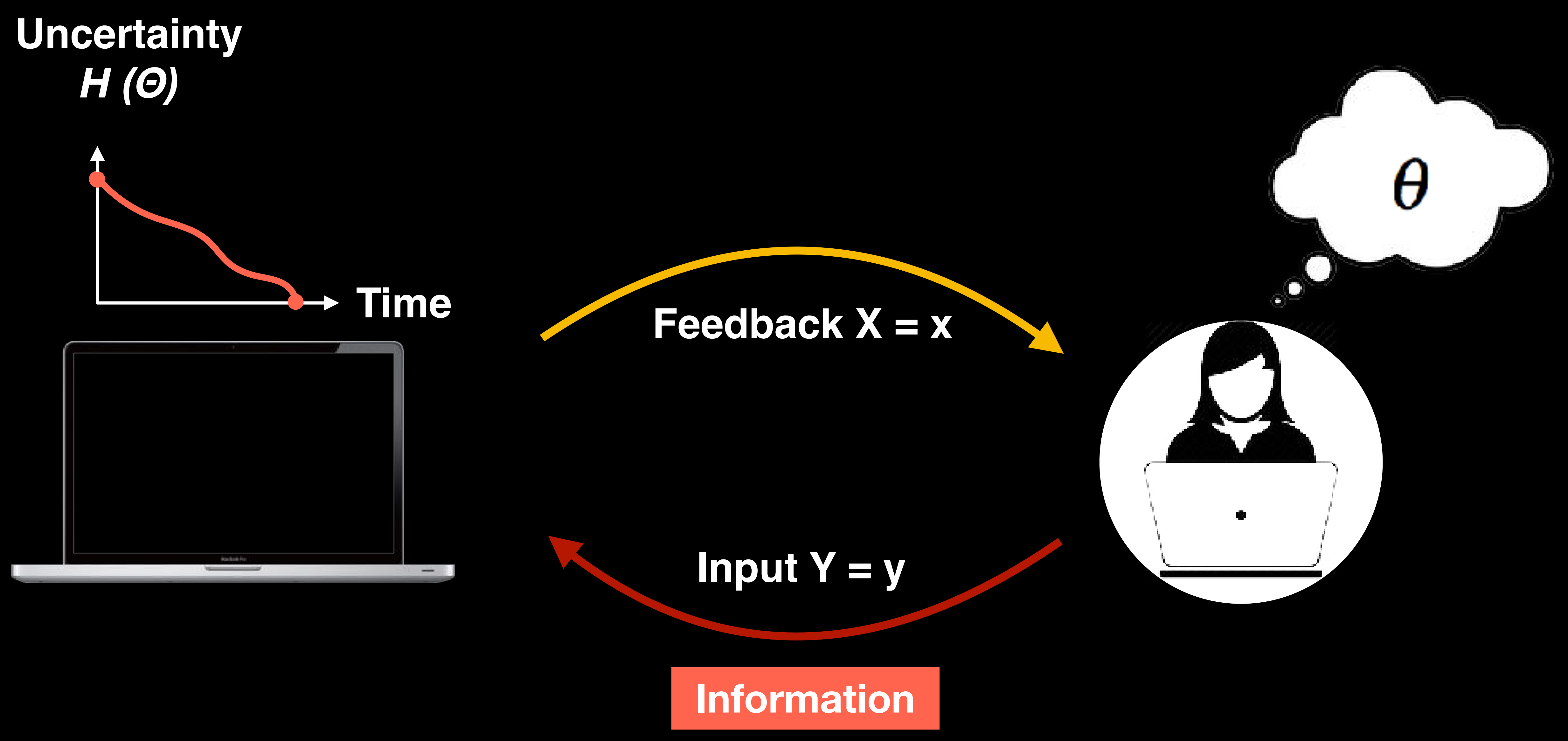
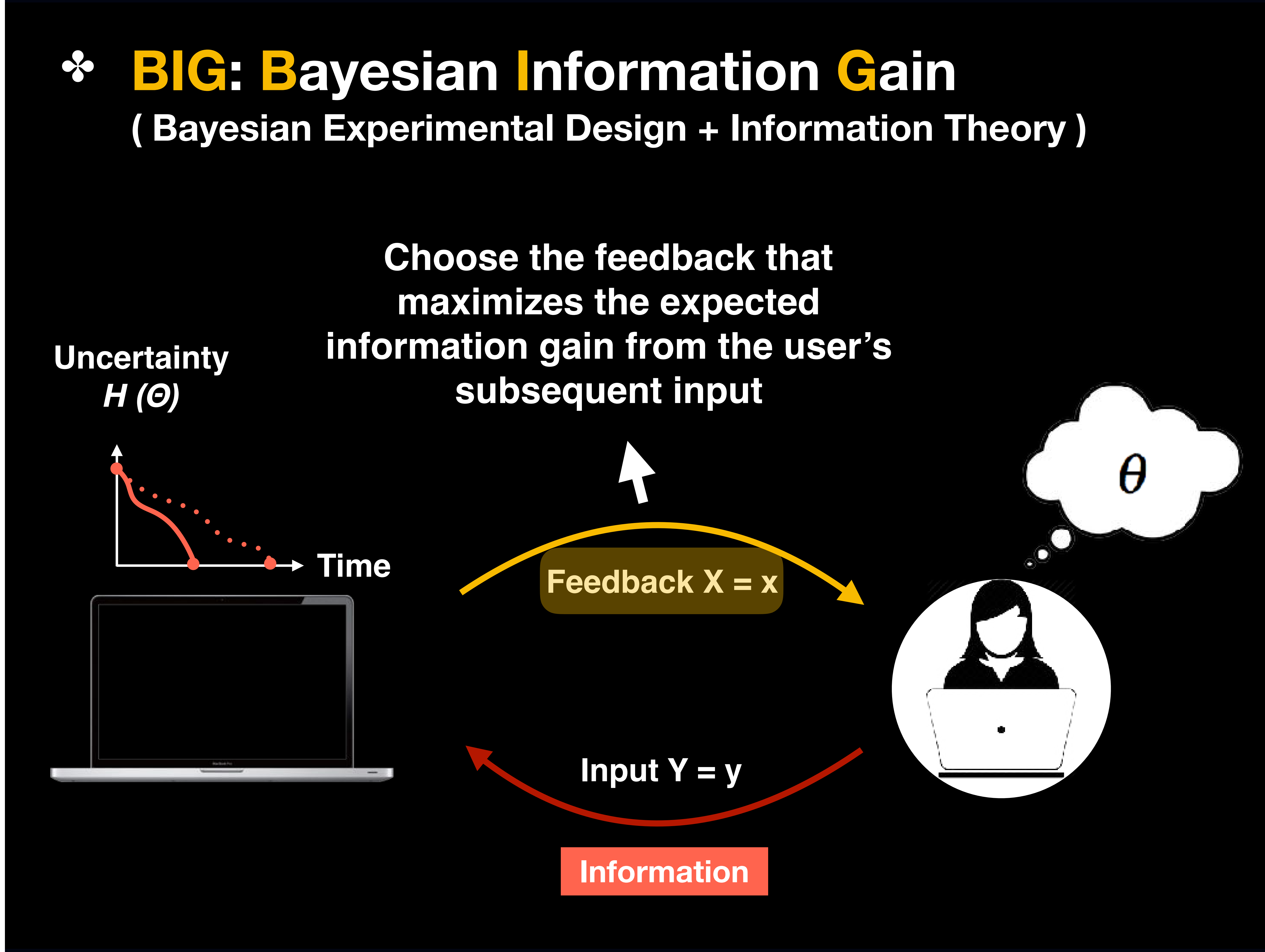


BIG: Bayesian Information Gain



✤ BIG: Bayesian Information Gain

(Bayesian Experimental Design + Information Theory)

- The computer's Uncertainty about the user's goal

$$H(\Theta) = -\sum_{i=1}^{n} P(\Theta = \theta_i) \log_2 P(\Theta = \theta_i)$$

- The computer's updated knowledge about the user's goal

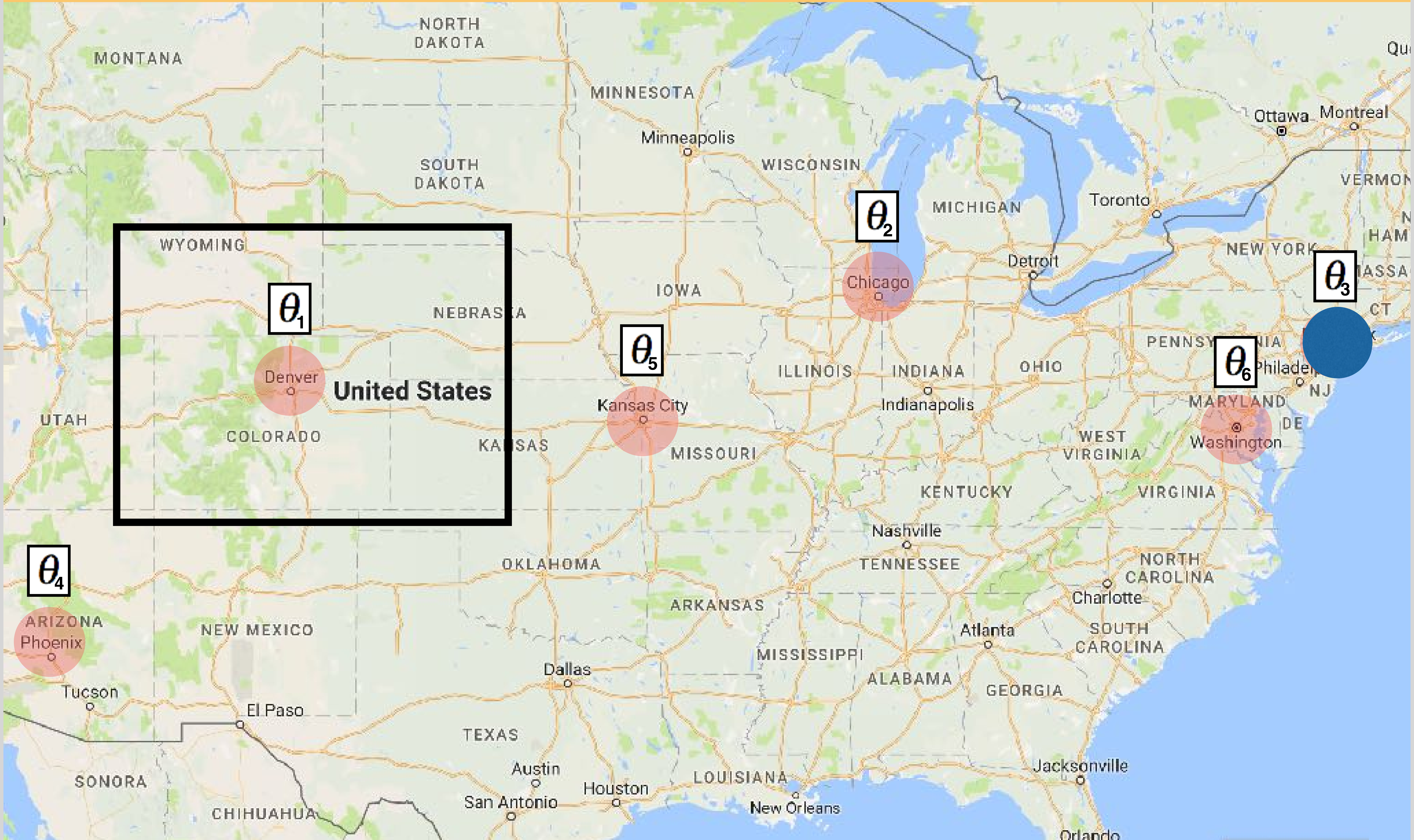
$$P(\Theta = \theta \mid X = x, Y = y) = \frac{P(Y = y \mid \Theta = \theta, X = x) P(\Theta = \theta)}{P(Y = y \mid X = x)}$$

- The information gained by the computer from the user's input

$$IG(\Theta \mid X = x, Y = y) = H(\Theta) - H(\Theta \mid X = x, Y = y)$$

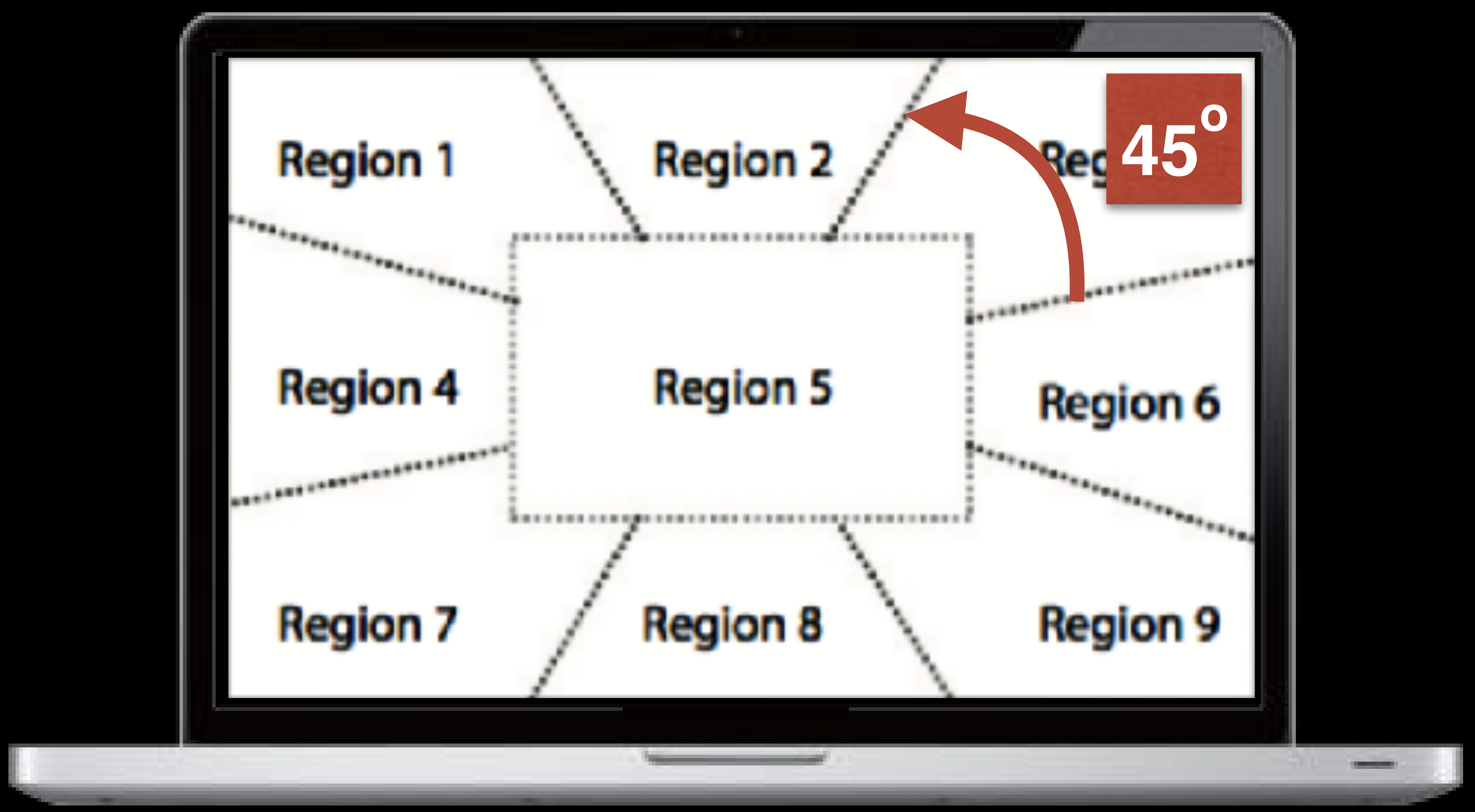
BIGnav:
Bayesian Information Gain Navigation

BIGnav:
Bayesian Information Gain Navigation

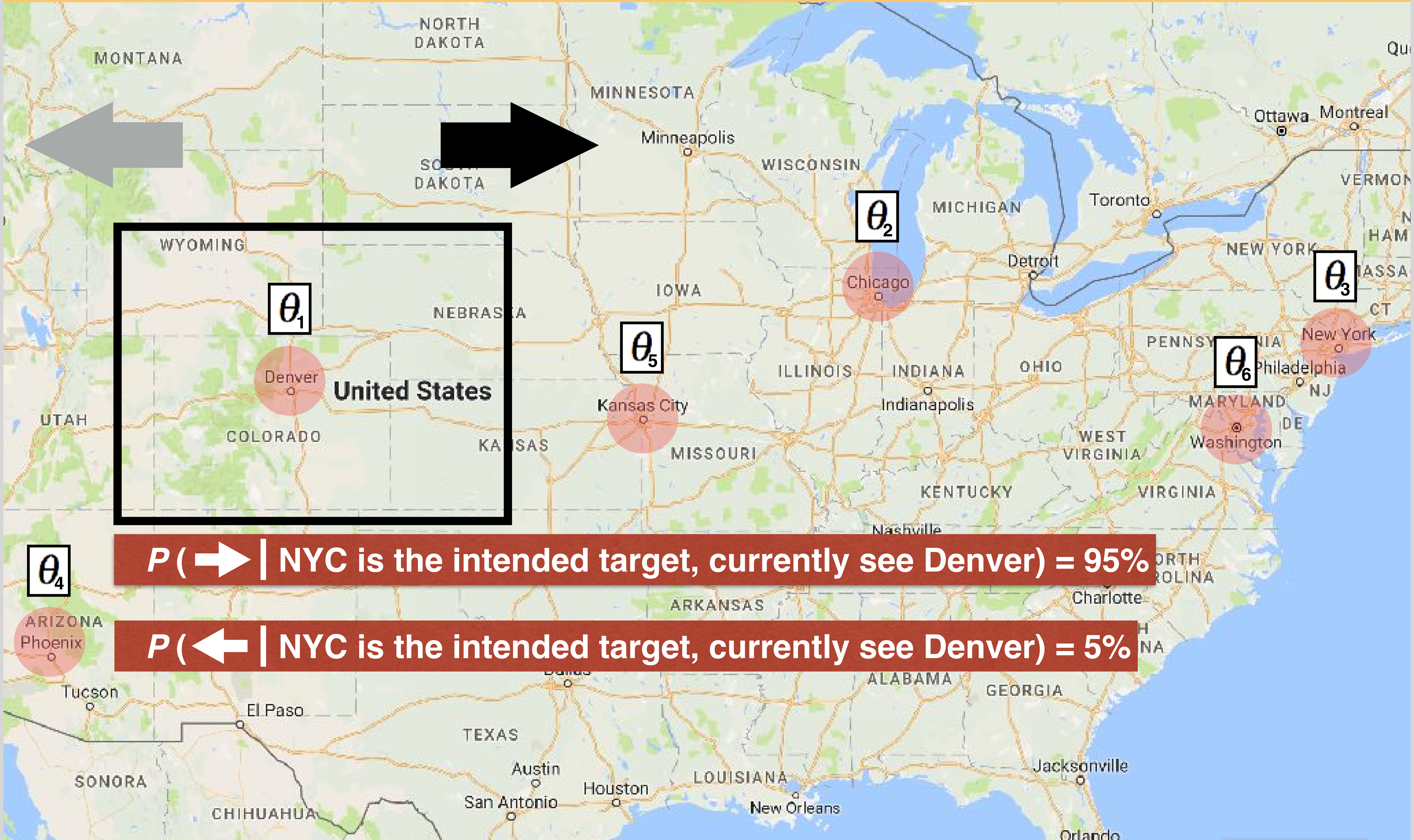


User actions:

8 pan directions
1 zoom-in region



BIGnav:
Bayesian Information Gain Navigation



P (→ | NYC is the intended target, currently see Denver) = 95%

P (← | NYC is the intended target, currently see Denver) = 5%

BIGnav:
Bayesian Information Gain Navigation

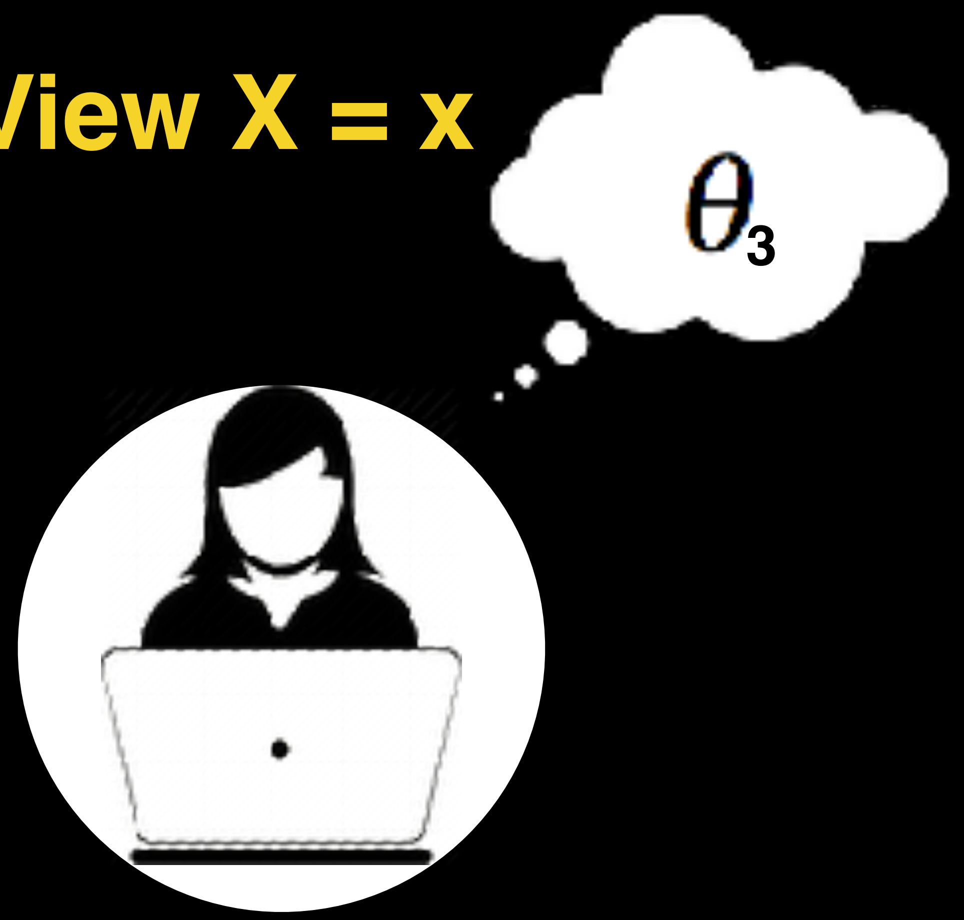
$$P(\Theta = \theta \mid X = x, Y = y)$$

Update its knowledge

$$P(\Theta = \theta_i)$$

User Input Y = y

View X = x



BIGnav:
Bayesian Information Gain Navigation

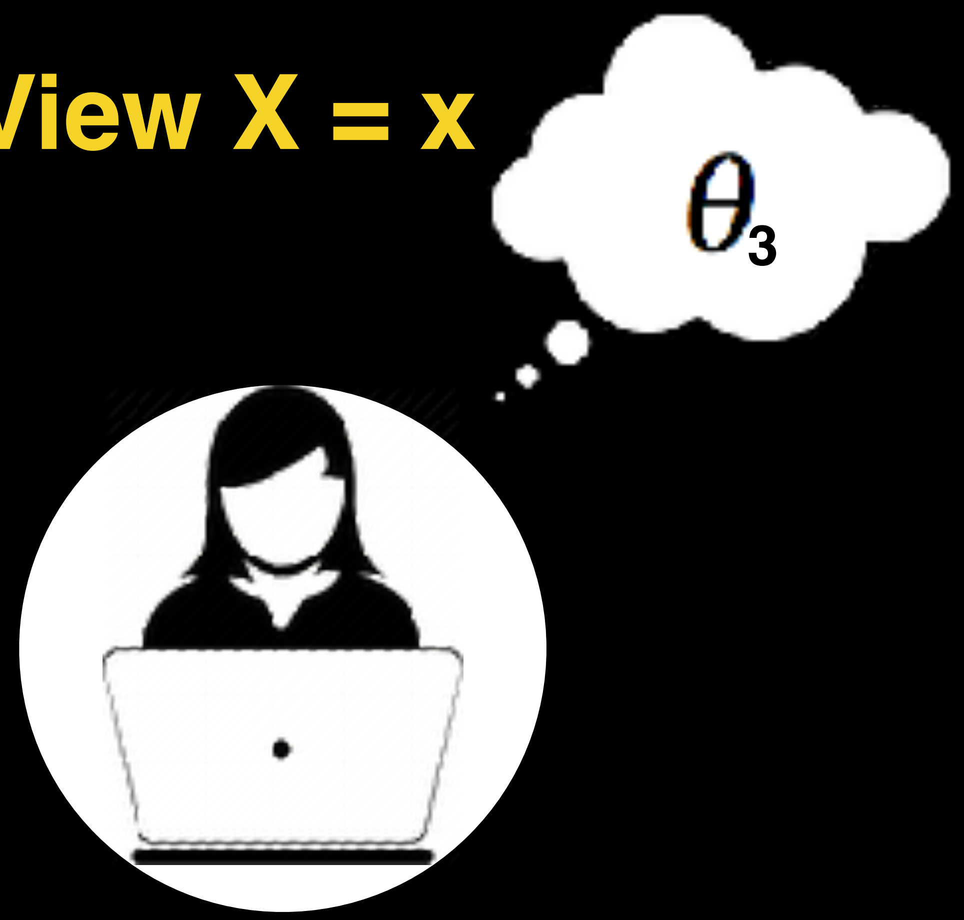
$$IG(\Theta|X=x,Y) = H(\Theta) - H(\Theta|X=x,Y)$$

Navigate to a new view that maximizes the expected information gain

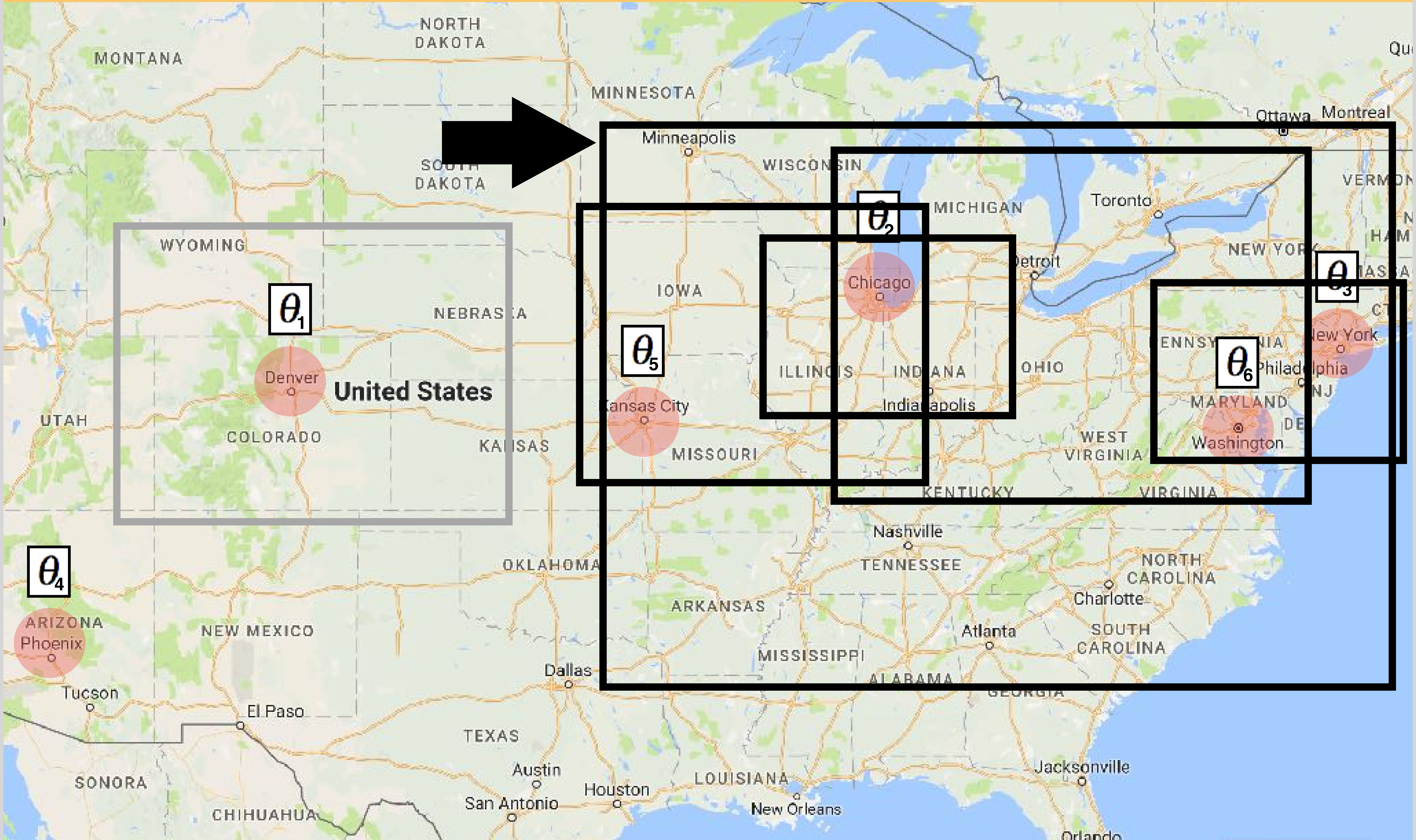
$$P(\Theta = \theta_i)$$

User Input Y = y

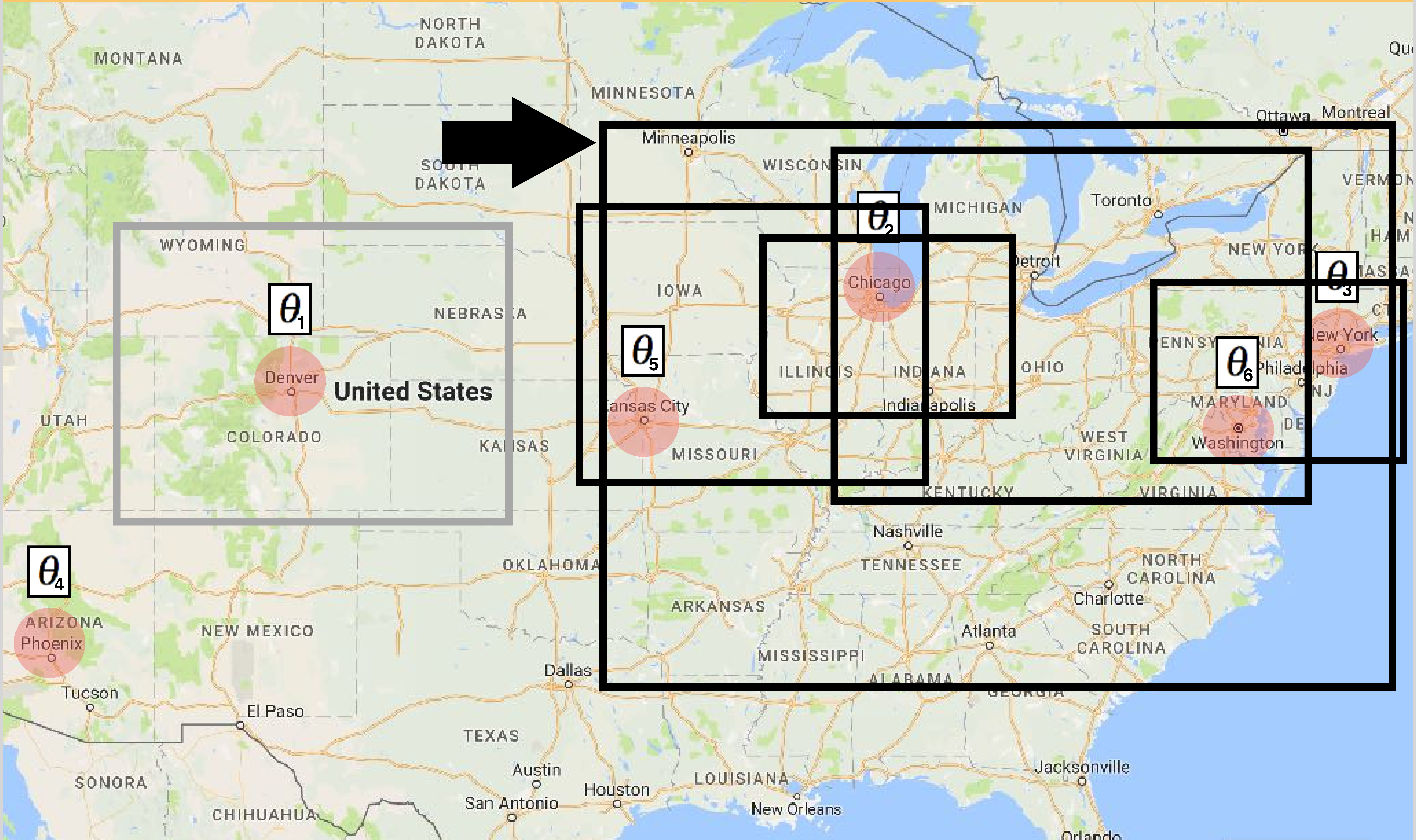
View X = x



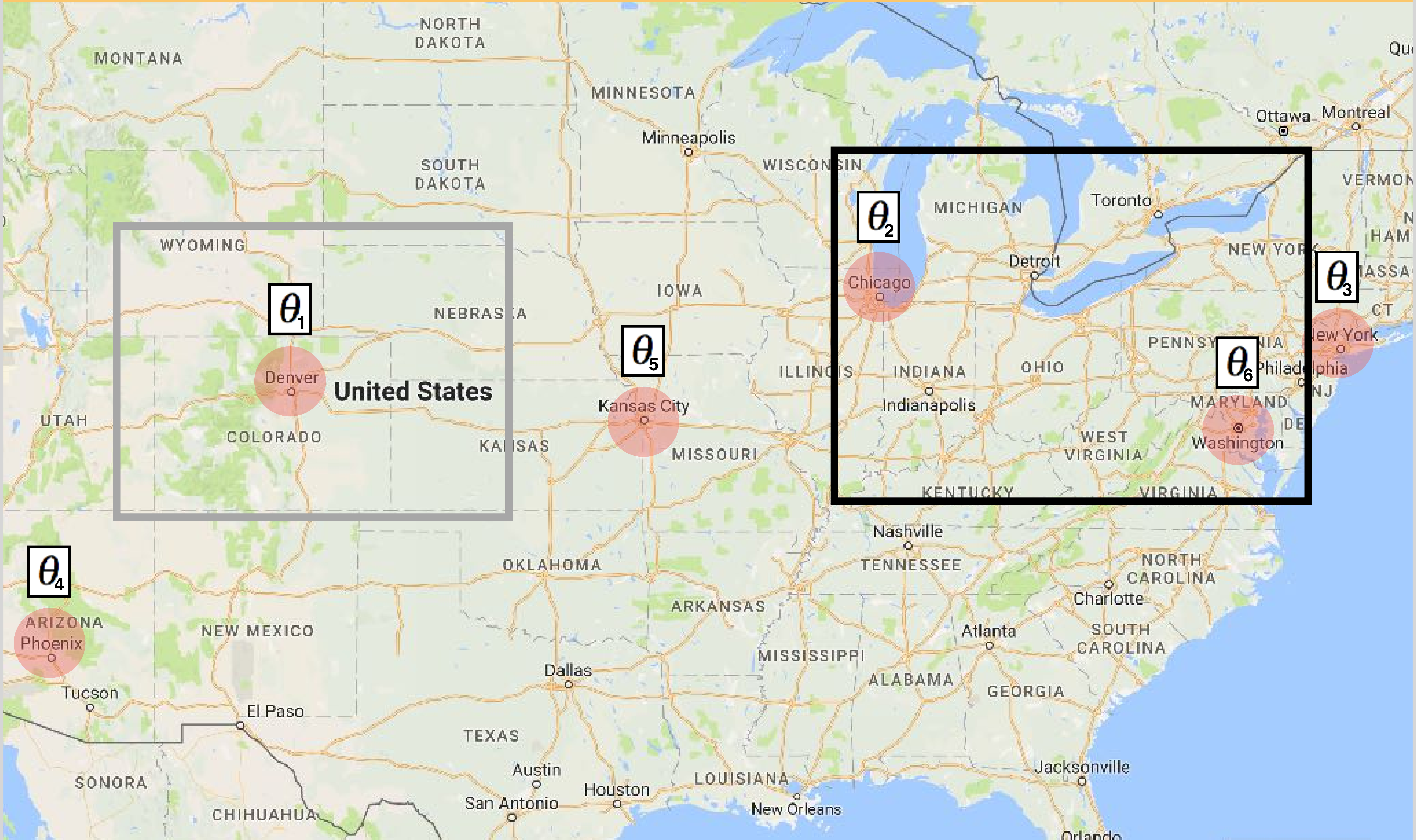
BIGnav:
Bayesian Information Gain Navigation



BIGnav:
Bayesian Information Gain Navigation



BIGnav:
Bayesian Information Gain Navigation



BIGnav:
Bayesian Information Gain Navigation

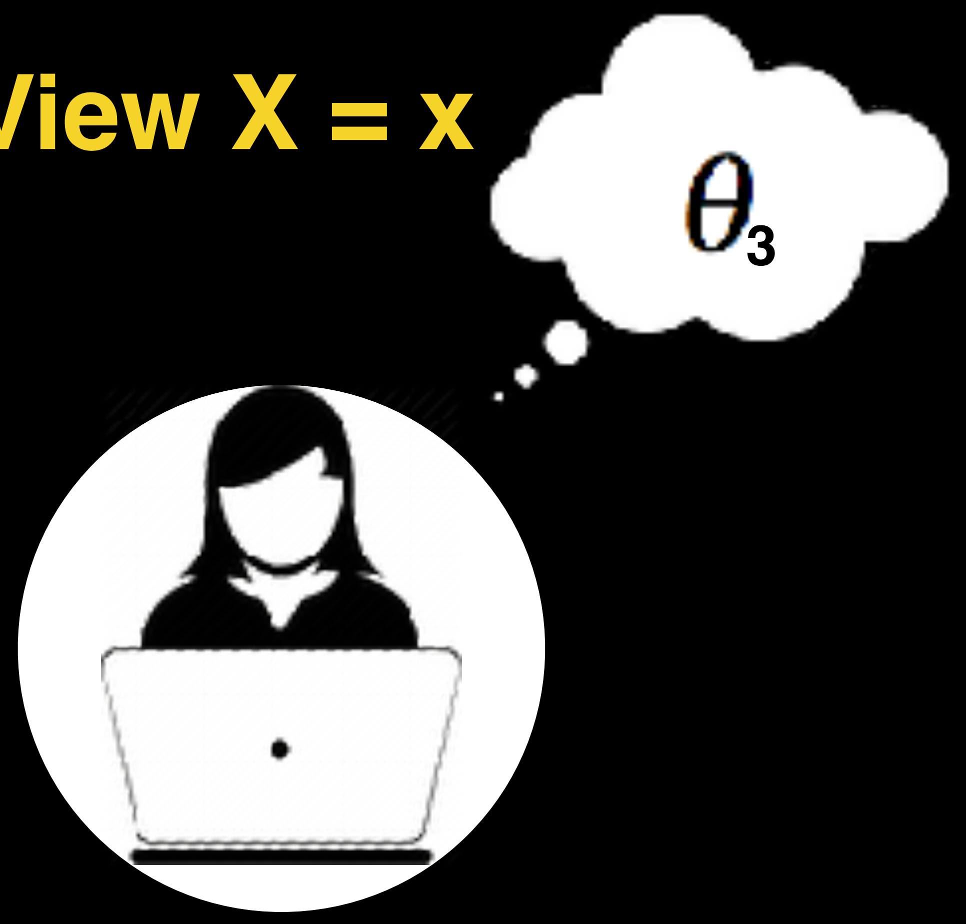
$$IG(\Theta|X=x,Y=y)=H(\Theta)-H(\Theta|X=x,Y=y)$$

Calculate the actual information gain

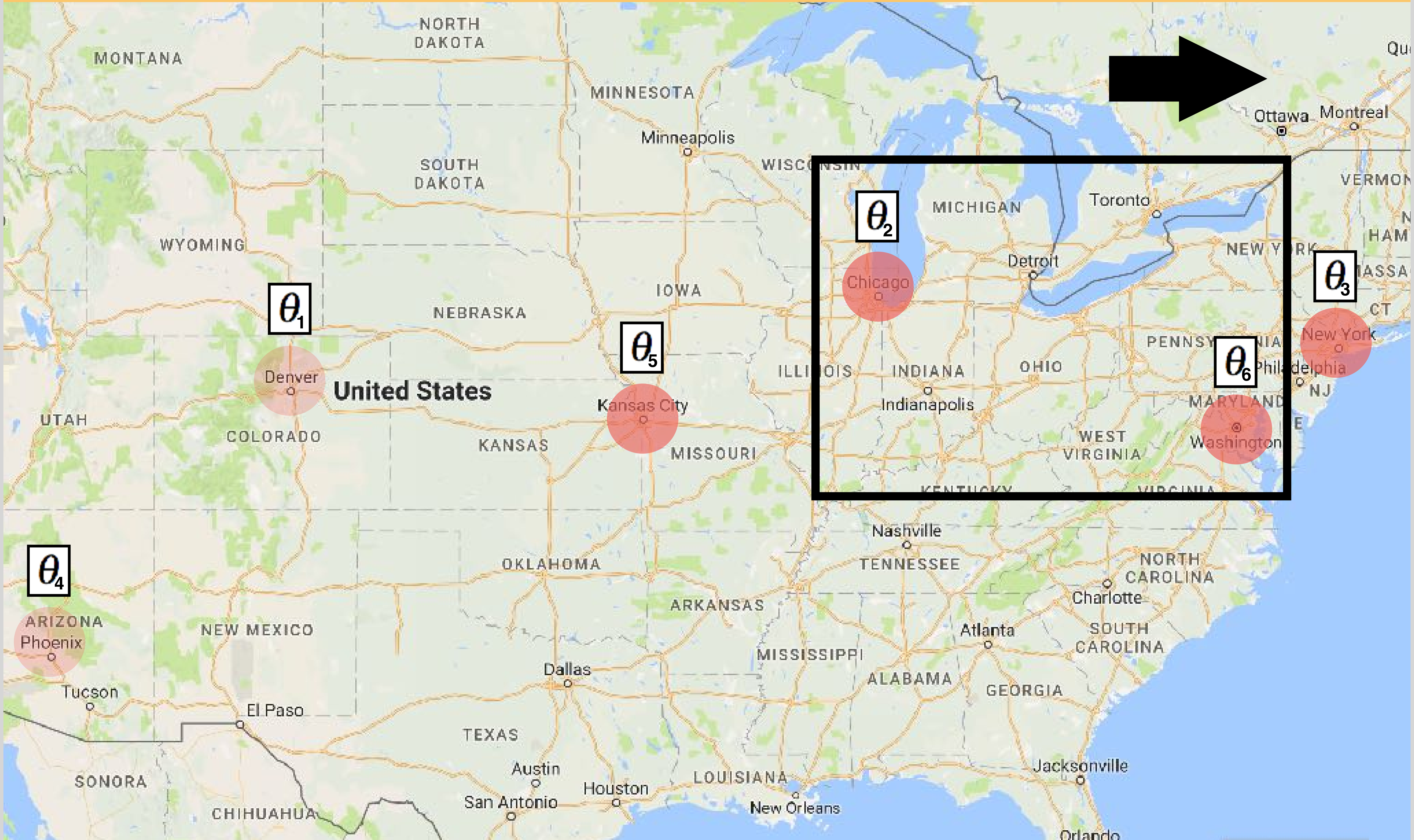
$$P(\Theta=\theta_i)$$

User Input Y = y

View X = x



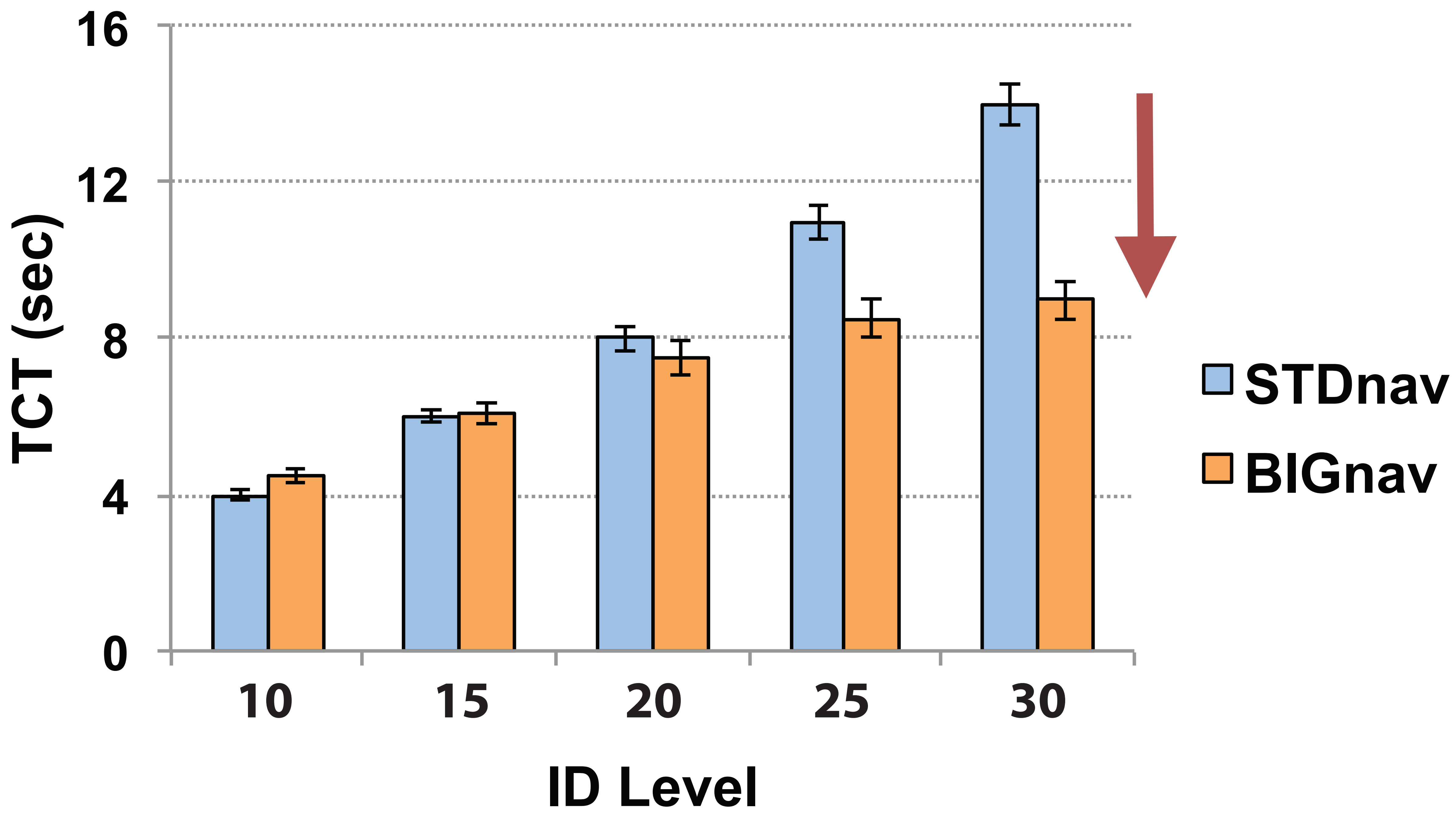
BIGnav:
Bayesian Information Gain Navigation



A map application - “3 steps to go to Paris”.
Europe map featuring large cities with their population as distribution.

A map application - “Navigate to Helsinki”.
Europe map featuring large cities with their population as distribution.

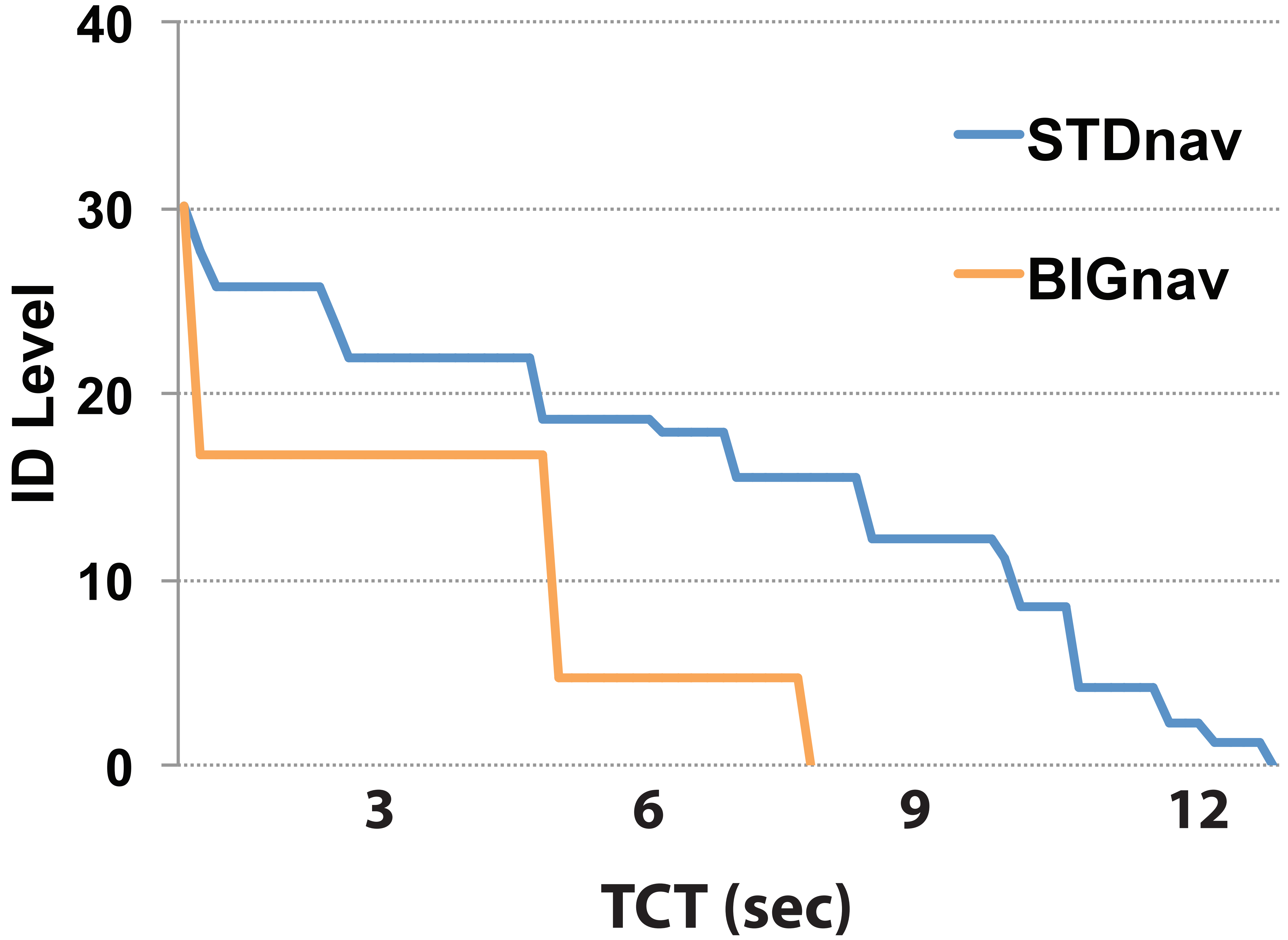
BIGnav



Up to 40% faster than pan-and-zoom navigation

Higher gain for targets further away

BIGnav



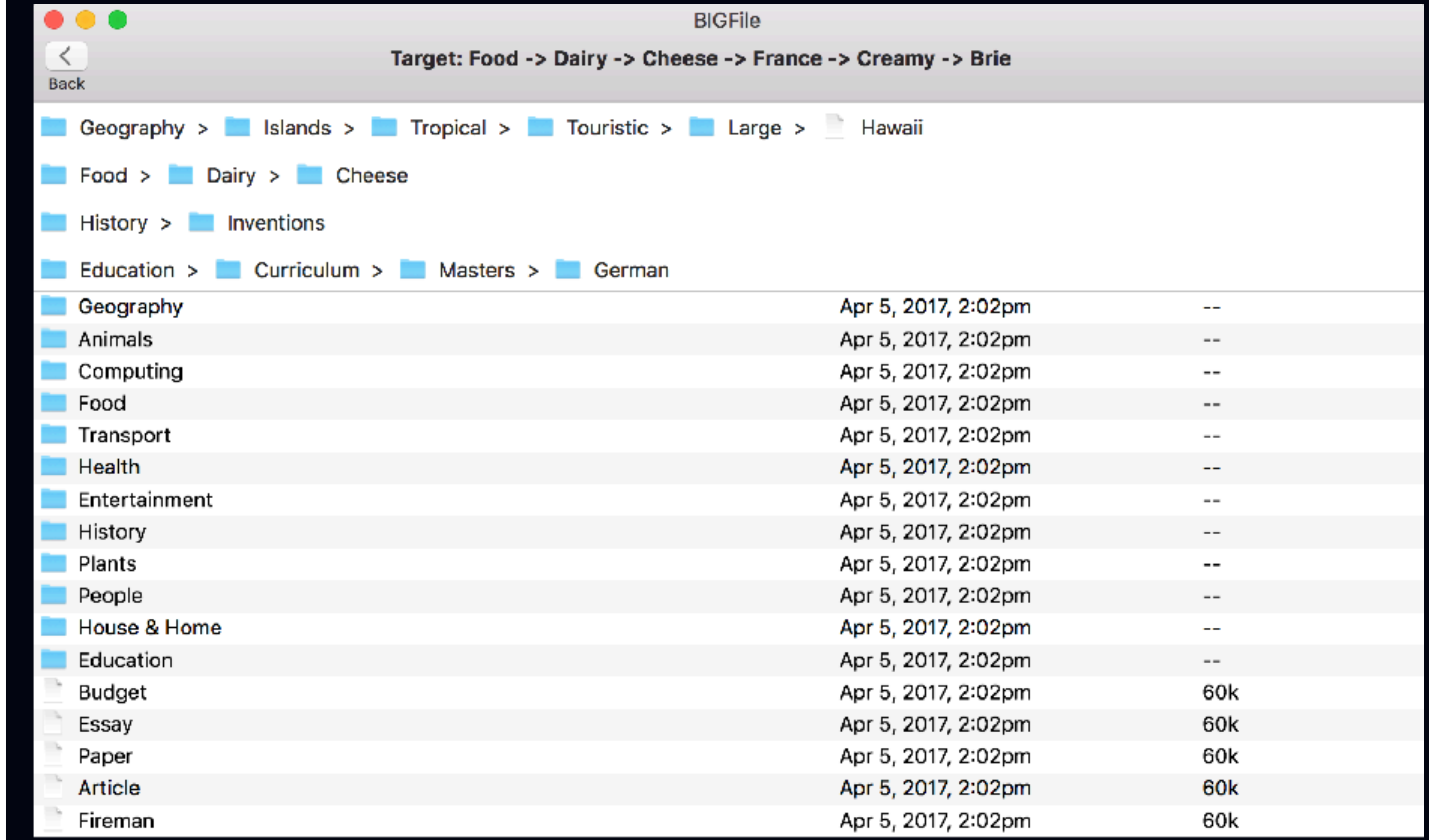
Incurs a high cognitive load

After each move,
long pause before next input

BIG move hard to predict

BIGfile

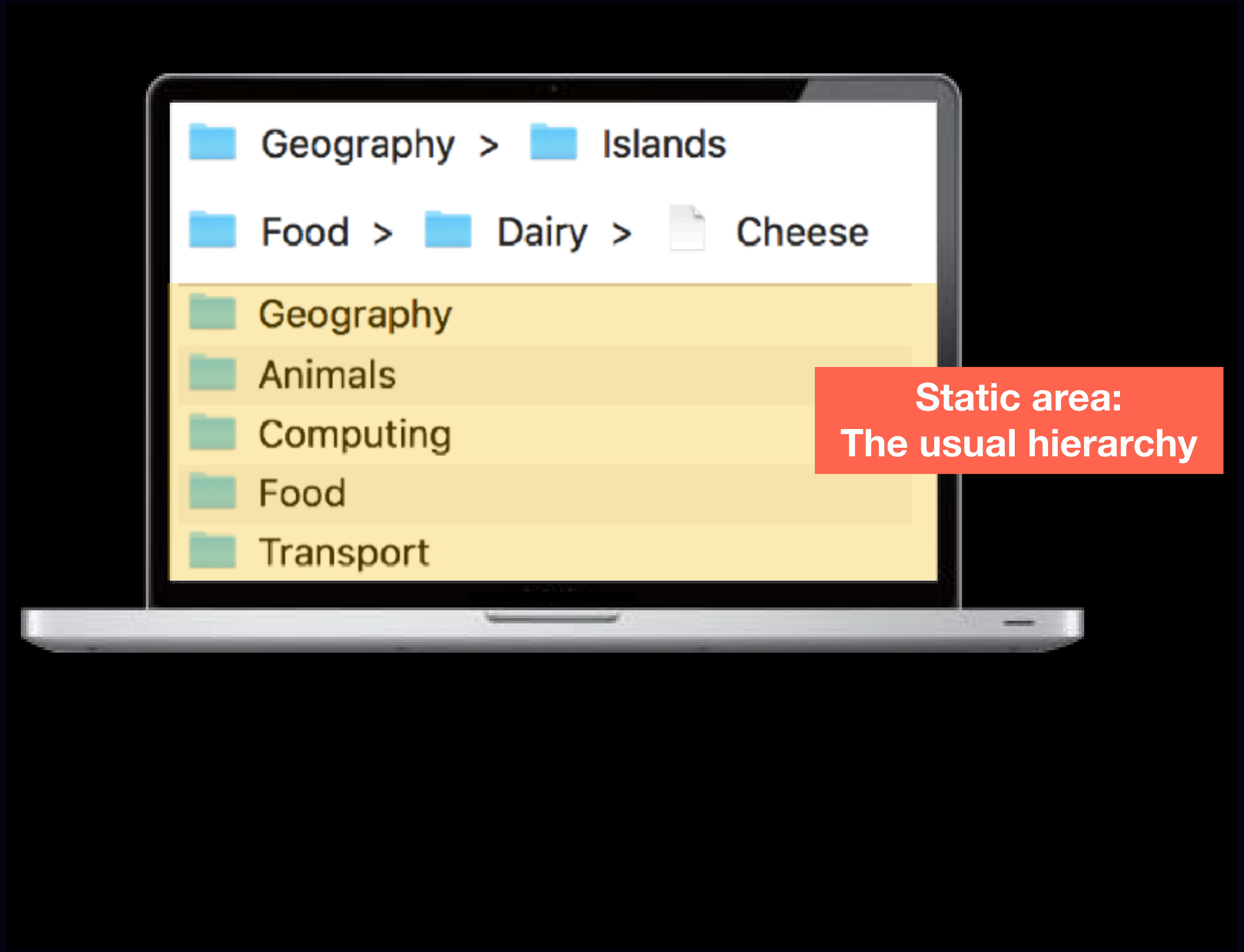
Same approach for file retrieval



Liu, Rioul, McGrenere, Mackay, Beaudouin-Lafon, 2018

BIGfile

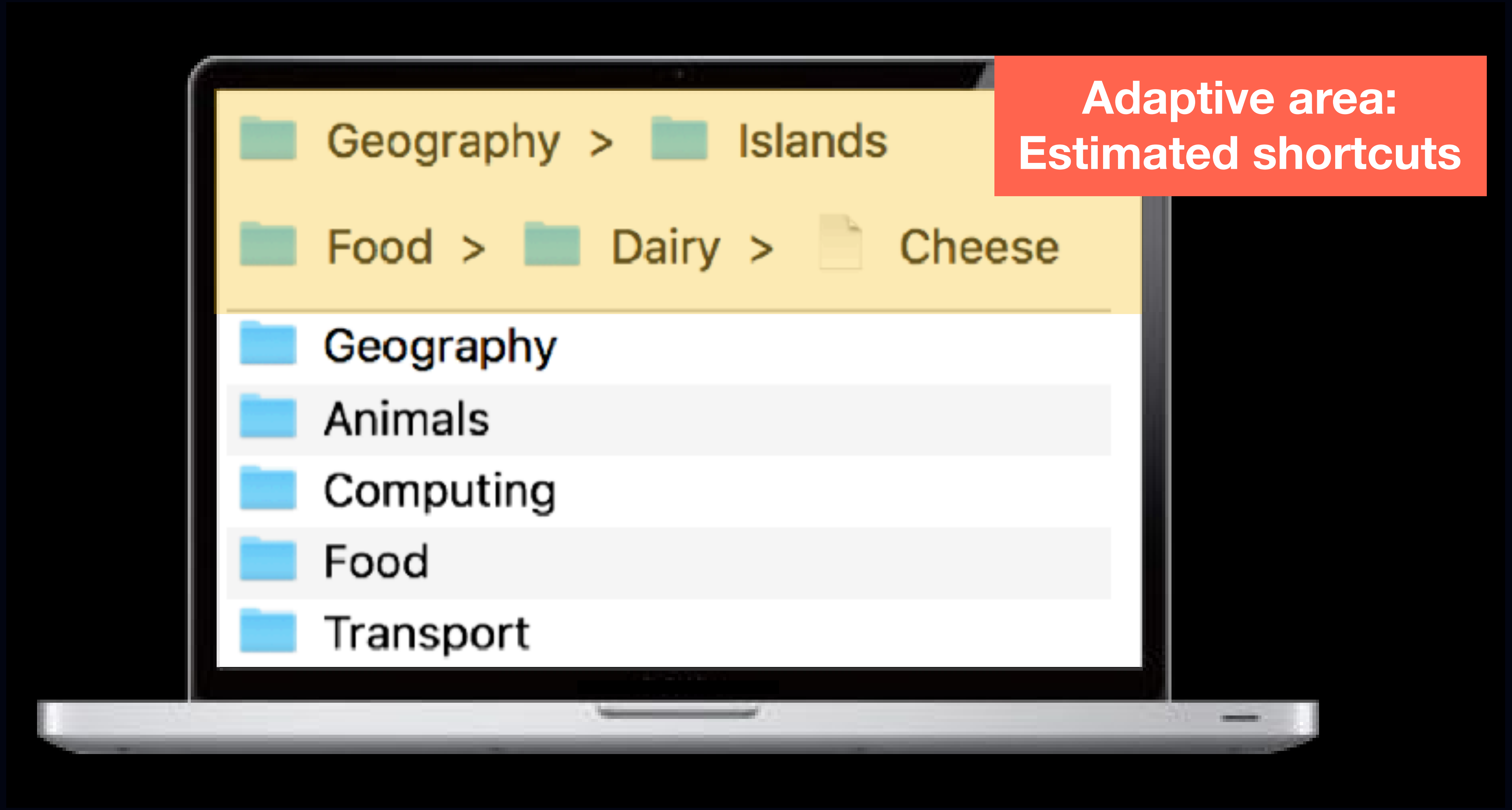
Same approach for file retrieval



Liu, Rioul, McGrenere, Mackay, Beaudouin-Lafon, 2018

BIGfile

Same approach for file retrieval

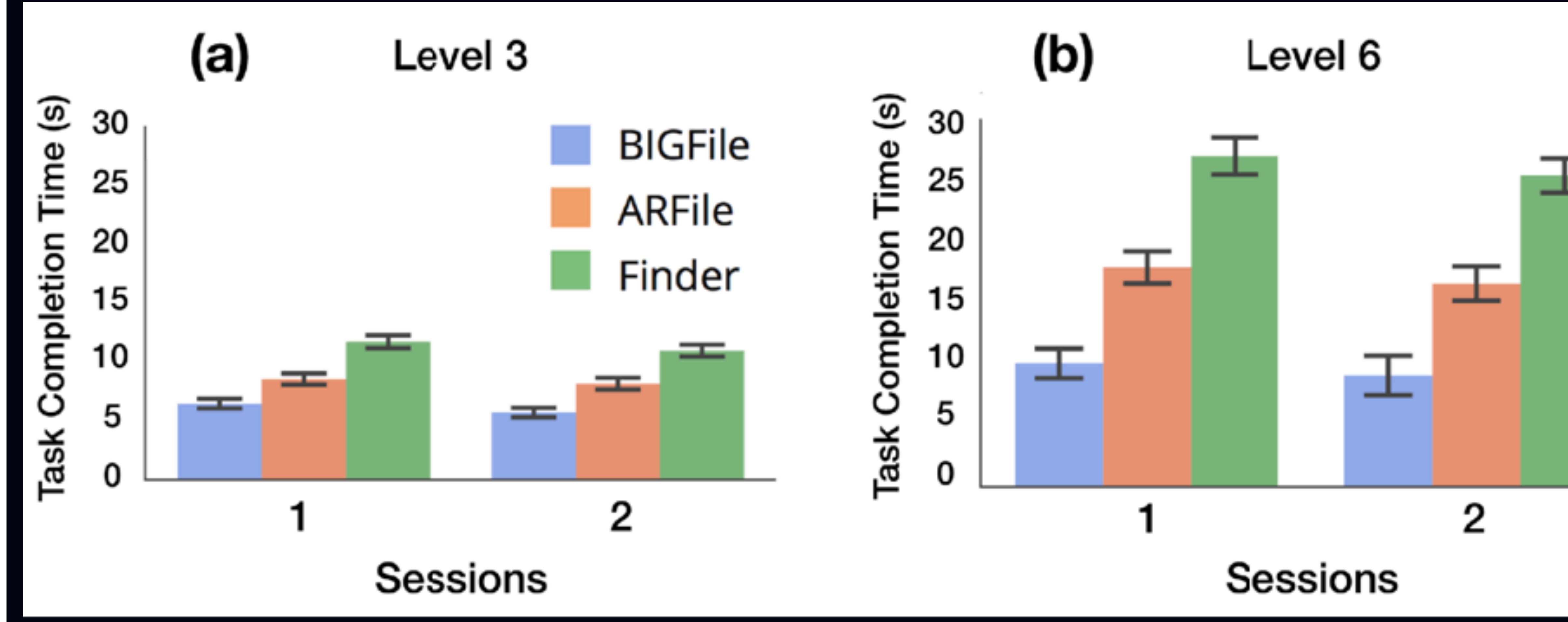


Liu, Rioul, McGrenere, Mackay, Beaudouin-Lafon, 2018

BIGfile

Same approach for file retrieval

Performance:
44% faster than best technique
64% faster than regular Finder



Liu, Rioul, McGrenere, Mackay, Beaudouin-Lafon, 2018

Conclusion

Information is a fruitful concept
for interaction

BUT
None of these techniques are
available in mainstream interfaces

Other possible applications:
text entry, command selection, …

Conclusion

Theory-driven HCI leads to generative theories that create novel and powerful techniques

Information theory is a source of inspiration and a tool for future human-computer partnerships

Merci!

Questions?

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