



# Solution principles for

## Uncertain Interaction

Per Ola Kristensson

Department of Engineering

University of Cambridge

# Visions of the Future

# Visions of the Future

- Ubiquitous sensing
  - Smart home, Internet of Things, etc.
- Pervasive agents
  - Spoken dialogue-based command and query interfaces
- Virtual reality
  - Portable office, training, immersive data analytics
- Phone without a phone
  - Optical see-through head-mounted displays with form factors comparable to everyday glasses

# Visions of the Future

- Ubiquitous sensing
  - Smart home, Internet of Things, etc.
- Pervasive agents

All assume fluid interfaces based on fundamentally **uncertain** interaction

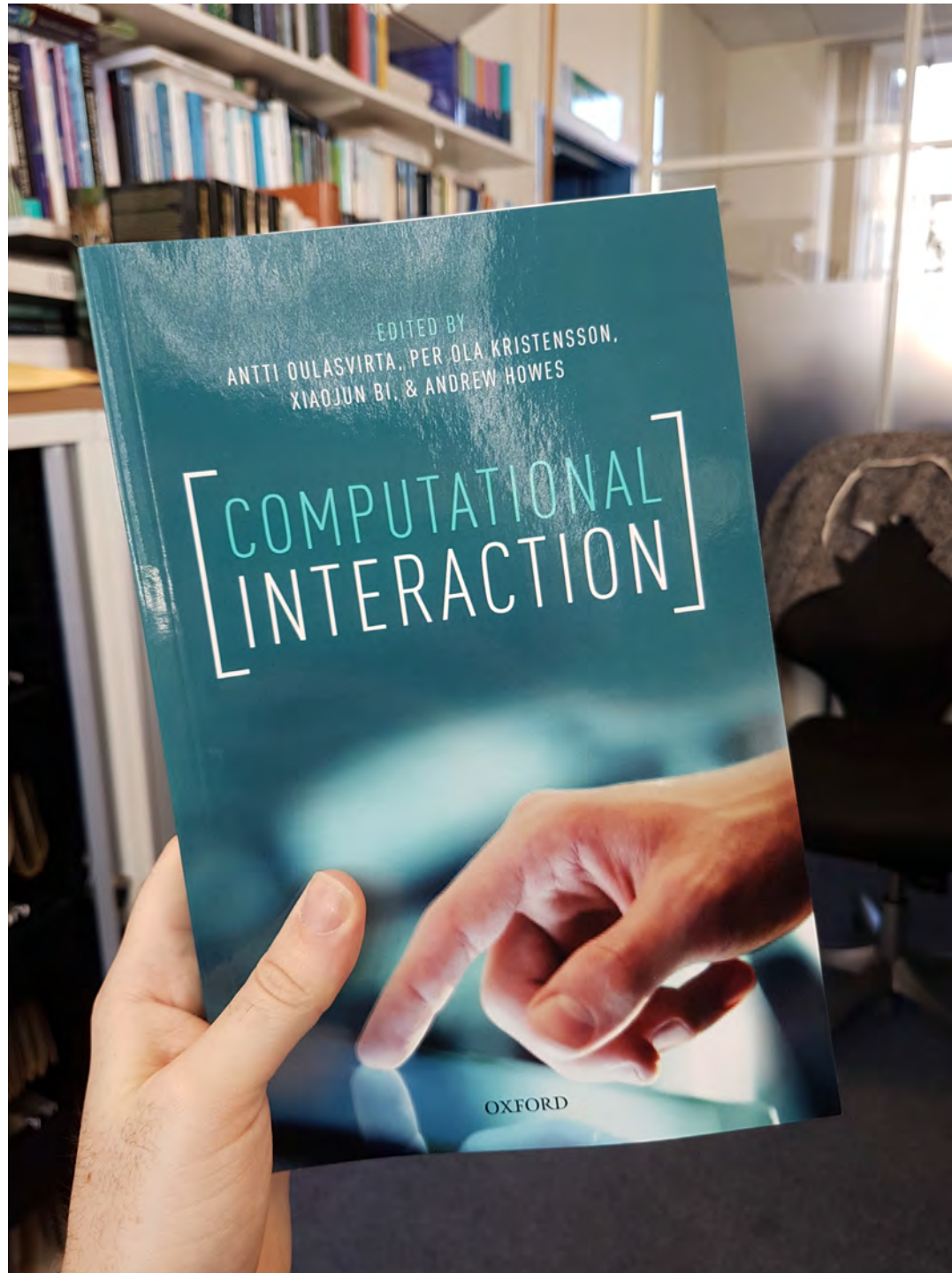
- Portable office, training, immersive data analytics
- Phone without a phone
  - Optical see-through head-mounted displays with form factors comparable to everyday glasses

# Computational interaction

- Classic human-computer interaction (HCI) method does not handle user interface design under uncertainty very well
- Classic HCI method is underpinned on eliciting user needs using a variety of processes and then an iterative process of design and evaluation, in which design is driven by design ingenuity rather than principles
- This means:
  - No automated design work
  - No explicit model
  - Data influenced design only through the designer
- Computational interaction is an emerging discipline in HCI which proposes user interface development by allowing algorithms to perform work, by explicit modelling, and by allowing data to directly influence design.

# Computational interaction

- Computational interaction would typically involve at least one of:
  - I. an explicit mathematical model of user-system behavior;
  - II. a way of updating that model with observed data from users;
  - III. an algorithmic element that, using this model, can directly synthesise or adapt the design;
  - IV. a way of automating and instrumenting the modeling and design process;
  - V. the ability to simulate or synthesise elements of the expected user-system behavior.



Intelligent text entry as an example  
of designing interaction under  
uncertainty







# Principles of intelligent text entry



MONK AT WORK. (From *Lacroix*.)

Kristensson, P.O. 2009. Five challenges for intelligent text entry methods. *AI Magazine* **30**(4): 85-94.

# Principles of intelligent text entry

1. Letters simplified to line marks



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# Principles of intelligent text entry

1. Letters simplified to line marks
2. Common word stems compressed into simple line marks or dots



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# Principles of intelligent text entry

1. Letters simplified to line marks
2. Common word stems compressed into simple line marks or dots
3. Common word stems identified by word frequency analysis of the book of psalms



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- In other words:



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- In other words:
  1. Optimise speed by minimising the amount of information users have to articulate



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# Principles of intelligent text entry

- In other words:
  1. Optimise speed by minimising the amount of information users have to articulate
  2. Exploit redundancies in natural languages by creating a language model



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# Principles of intelligent text entry

- ...which can often be thought of as an inference problem:



$$P(\text{hypothesis}|\text{input}) = \frac{P(\text{input}|\text{hypothesis})P(\text{hypothesis})}{P(\text{input})}$$



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# Hey, Professor Touchscreen, keep your fingers off our Qwerty keyboards

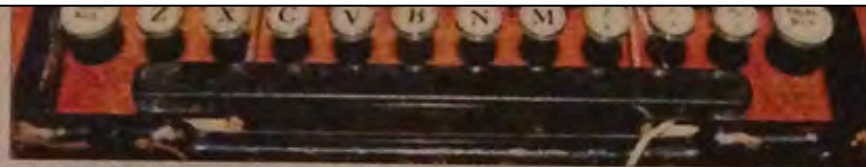
There aren't many inventions from the 19th century that remain in daily use across the world.



composer), developed in the Thirties. Crucially, this version allows your fingers

Why do nearly all text entry methods fail?

Ever since it was first produced in 1873, we have stuck with it. First on clunky, mechanical typewriters with their pleasing chika-chip-cha-chip-DING-ziiiiiiip, then with electronic word processors and computers. Even now, touchscreen smartphones and iPads all



**The typewriter keyboard was designed to stop keys jamming**

their funky new KALQ board, which has all the vowels on the right-hand side

order. But this meant that the mechanical levers, attached

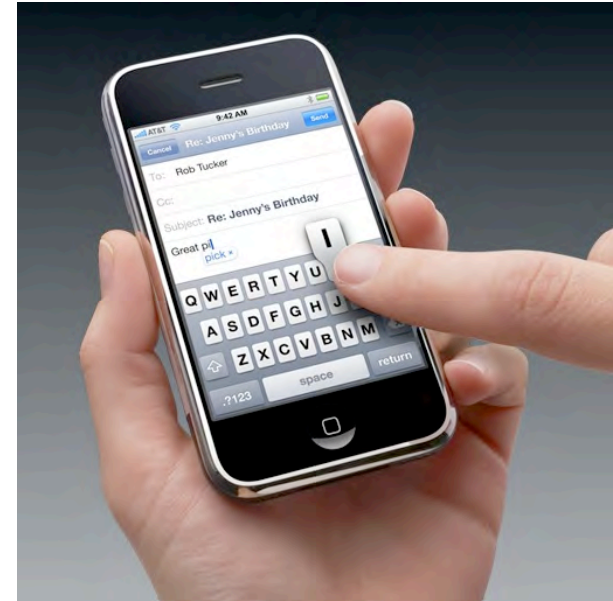
that would cause snapped fingers with a Qwerty board.

And if it's supersonic typing you are after, you should have seen the old stenographers at work at the Old Bailey, who used strange machines that worked like pianos – they struck chords

ALAMY

# Mainstream mobile text entry methods

Λ B C D E  
Γ G h i<sup>2</sup> J  
<sup>1</sup>K<sup>2</sup> L M N O  
P q R S<sup>1</sup> †<sub>2</sub>  
U V W<sup>1</sup> X<sup>2</sup> y  
0 i 2 3<sup>1</sup> 4  
5 6 7 8 9



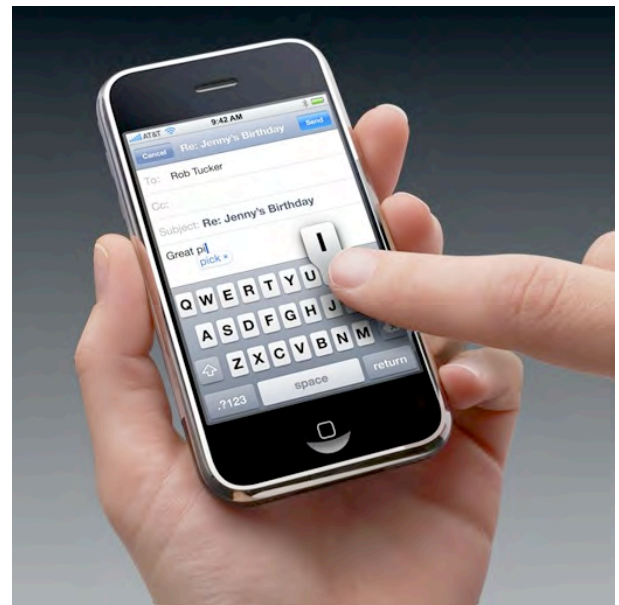


# Mainstream mobile text entry methods

**Graffiti**

0	1	2	3	4
5	6	7	8	9

Handwritten characters for Graffiti: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U, V, W, X, Y, Z.

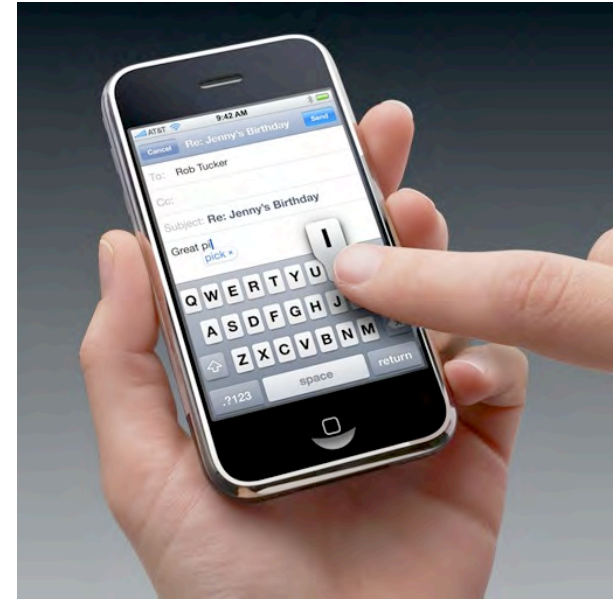


# Mainstream mobile text entry methods

Graffiti



Multi-tap and predictive text



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Graffiti



Multi-tap and predictive text



Touchscreen keyboards





# Mainstream mobile text entry methods

Graffiti



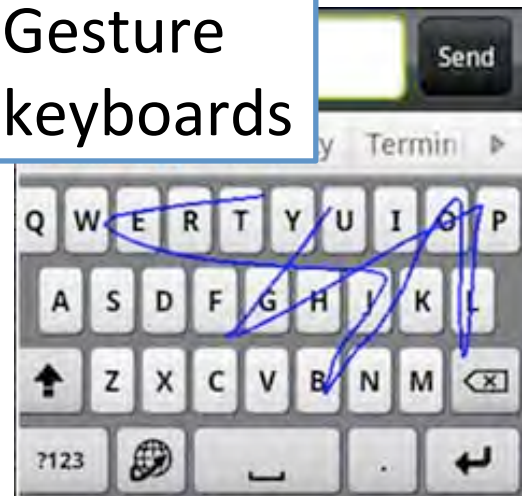
Multi-tap and predictive text



Touchscreen keyboards



Gesture keyboards



# Mainstream mobile text entry methods

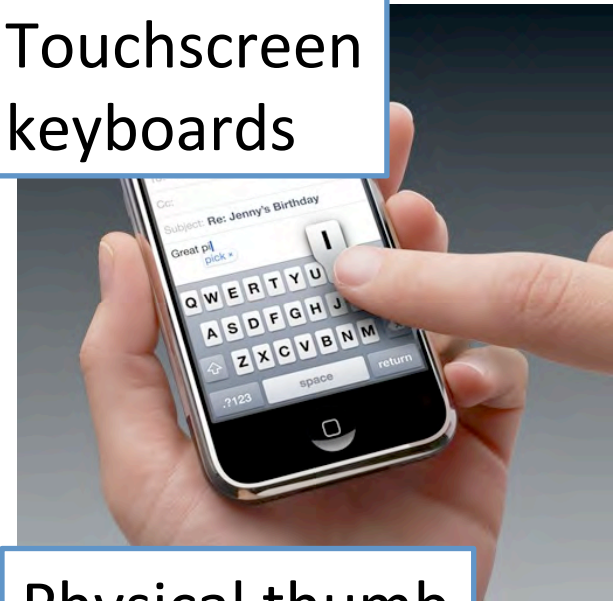
Graffiti



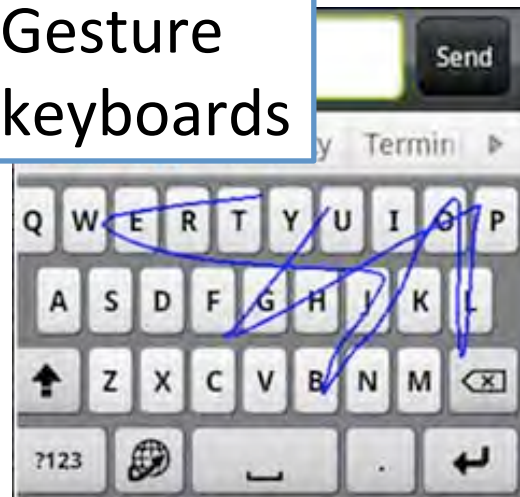
Multi-tap and predictive text



Touchscreen keyboards



Gesture keyboards



Physical thumb keyboards





# Mainstream mobile text entry methods

- Entry and error rate
  - Learning curve, familiarity and immediate efficacy
  - Form factor, preparation time and comfort
  - User engagement
  - Visual attention and cognitive resources
  - Privacy
  - Single vs. multi-character entry
  - Specification vs. navigation
  - One-handed vs. two-handed
  - Task integration
  - Robustness
  - Device independence
  - Computational demands
  - Manufacturing and support cost
  - Localisation
  - Market acceptance
- 

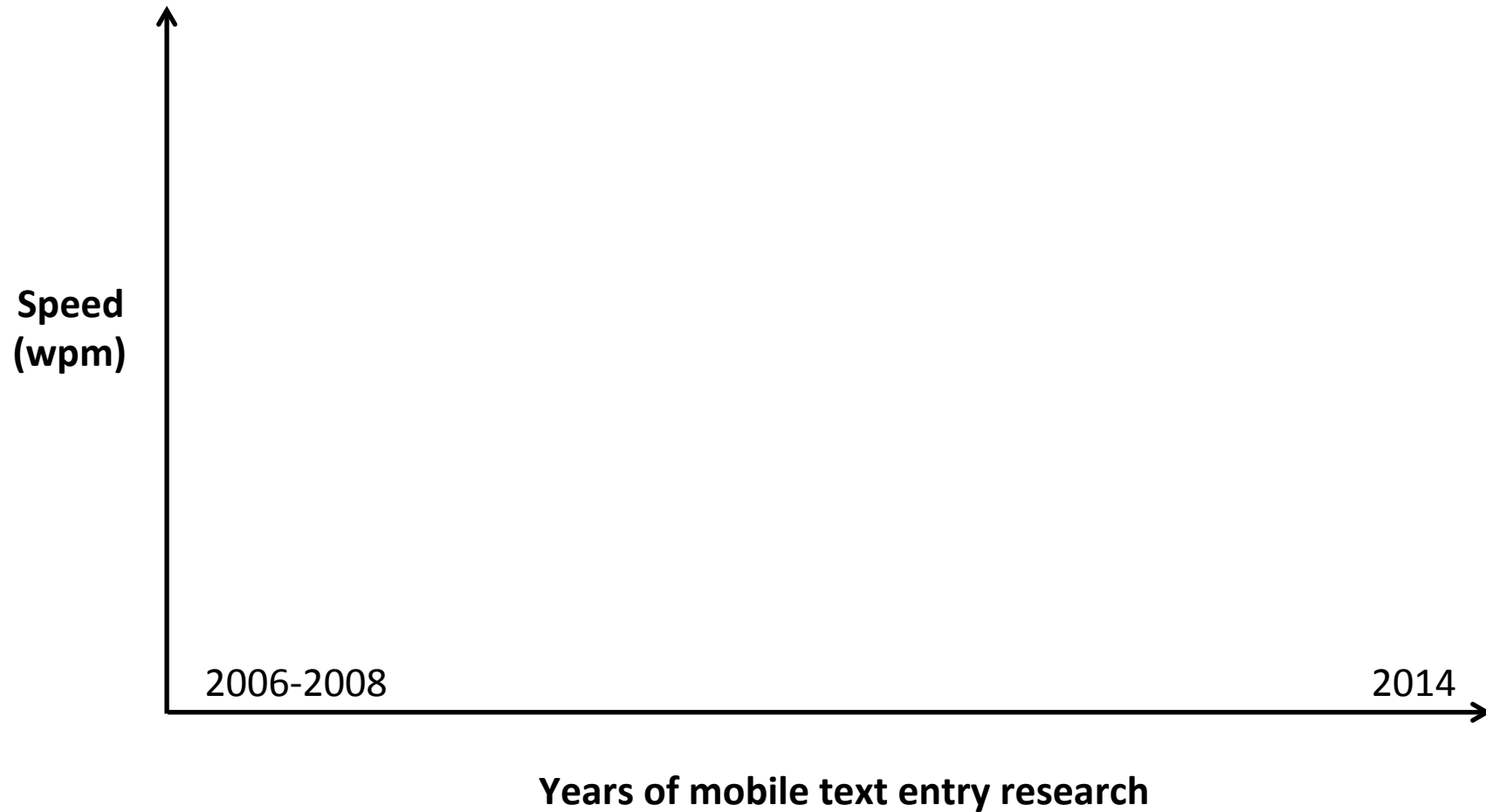
# Mainstream mobile text entry methods

- Entry and error rate
- Learning curve, familiarity and immediate efficacy
- Specification vs. navigation
- One handed vs. two
- **High effective entry rate**
  - Among the fastest of their generation
- **High familiarity and high immediate efficacy**
  - Either extremely easy-to-learn or very similar to existing technology (or both)
- Single vs. multi-character entry
- support cost
- Localisation
- Market acceptance

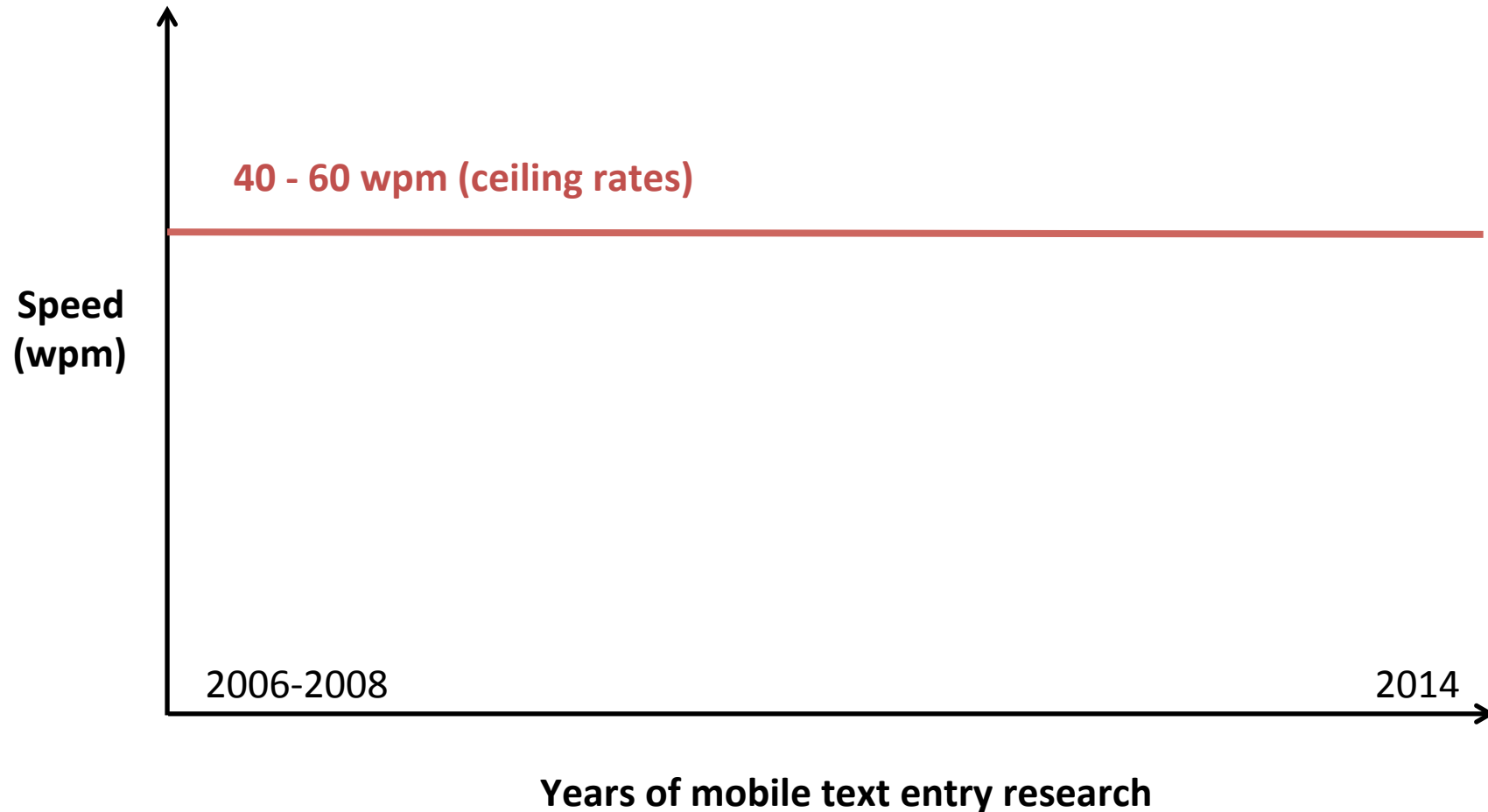
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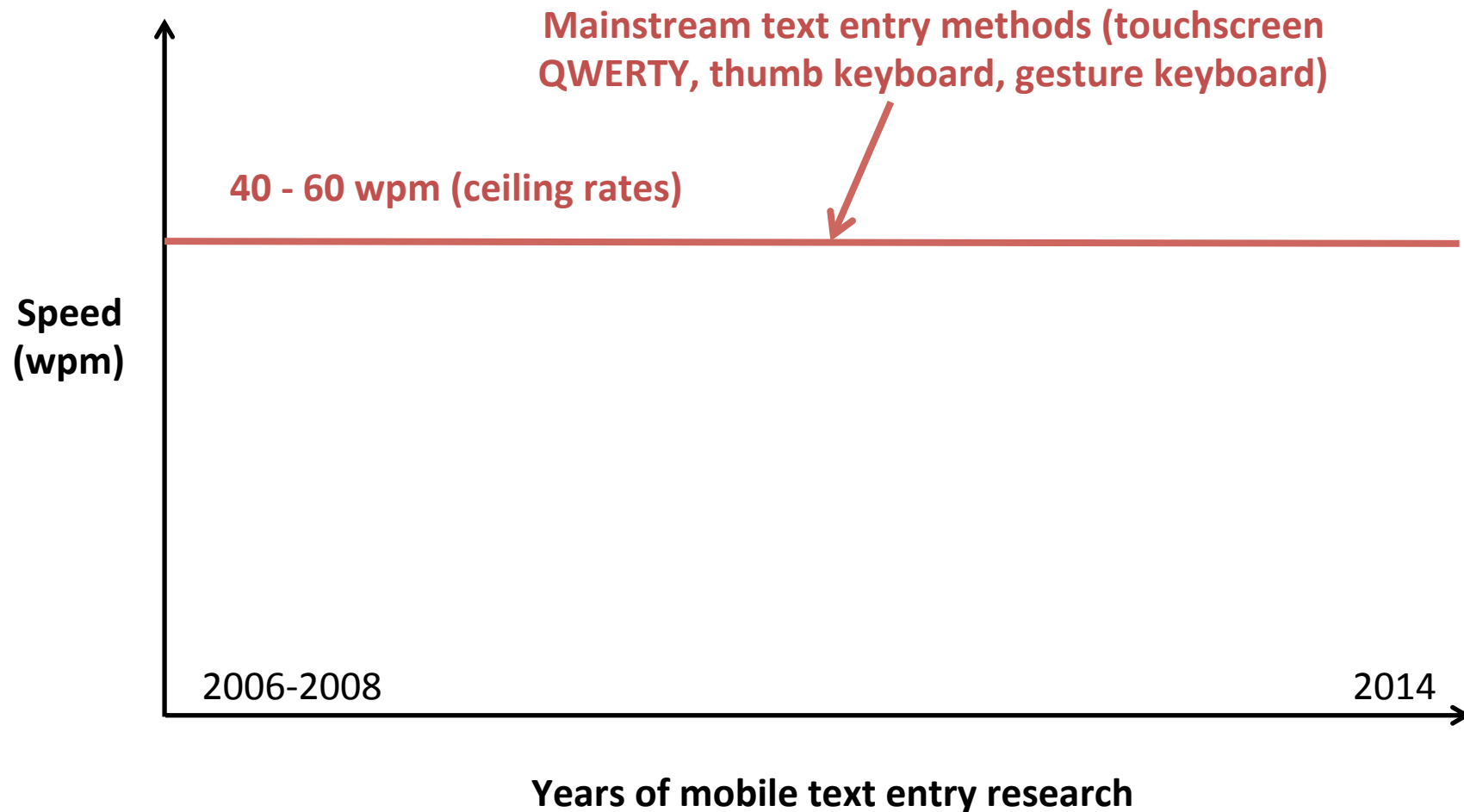
# Mobile text entry: the state of the art



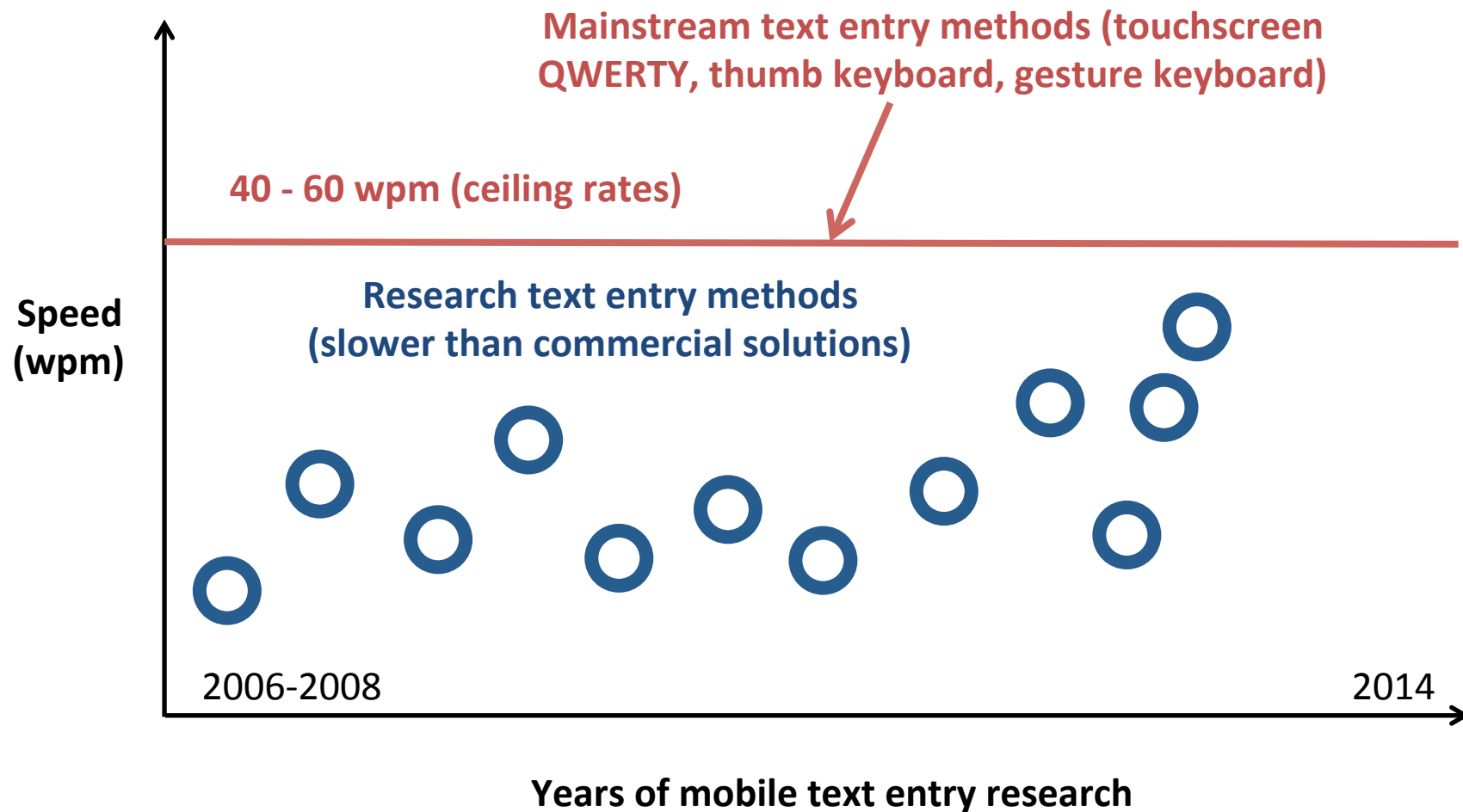
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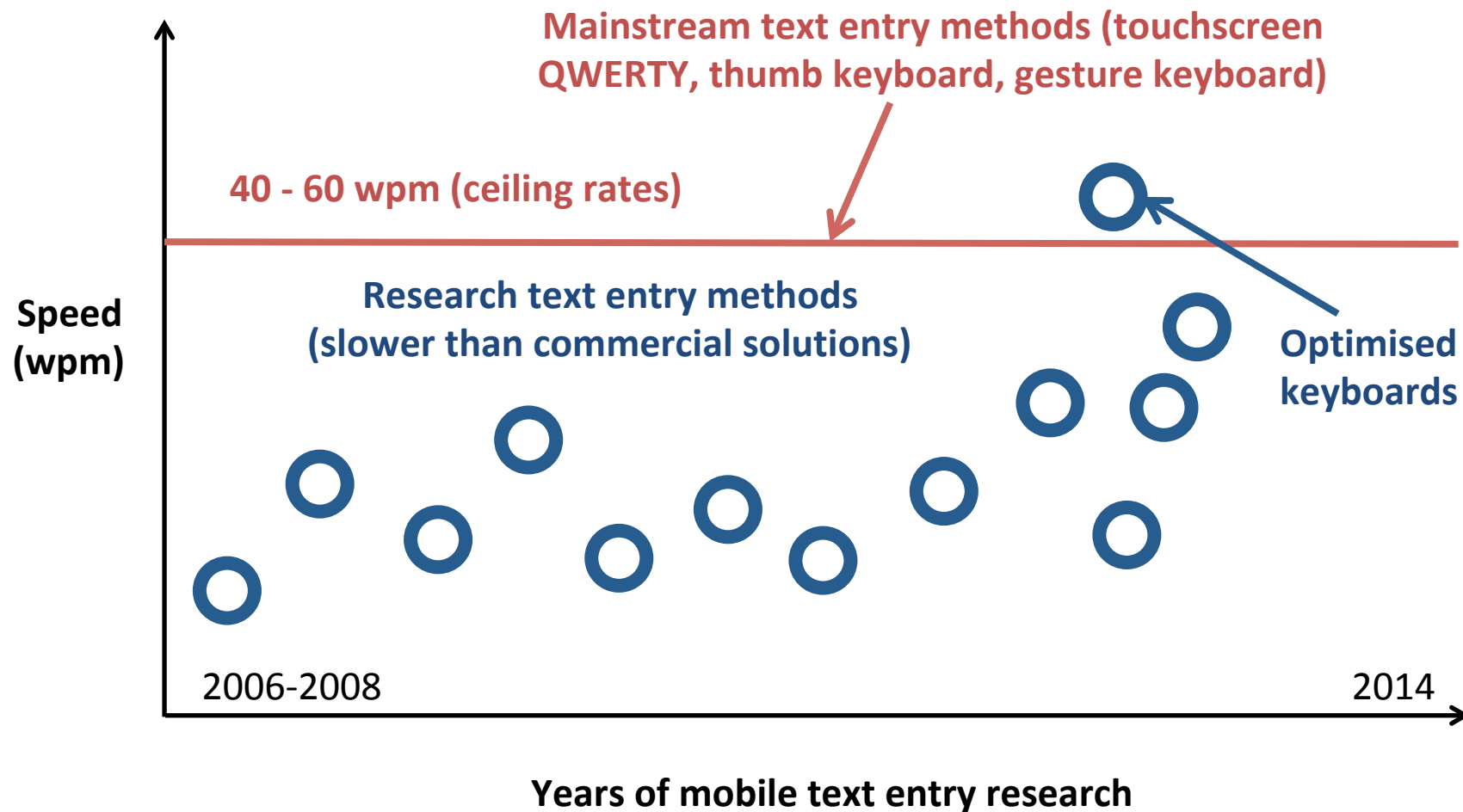
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# The cross-over point

Performance

Time

# The cross-over point

Performance

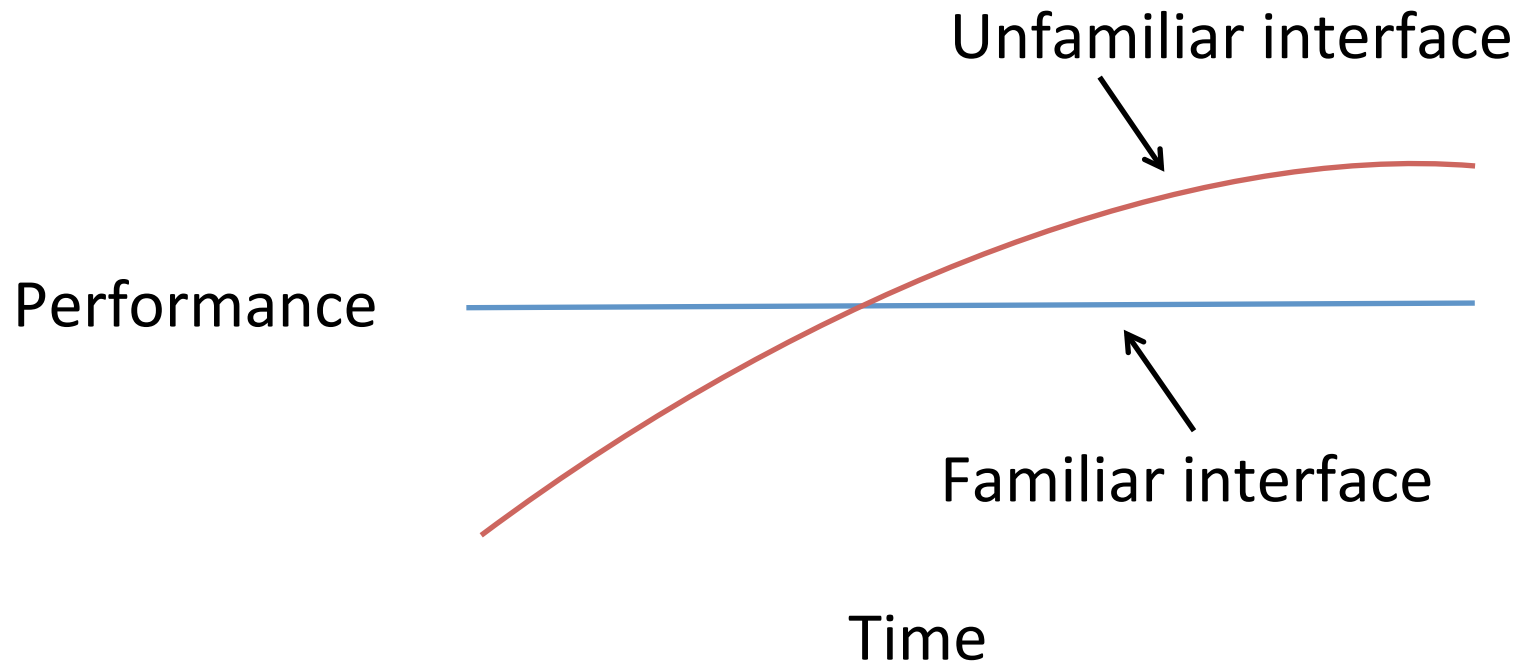


Familiar interface

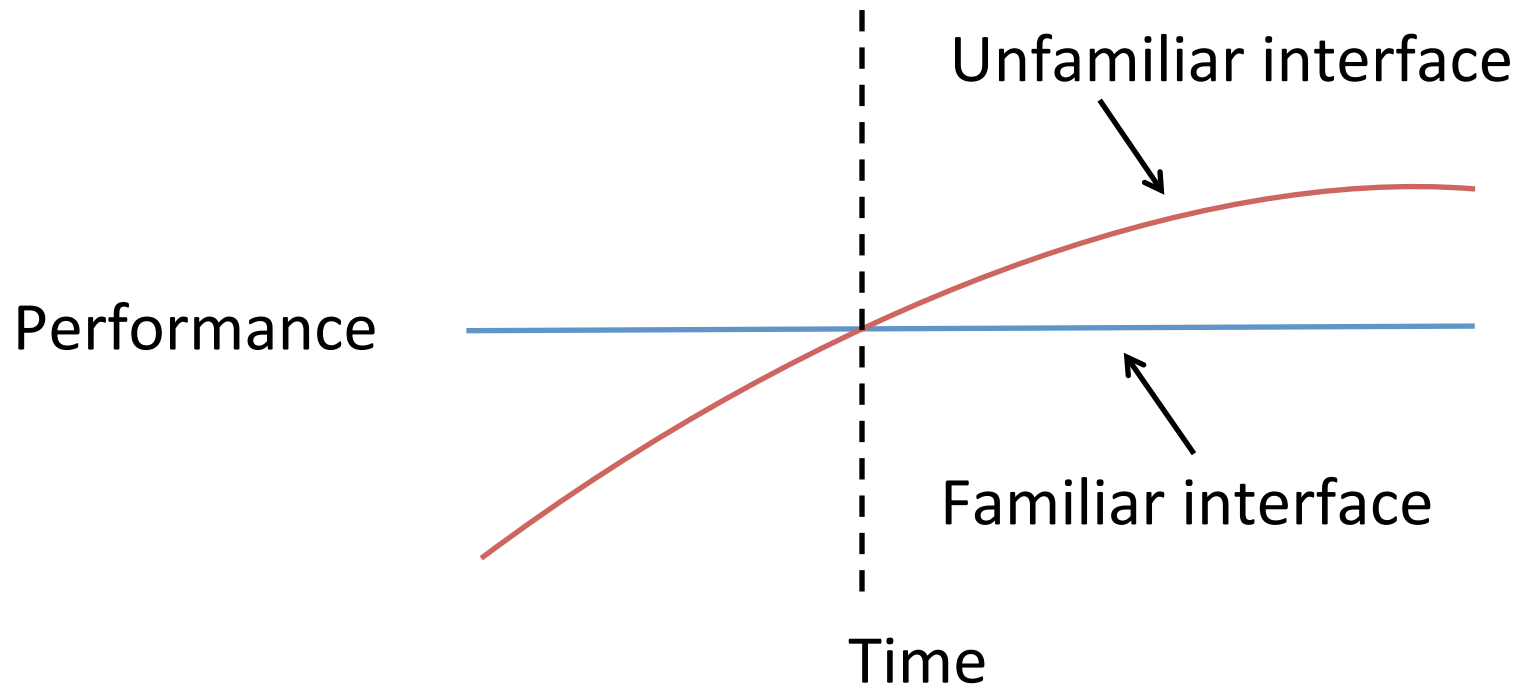


Time

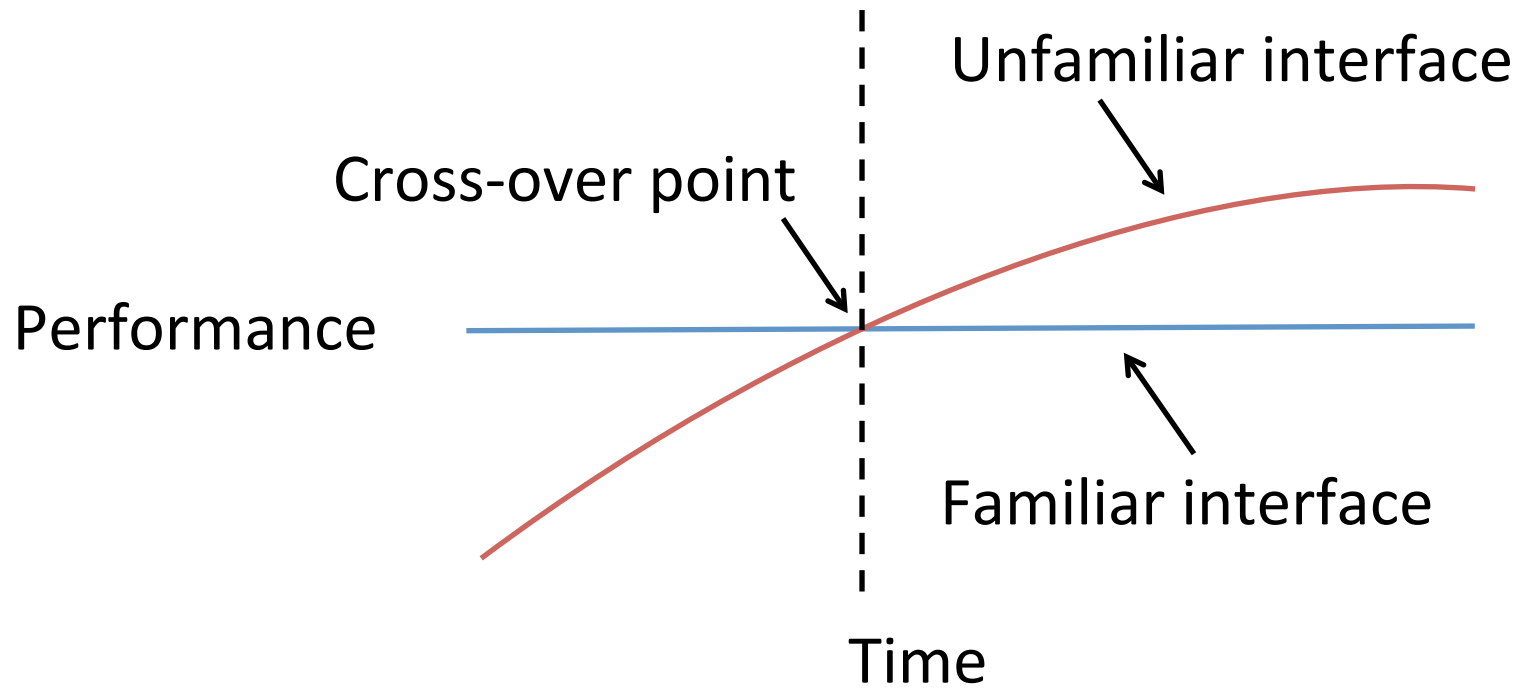
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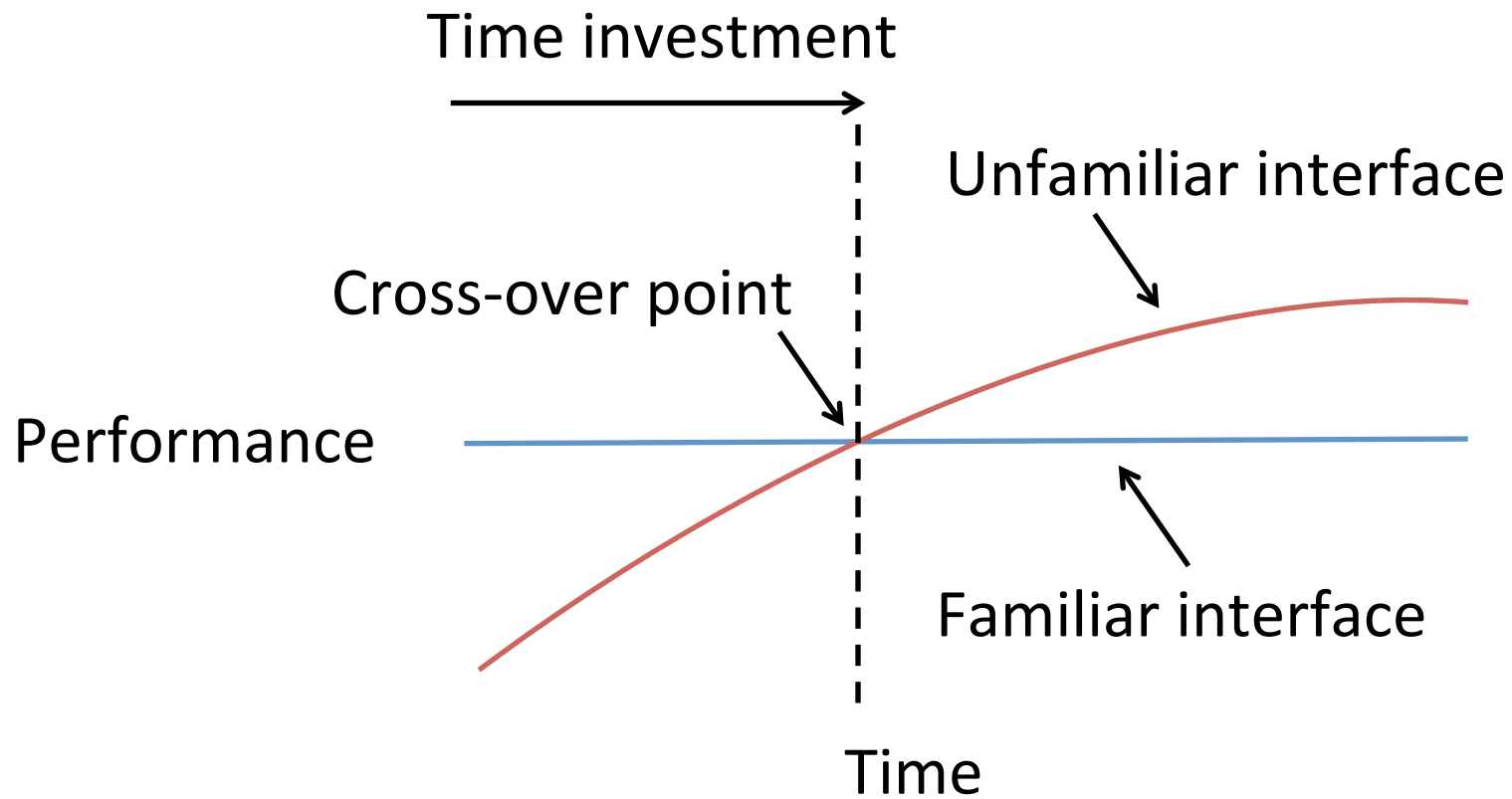
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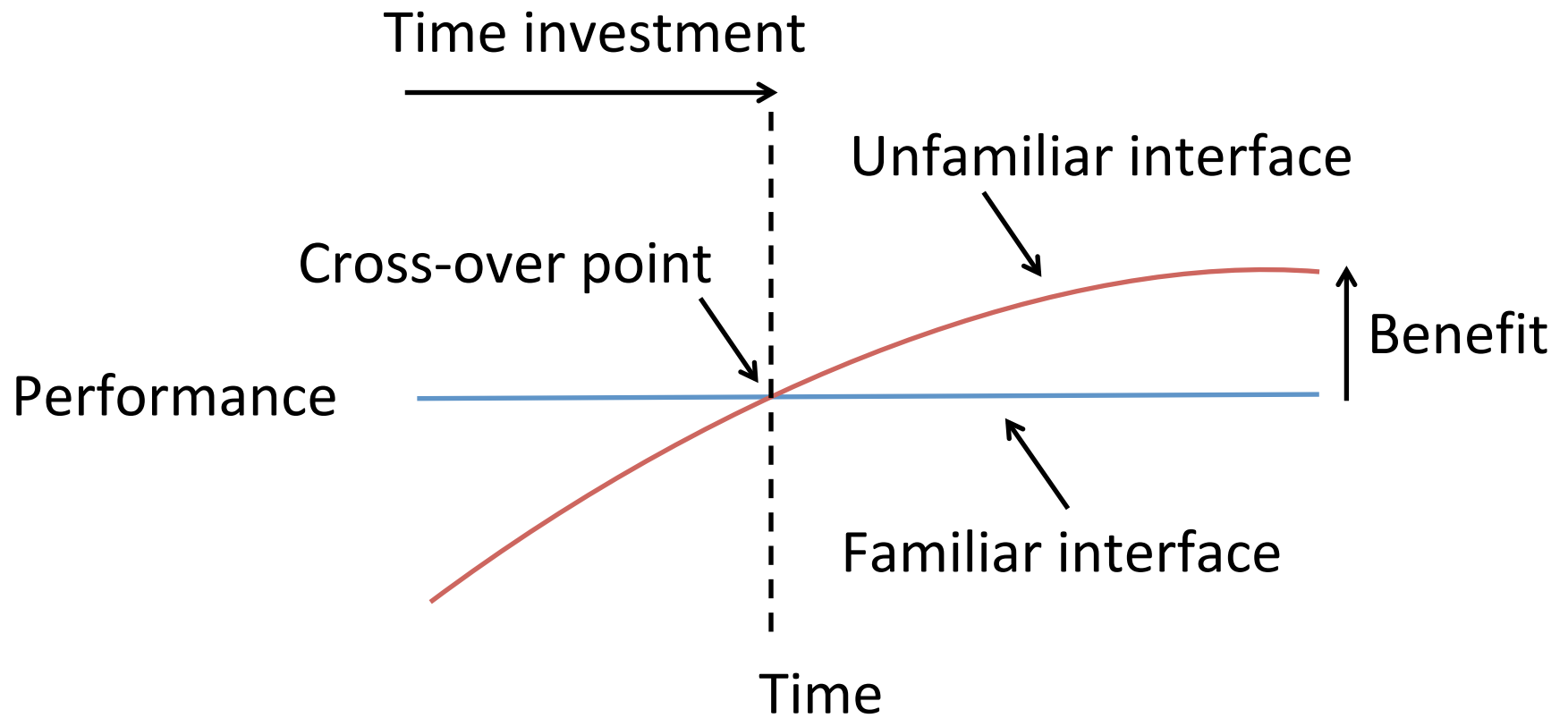
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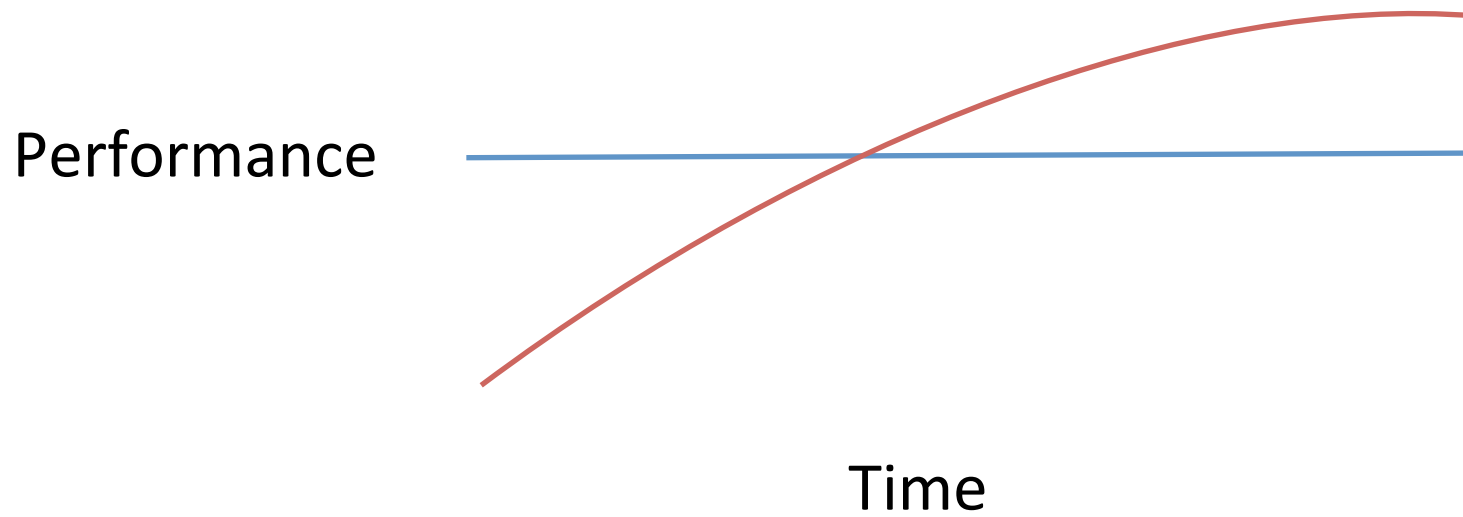


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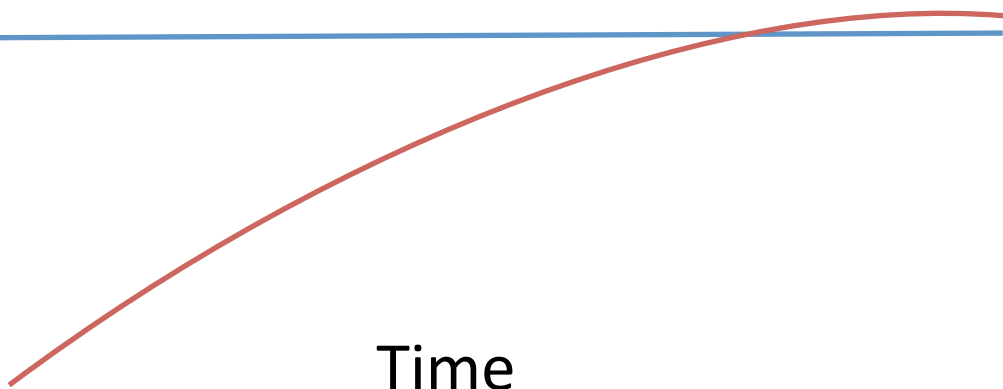


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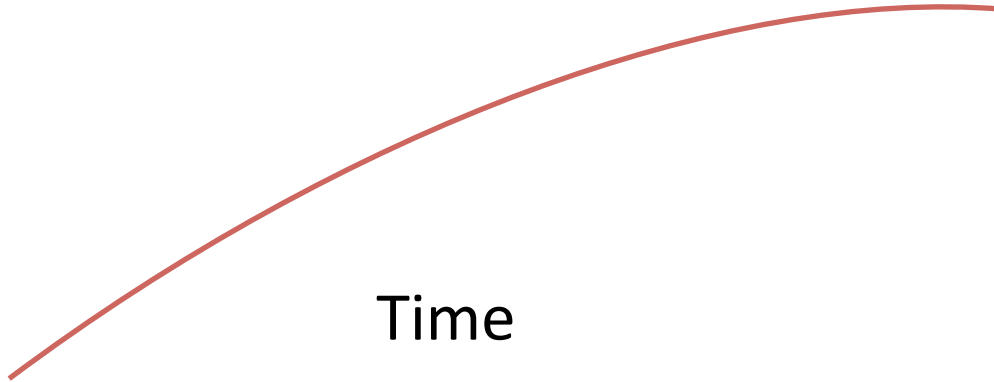
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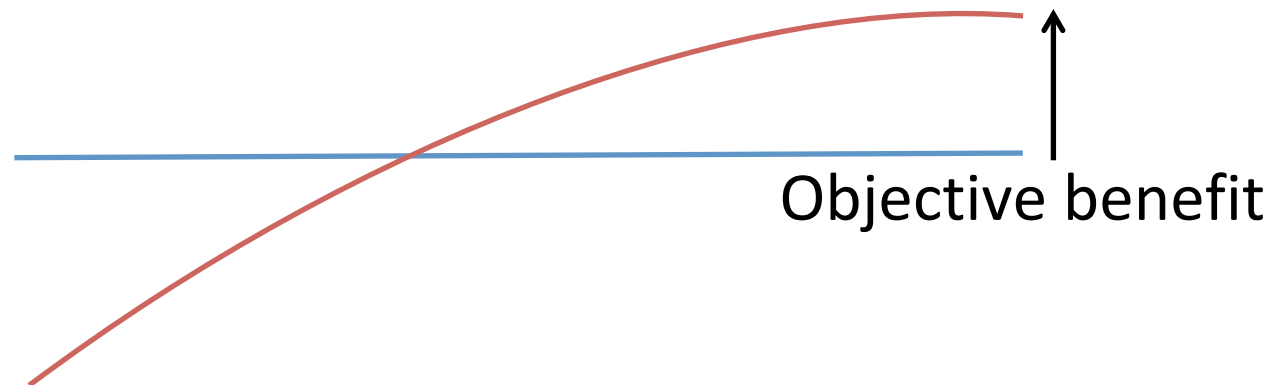
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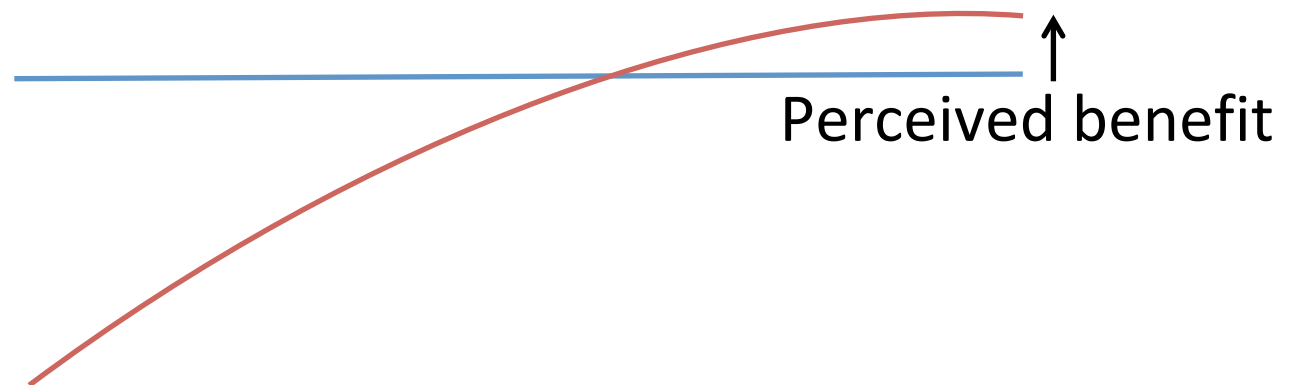
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Nicosia, M., Oulasvirta, A. and Kristensson, P.O. 2014. Modeling the perception of user performance. In *Proceedings of the 32nd ACM Conference on Human Factors in Computing Systems (CHI 2014)*. ACM Press: 1747-1756.

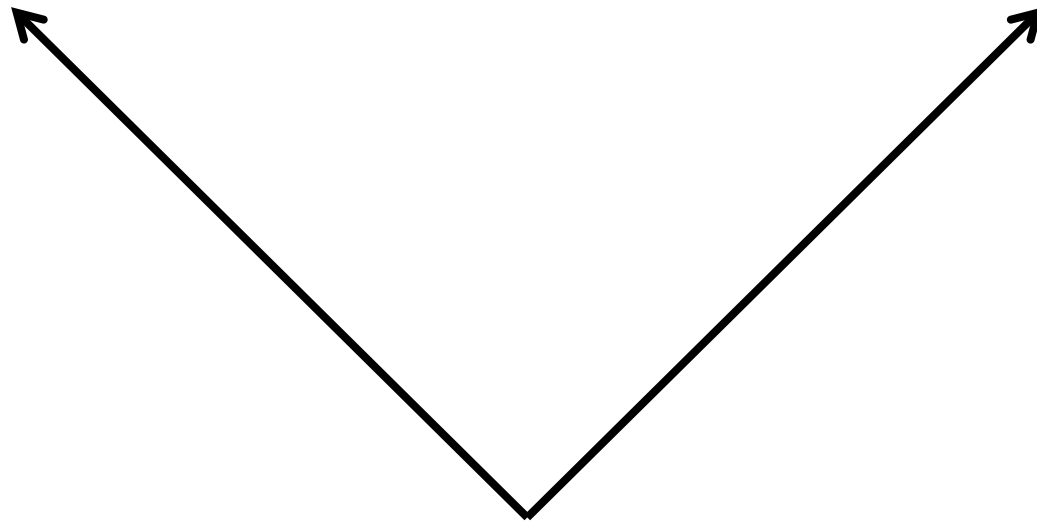
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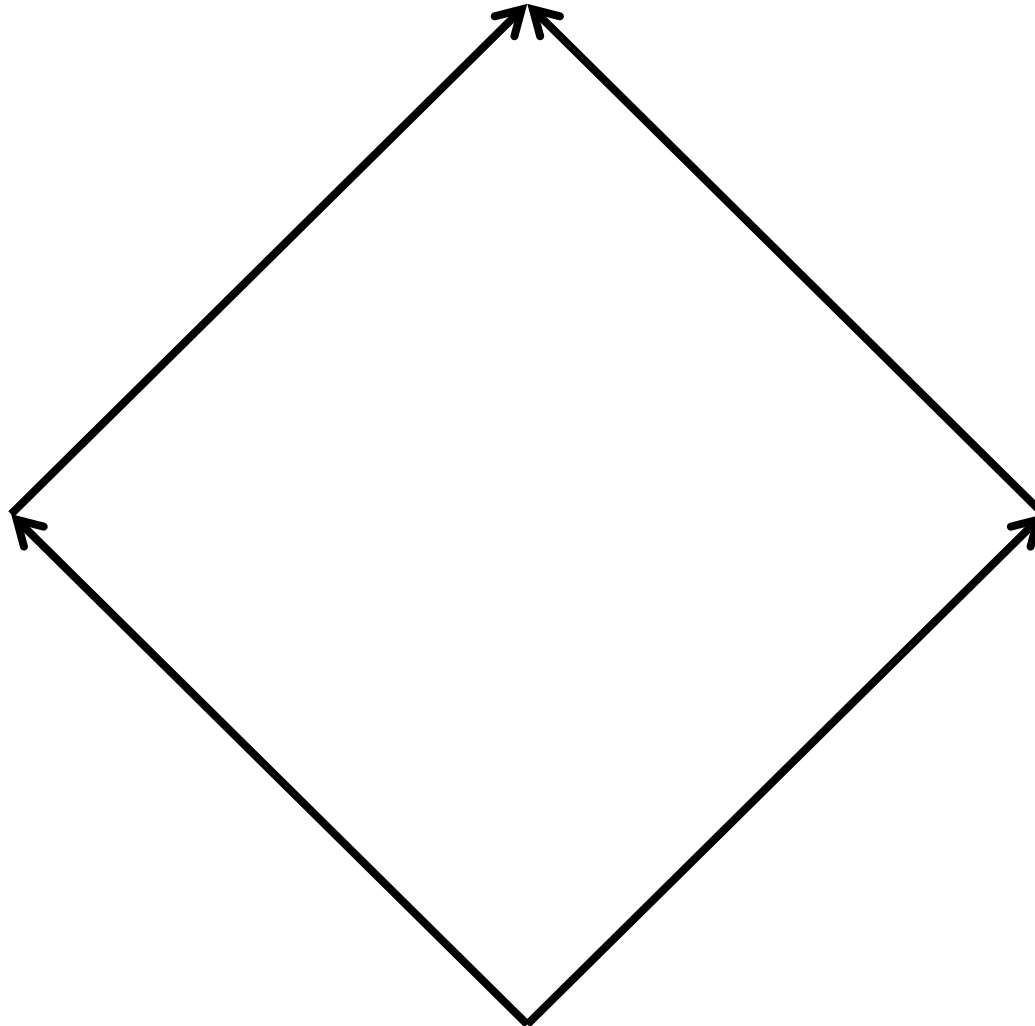
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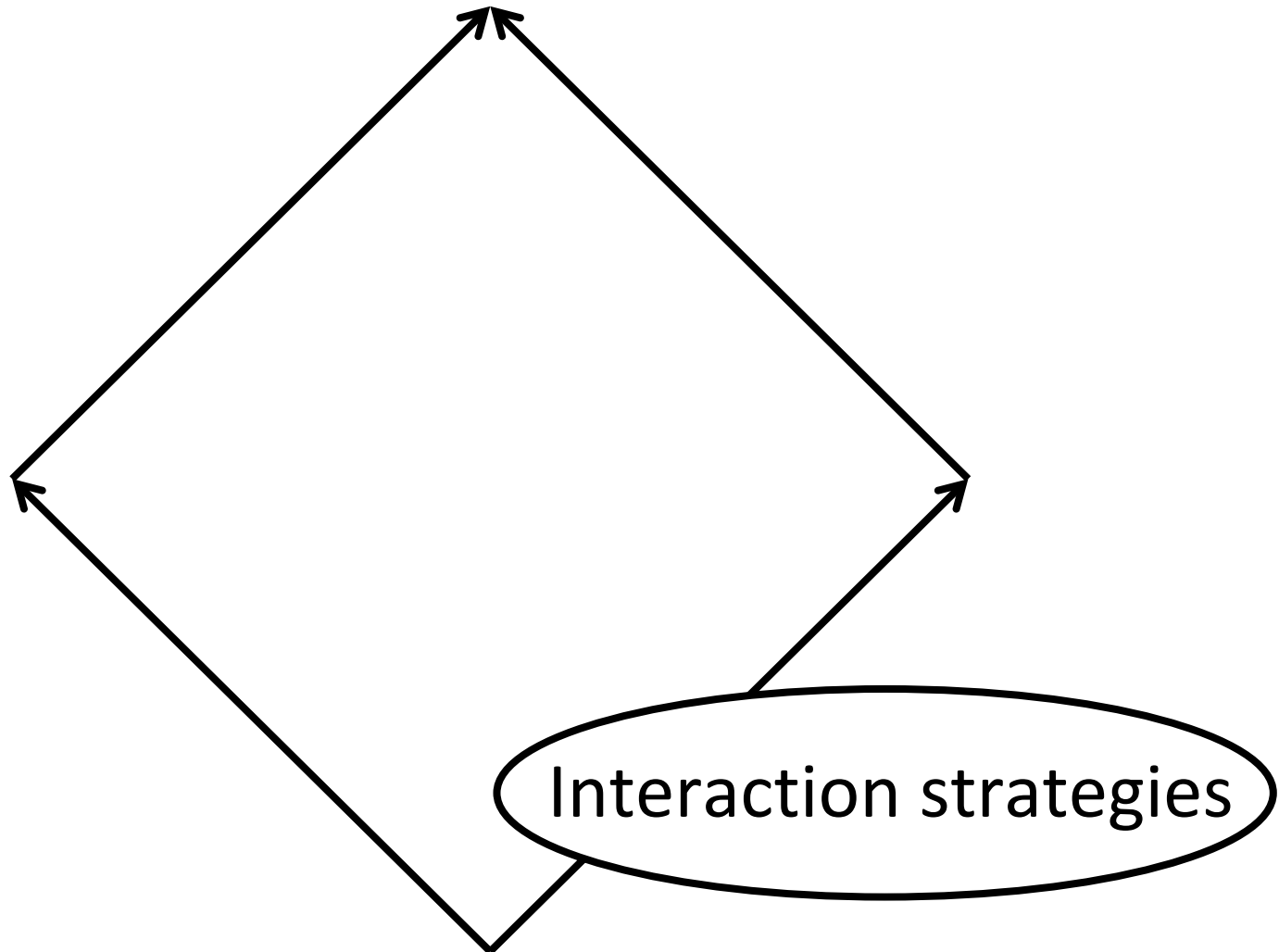


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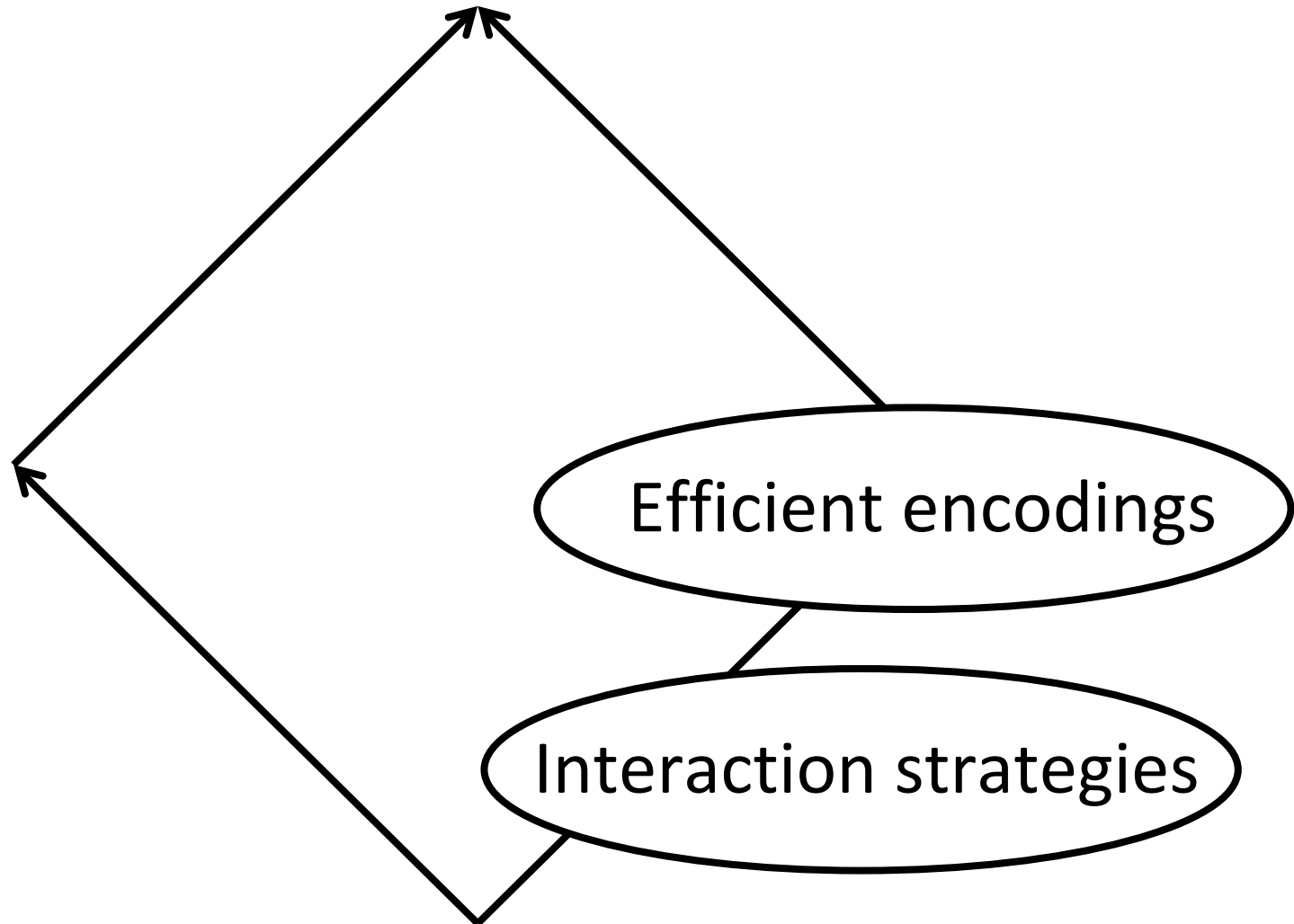




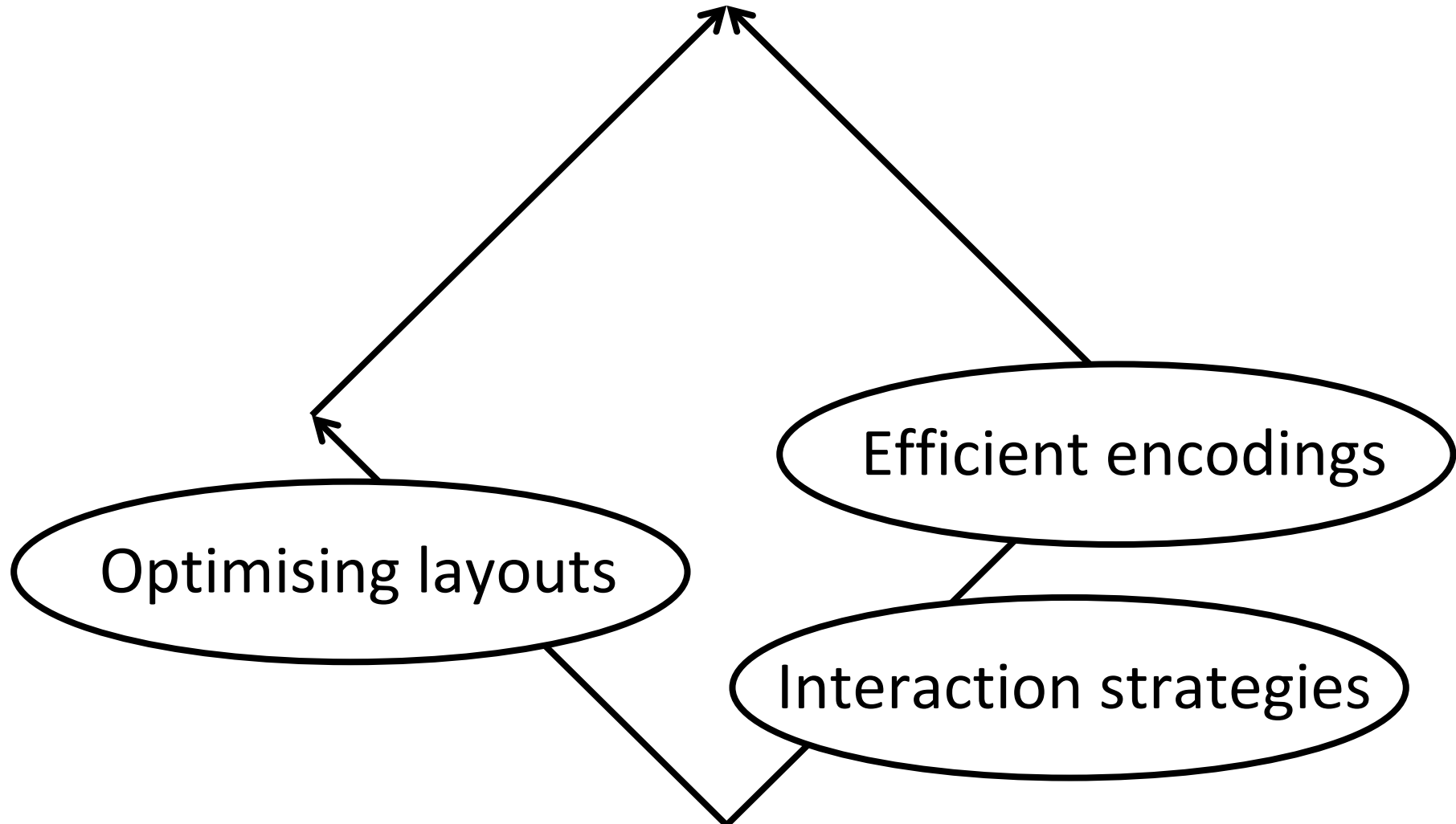
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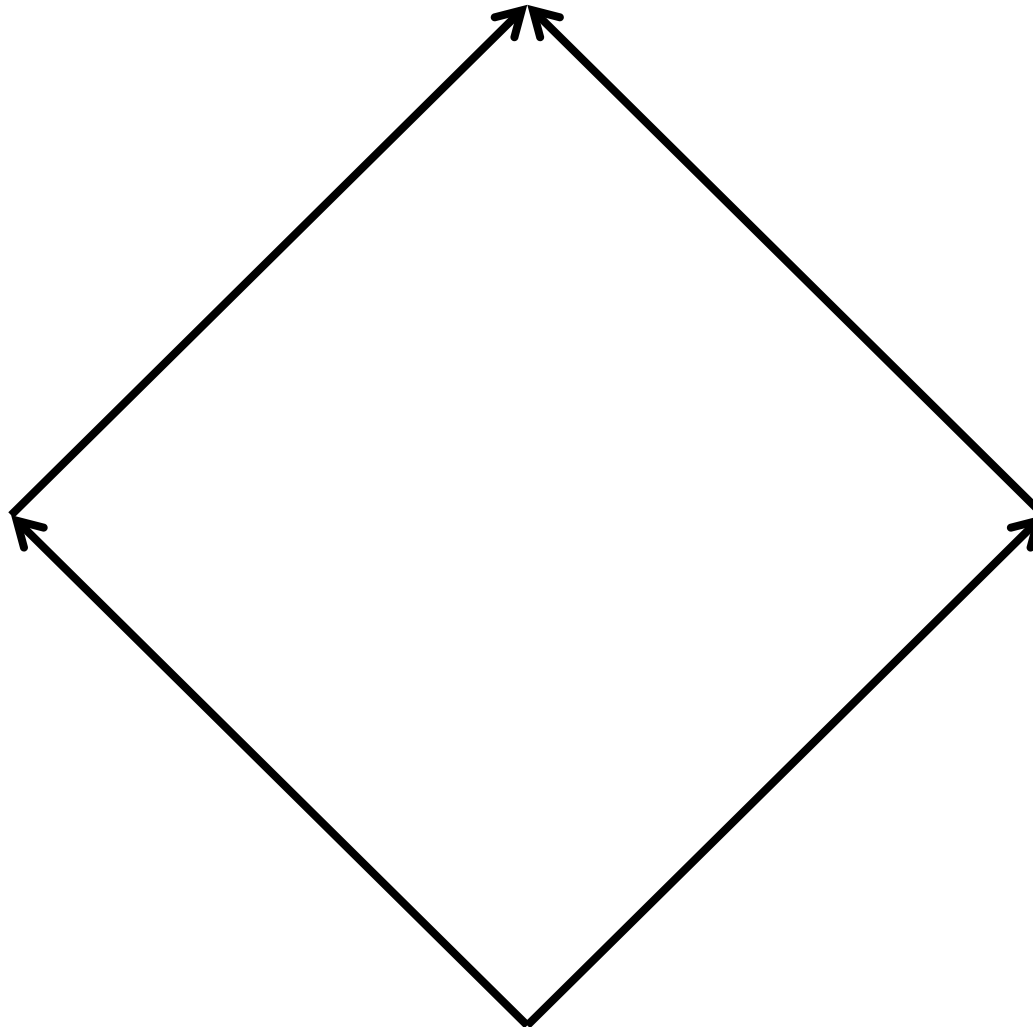
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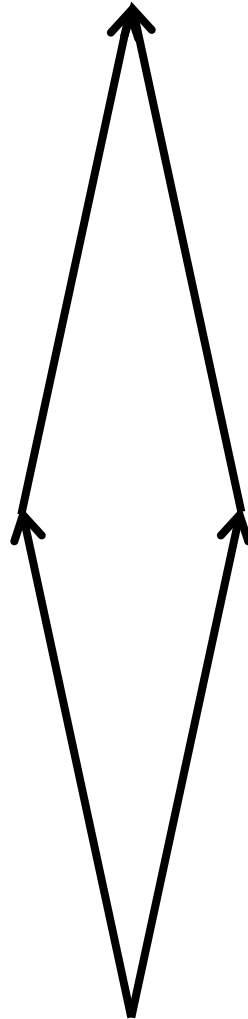
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# The narrow design space



The narrow design space



# Solution principles

- From closed to open-loop
  - Avoid the need for a visual feedback loop
- Continuous novice-to-expert transition
  - Avoid explicit learning
- Path dependency
  - Avoid redesigning the interaction layer
- Flexibility
  - Enable users to compose and edit in a variety of styles without explicit mode switching
- Probabilistic error correction
  - Use the hypothesis space to design optimal error correction strategies
- Fluid regulation of uncertainty
  - Allow users to seamlessly influence the inference process
- Efficiency
  - Let users' creativity be the bottle-neck

# From Closed to Open Loop



# Reimaging the keyboard

Just then, the white |

Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# How gesture keyboards work

Just then, the white |

Q	W	E	R	T	Y	U	I	O	P
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# How gesture keyboards work

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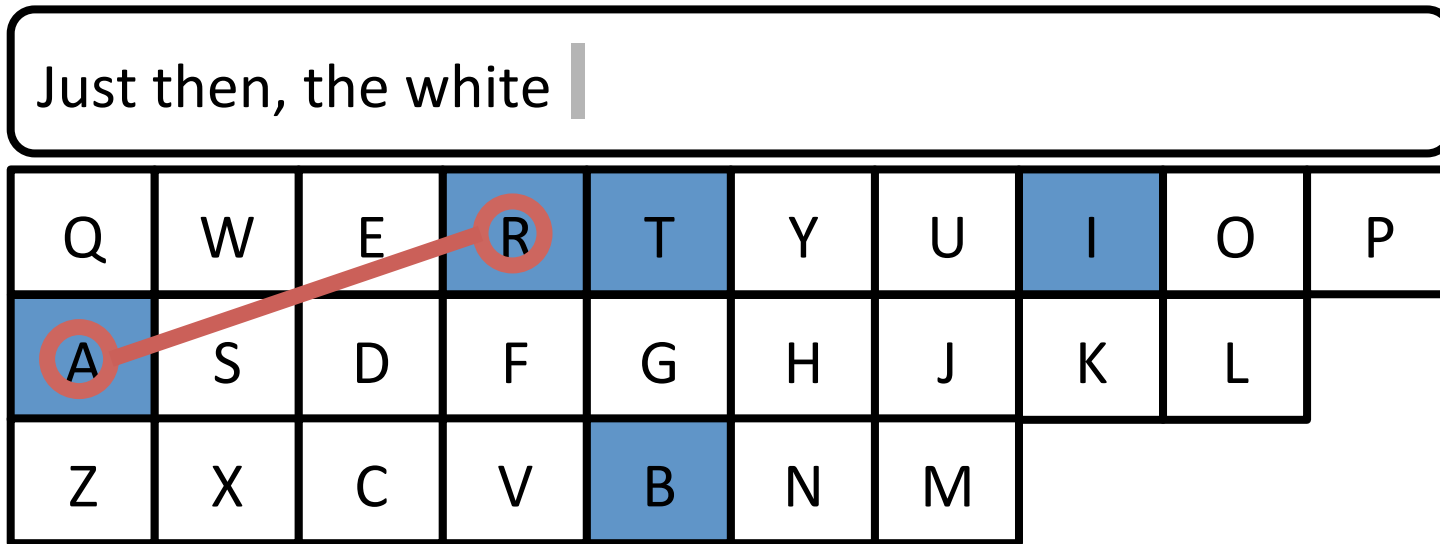
# How gesture keyboards work

Just then, the white |

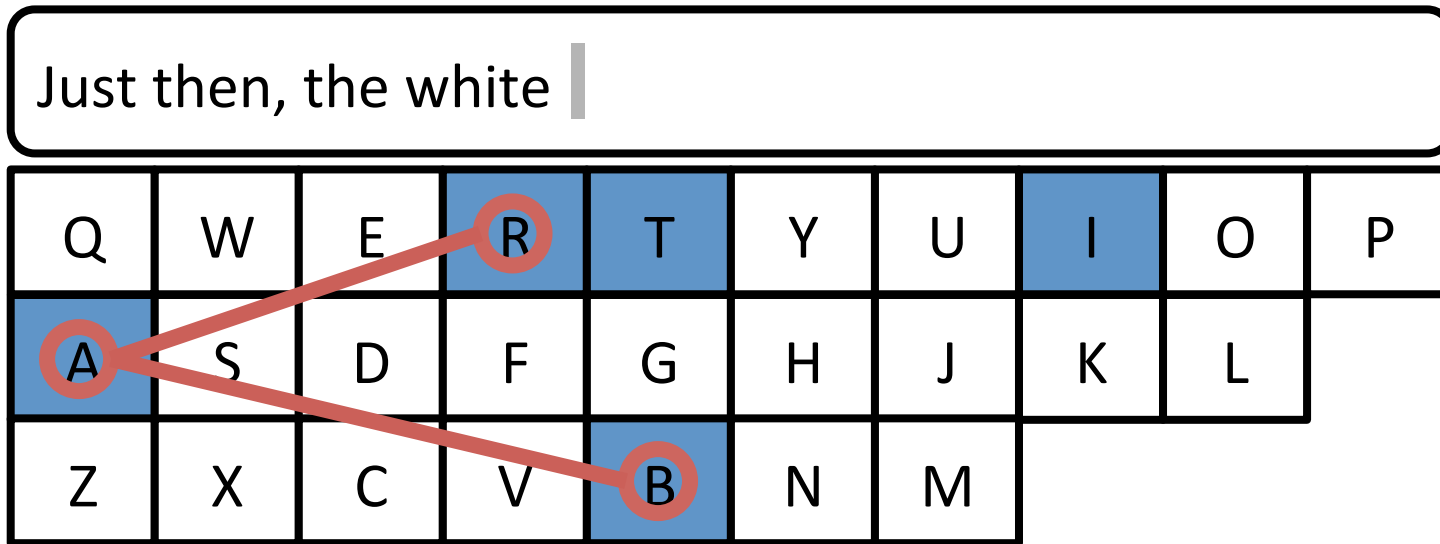
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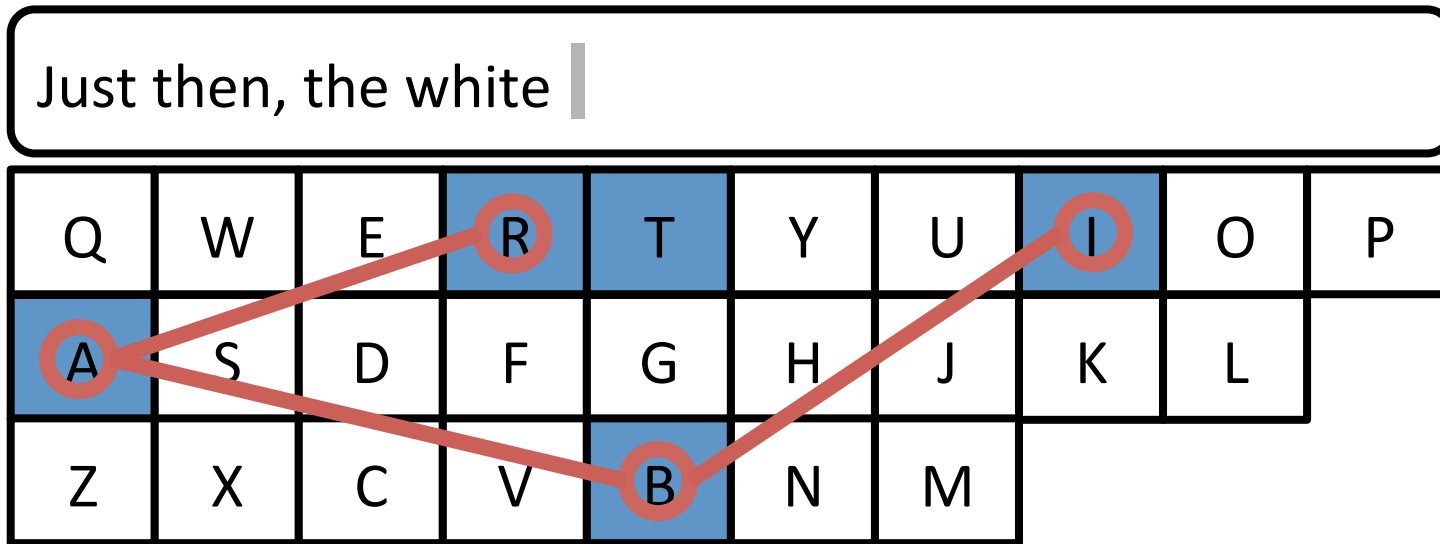
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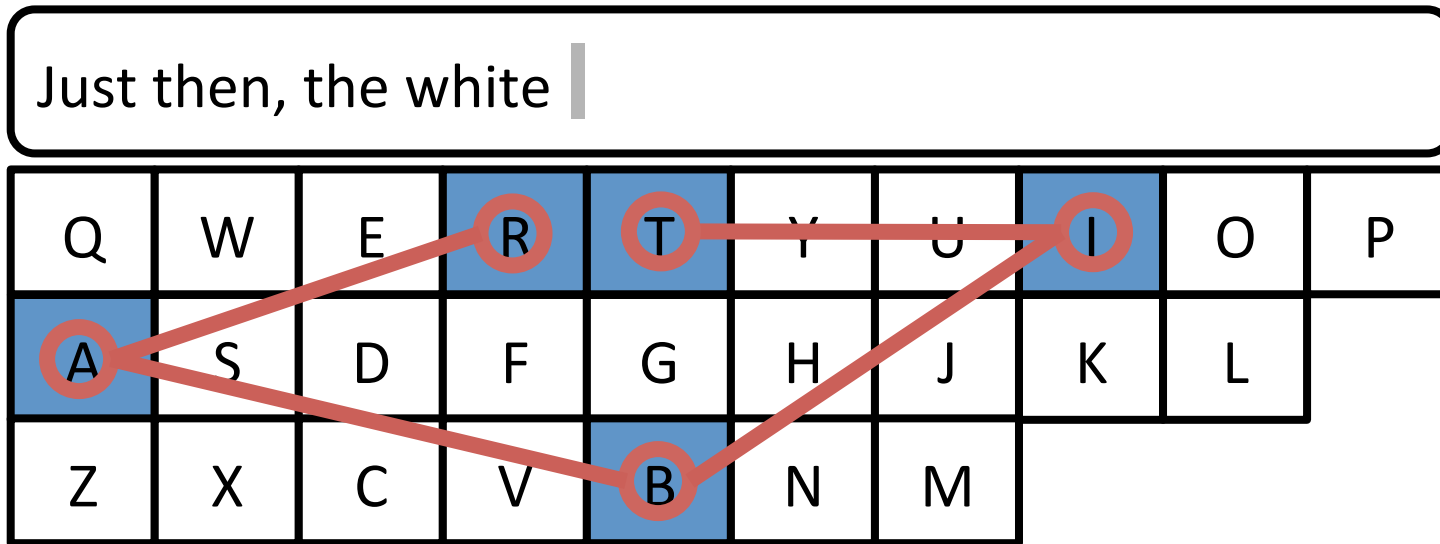
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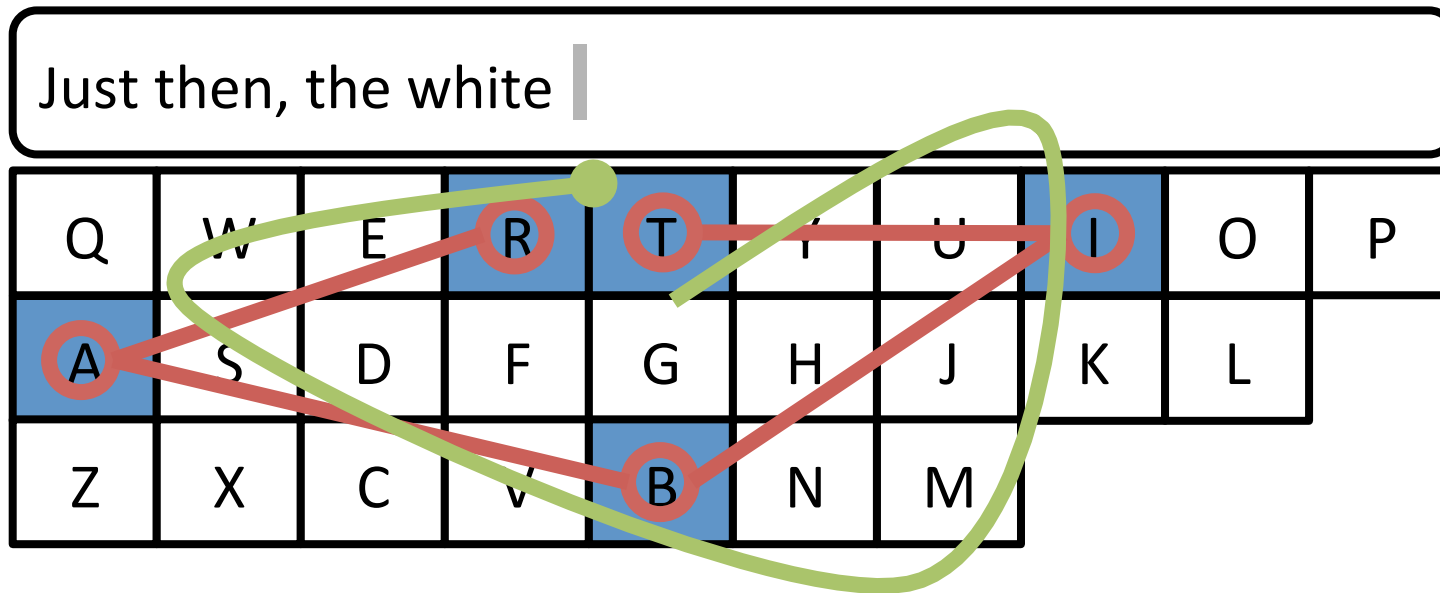
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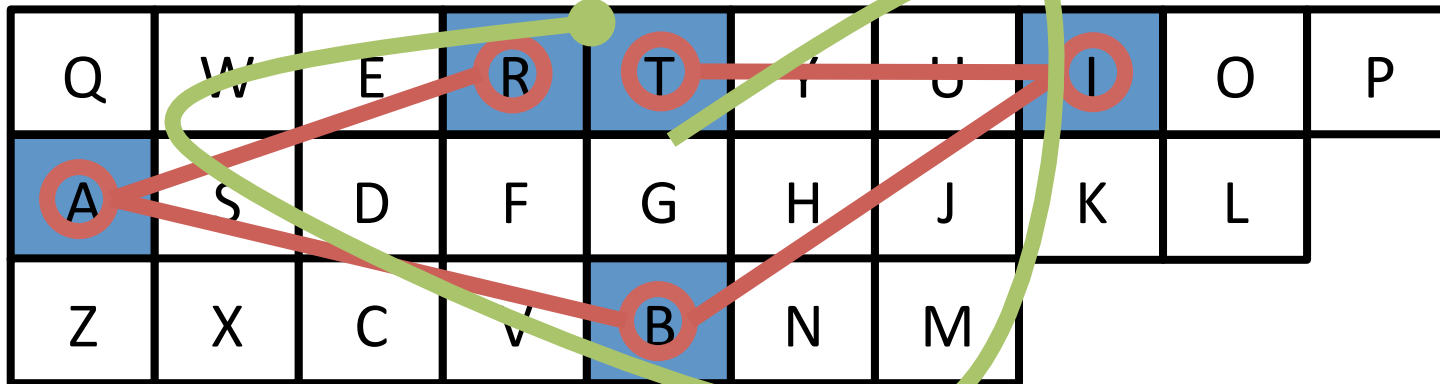
# How gesture keyboards work



# How gesture keyboards work

Prior probability

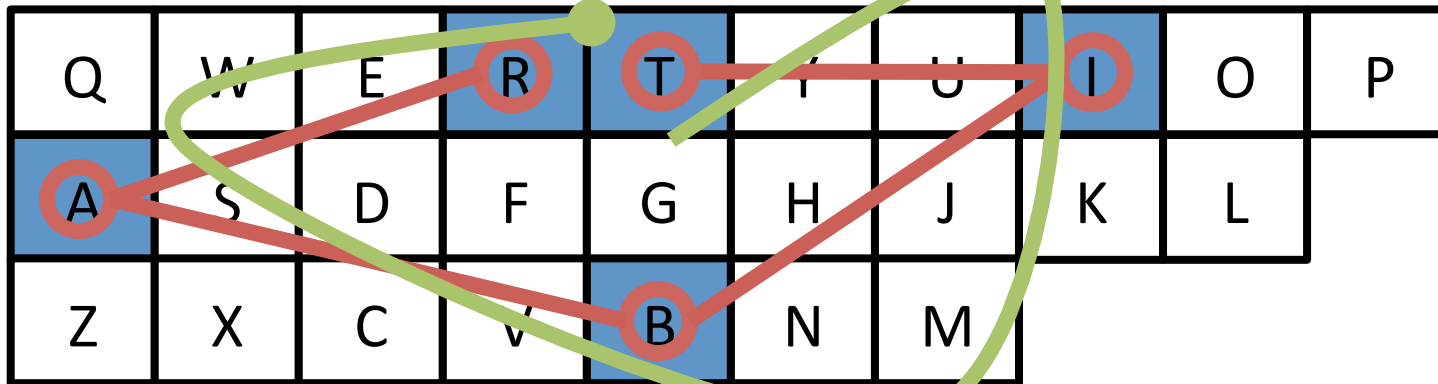
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Prior probability

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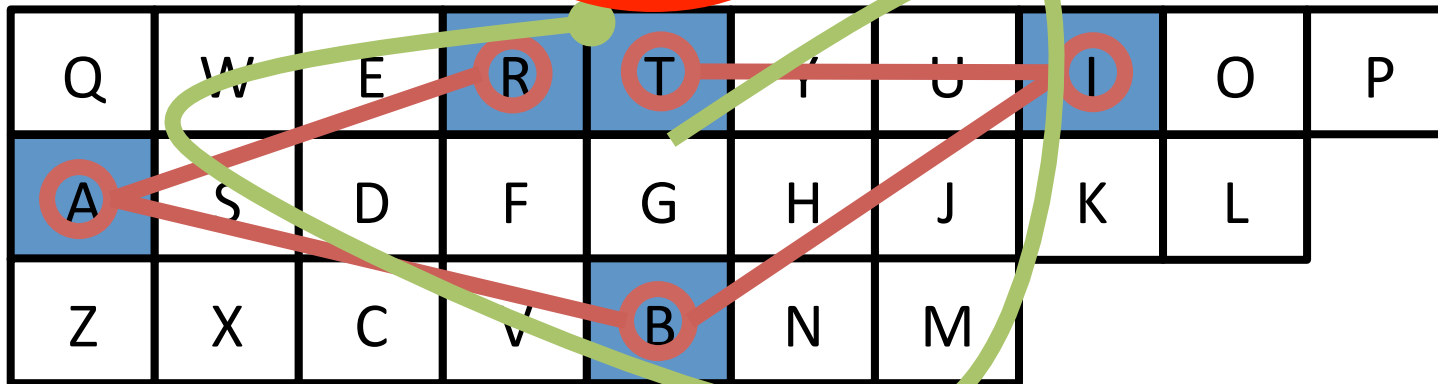
Likelihood

# How gesture work

Prior probability

Posterior probability

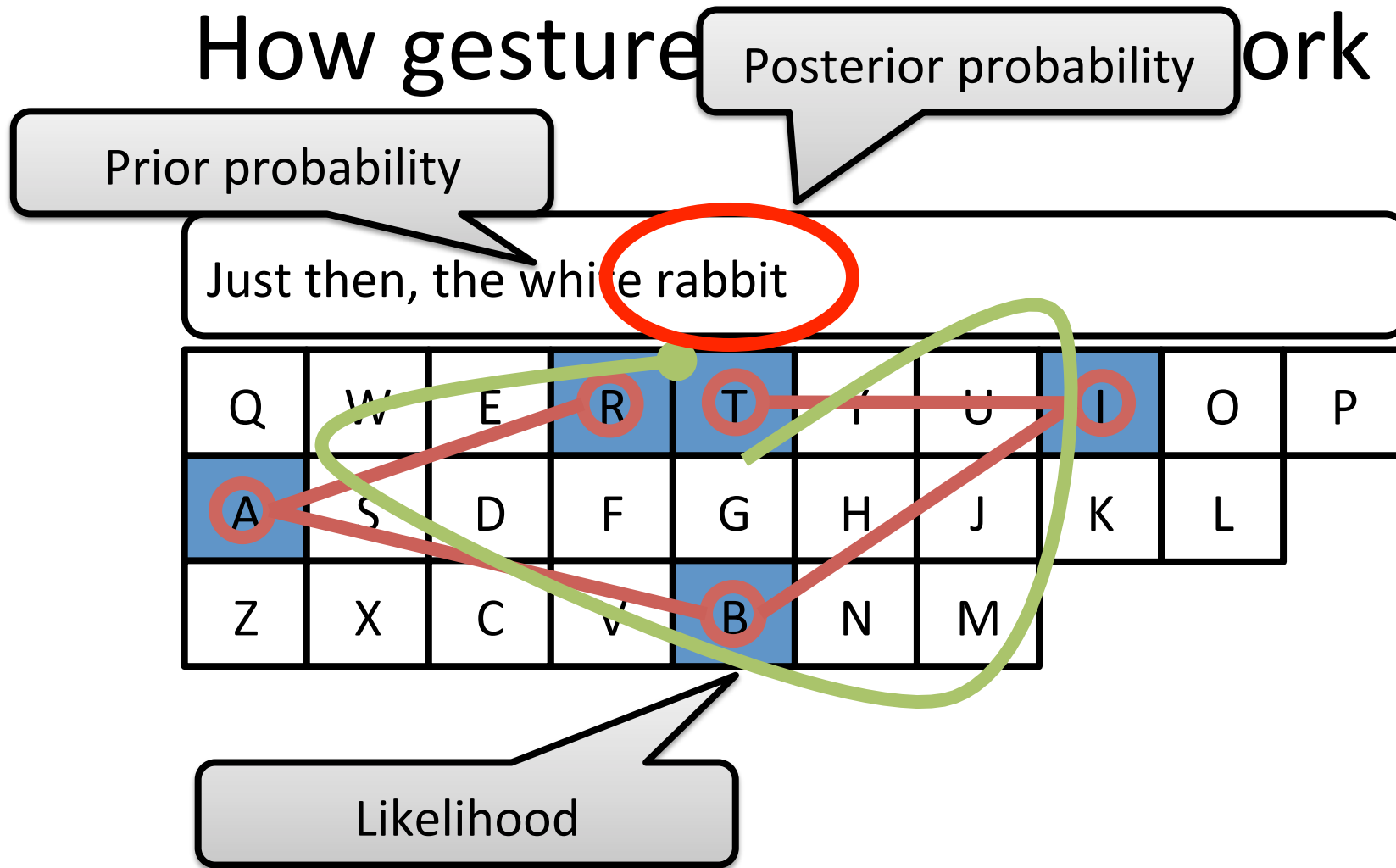
Just then, the white rabbit



Likelihood



# How gesture work



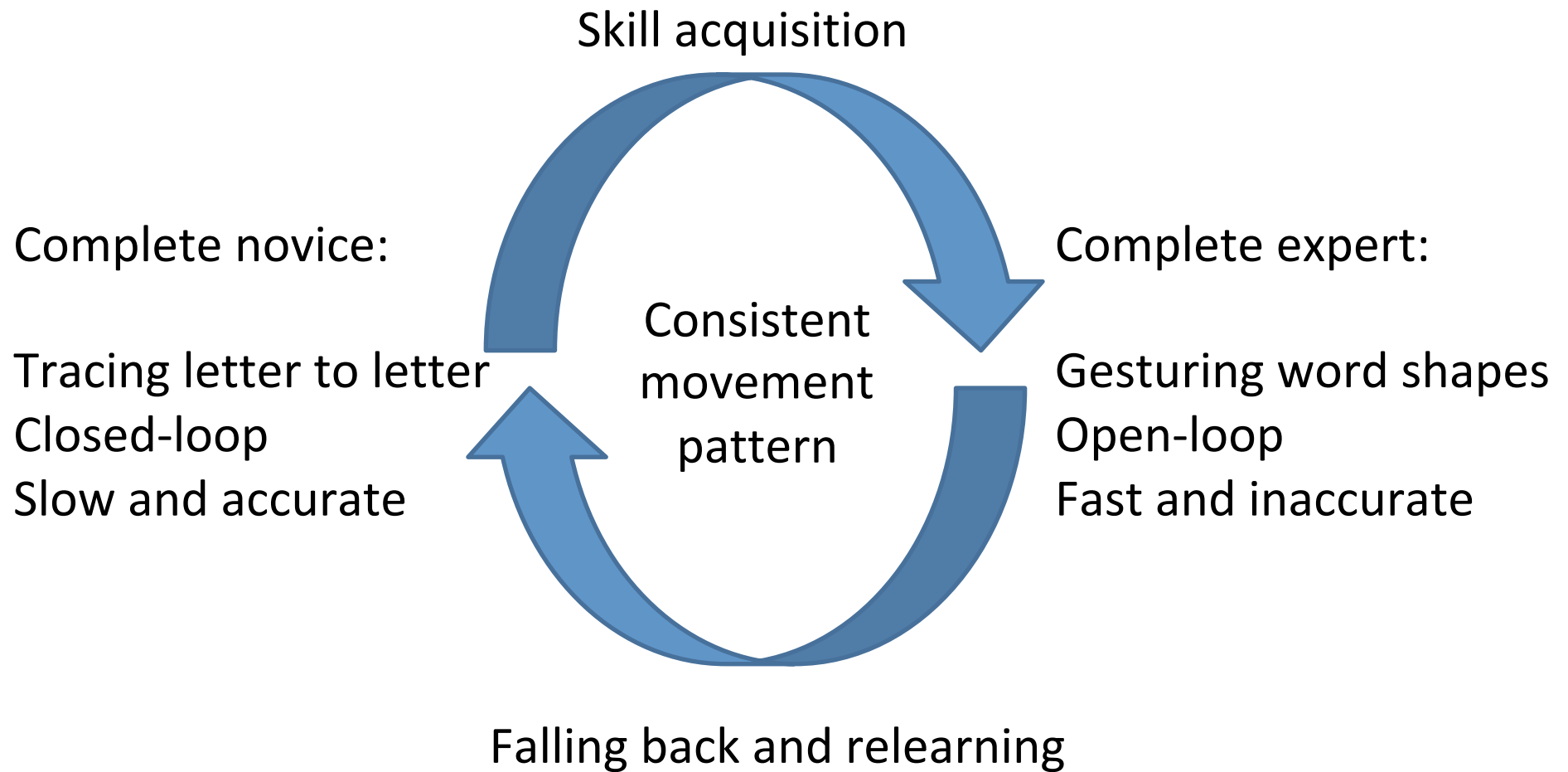
**Decoding noisy gestures into text using a combination of gesture recognition and language modelling**

# Closed- and open-loop

- Closed-loop:
  - Continuous feedback-driven interaction
  - Visually-guided motion
  - Slow and precise
  - Modelled well by the “crossing law”
    - Average movement time =  $a + b \log_2(D/W+1)$ ;  $a$  and  $b$  are linear regression coefficients;  $D$  and  $W$  are the distance and width to the crossing goal respectively
- Open-loop:
  - Not feedback-driven
  - Direct recall from motor memory
  - Fast and imprecise
  - No good model exists
- Gesture keyboard interaction is a mix of closed- and open-loop interaction

# Continuous Novice-to-Expert Transition

# Continuous transition from novice to expert behaviour



# Path Dependency

# Clio and the Economics of QWERTY

By PAUL A. DAVID\*

Cicero demands of historians, first, that we tell true stories. I intend fully to perform my duty on this occasion, by giving you a homely piece of narrative economic history in which “one damn thing follows another.” The main point of the story will become plain enough: it is sometimes not possible to uncover the logic (or illogic) of the world around us except by understanding how it got that way. A *path-dependent* sequence of economic changes is one of which important influences upon the eventual outcome can be exerted by temporally remote events, including happenings dominated by chance elements rather than systematic forces. Stochastic processes like that do not converge automatically to a fixed-point distribution of outcomes, and are

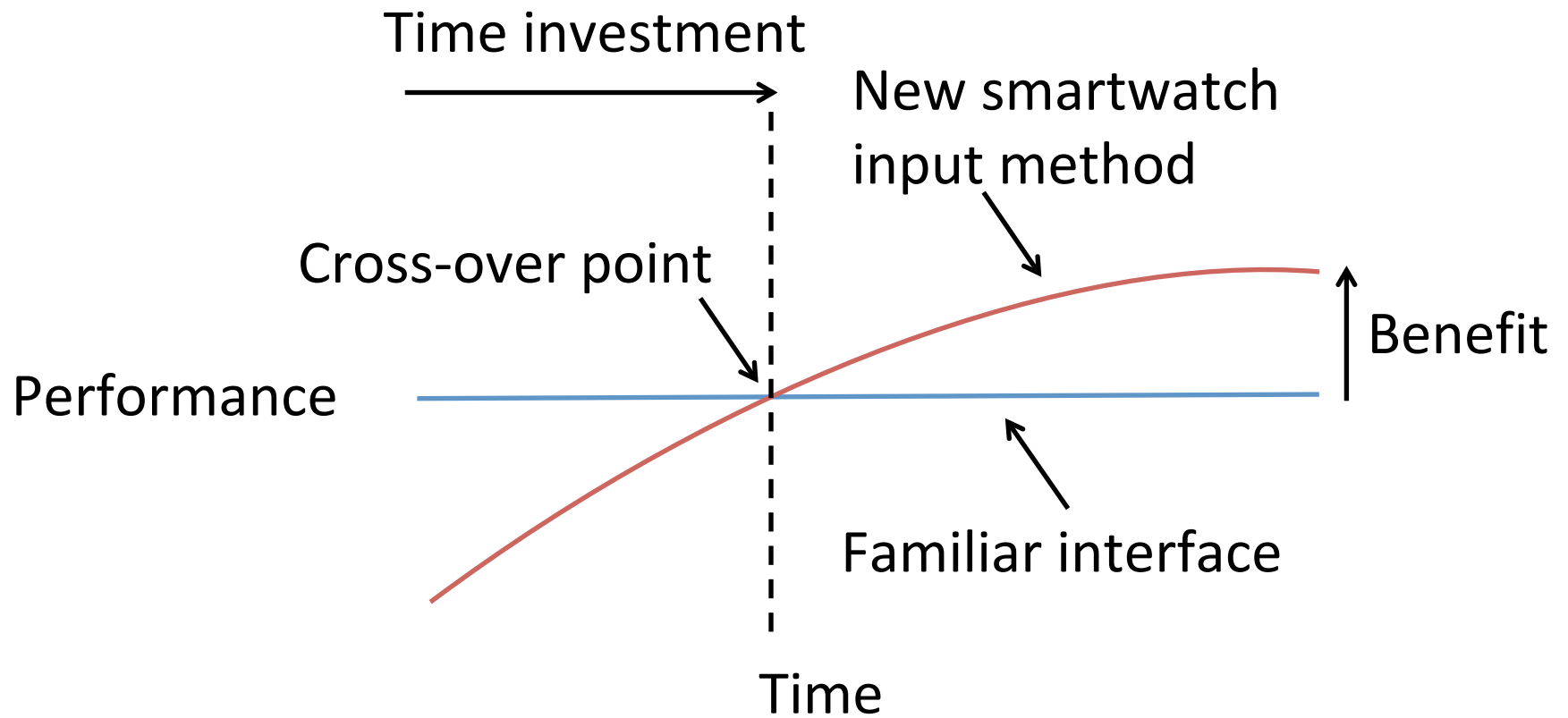
## I. The Story of QWERTY

Why does the topmost row of letters on your personal computer keyboard spell out QWERTYUIOP, rather than something else? We know that nothing in the engineering of computer terminals requires the awkward keyboard layout known today as “QWERTY,” and we all are old enough to remember that QWERTY somehow has been handed down to us from the Age of Typewriters. Clearly nobody has been persuaded by the exhortations to discard QWERTY, which apostles of DSK (the Dvorak Simplified Keyboard) were issuing in trade publications such as *Computers and Automation* during the early 1970’s. Why not? Devotees

# Example: typing on a smartwatch

- Small screen size is obviously a constraint
- Many naïve solutions:
  - Progressive zooming techniques
  - Reduce keyset (à la the old telephone keypad techniques)
  - Various multi-stroke strategies
- **All slow**
- **All demand user learning** (no immediate efficacy)

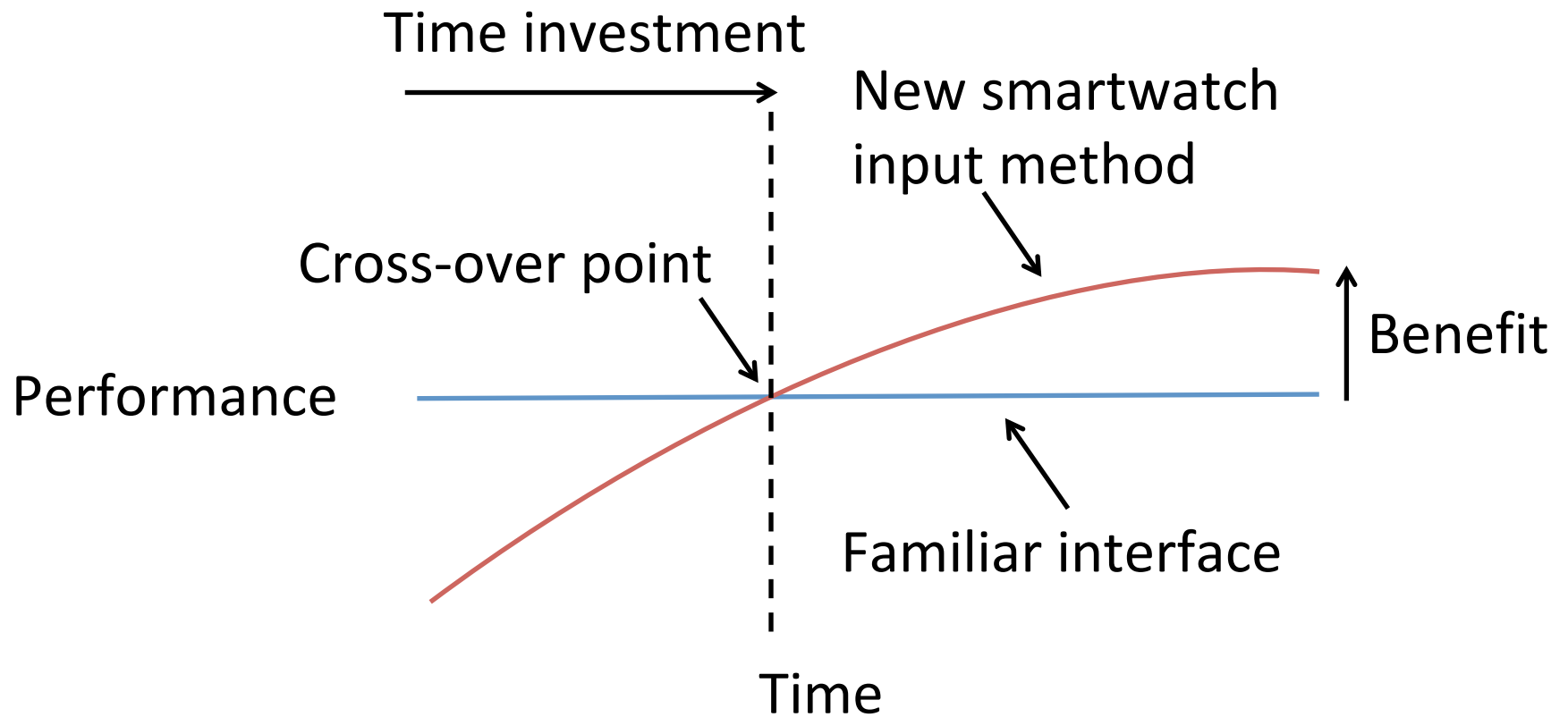
# The cross-over point





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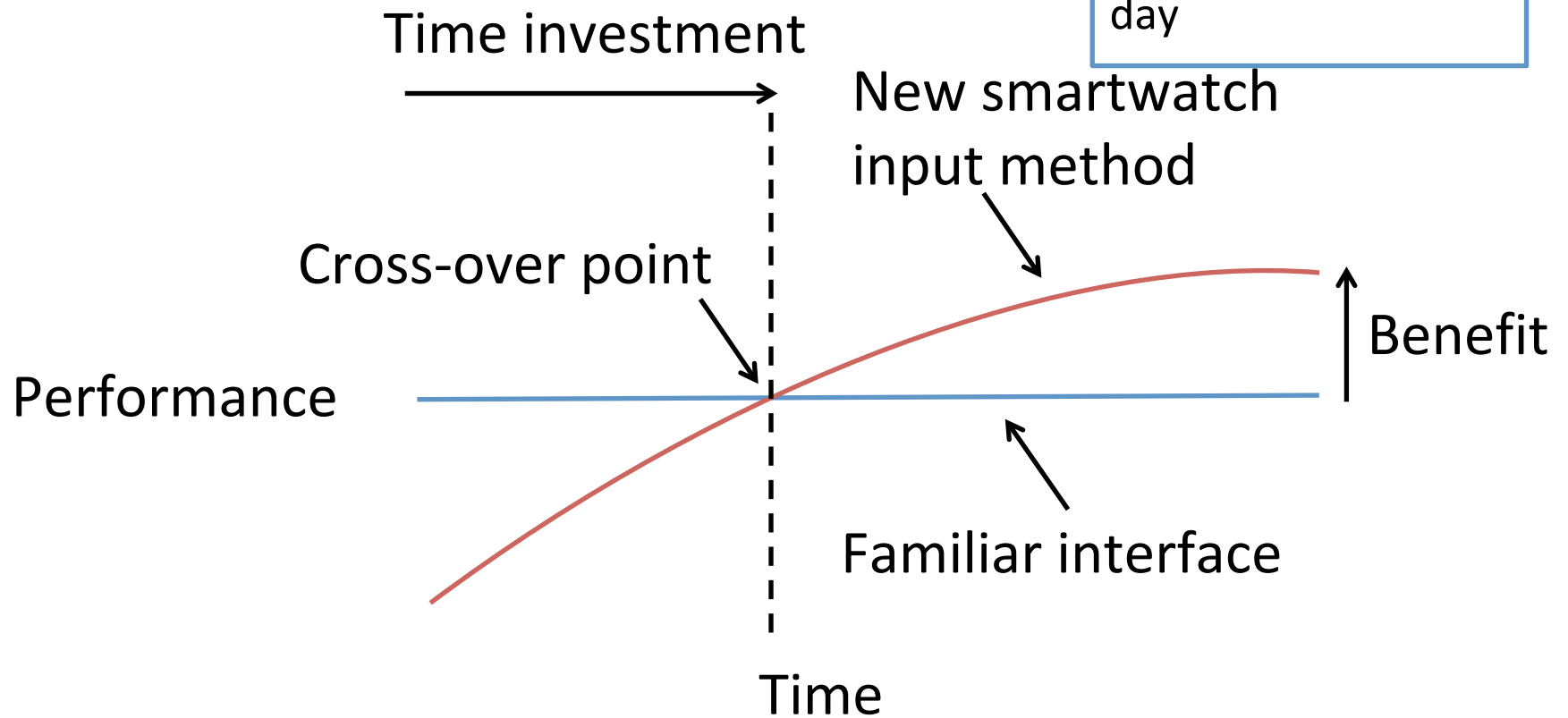
= 40 hours of **dedicated** practice



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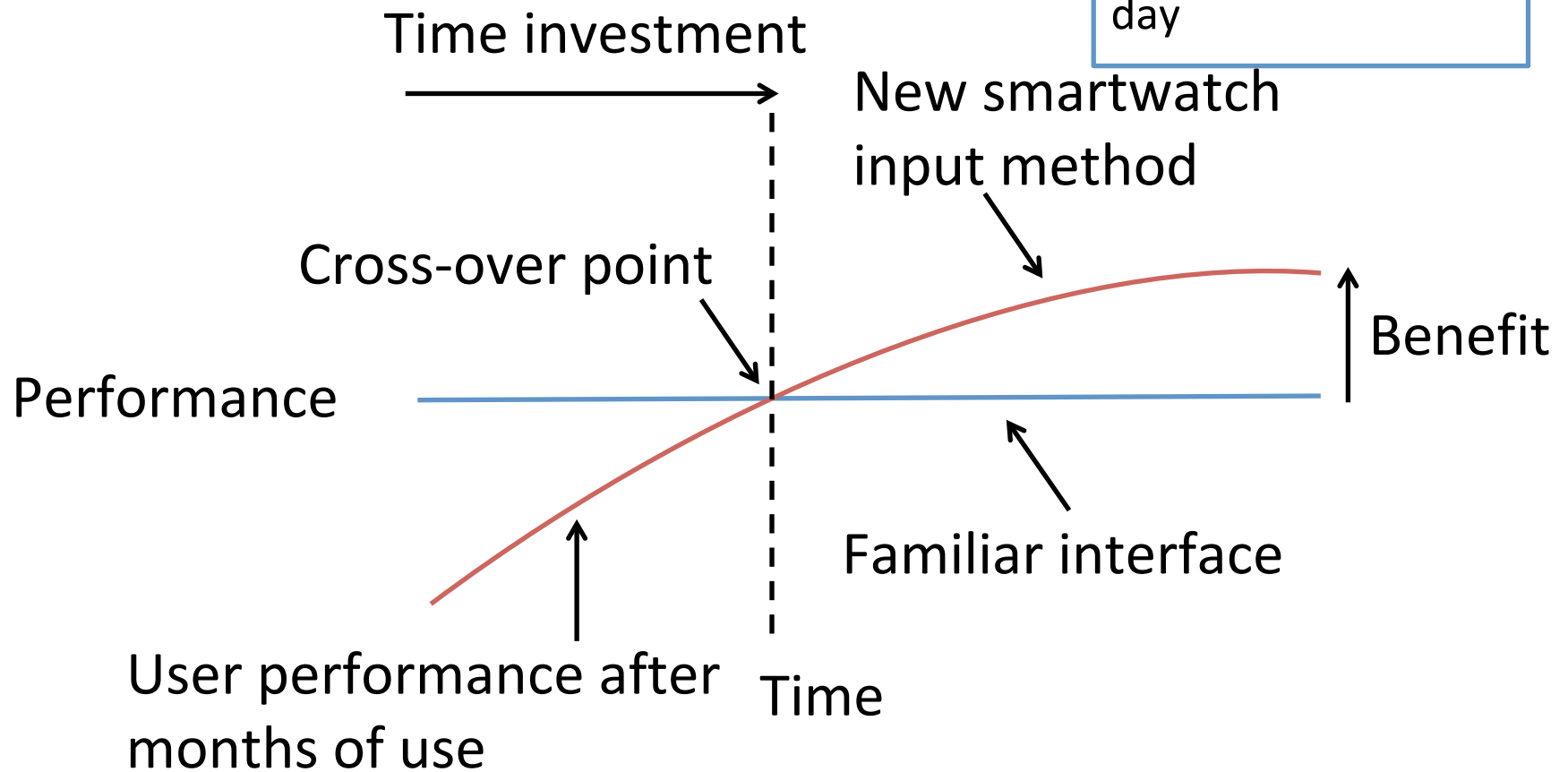
Assume the user types for five minutes on their smartwatch every day



# The cross-over point

= 40 hours of **dedicated** practice

Assume the user types for five minutes on their smartwatch every day



# The cross-over point

Assume the user types for five minutes on their smartwatch every day

= 40 hours of **dedicated** practice

Time investment

New smartwatch  
input method

Cross-over point  
reached after **480**  
**days**

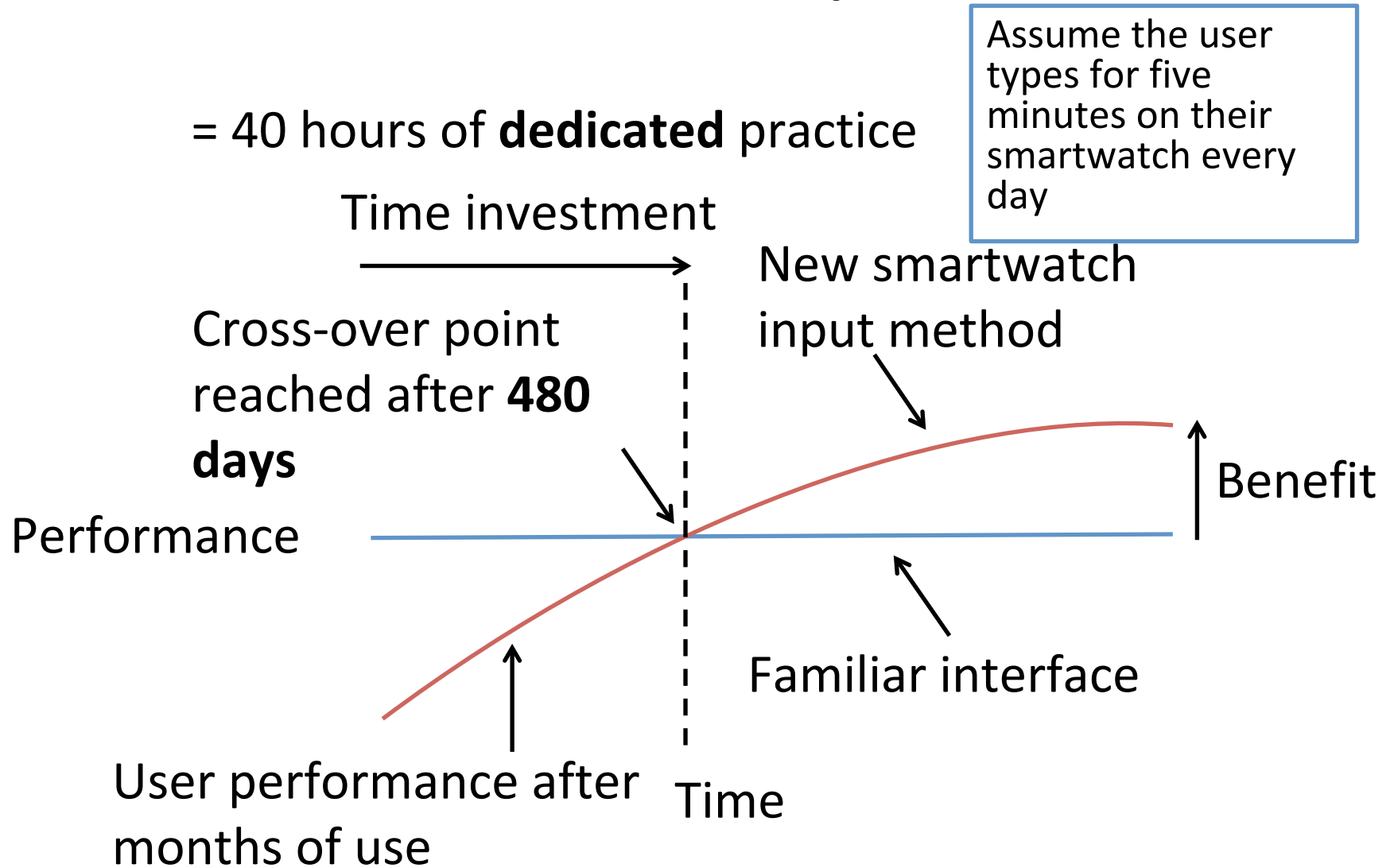
Performance

Benefit

Familiar interface

User performance after  
months of use

Time



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- Localisation
- Market acceptance

# Mainstream mobile text entry methods

- Entry and error rate
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- Specification vs. navigation
- One handed vs. two
- **High effective entry rate**
  - It takes a very long time to learn QWERTY (or learn a new layout)
- **High efficacy**
  - Similar to
- Speed of entry
- Localisation
- Market acceptance

# Mainstream mobile text entry methods

- Entry and error rate
- Learning curve, familiarity and immediate efficacy
- Specification vs. navigation
- One handed vs. two
- **High effective entry rate**
  - It takes a very long time to learn QWERTY (or learn a new layout)
  - Users are familiar with touchscreen QWERTY
- **High efficacy**
  - Similar to
- Localisation
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# Mainstream mobile text entry methods

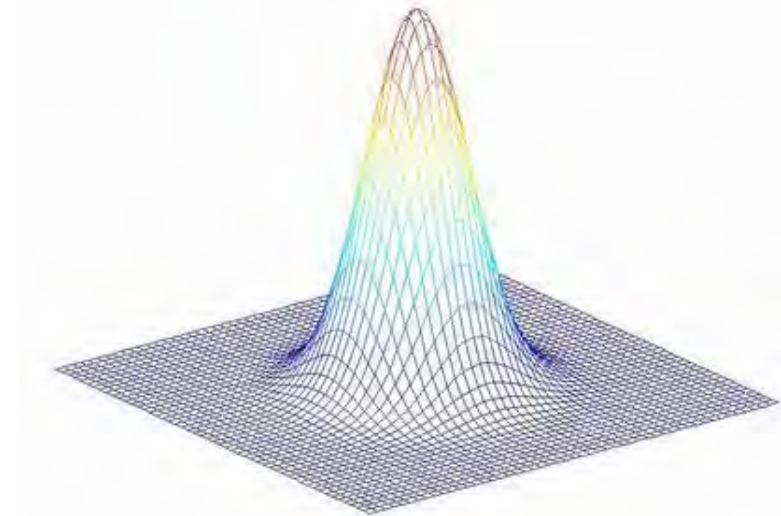
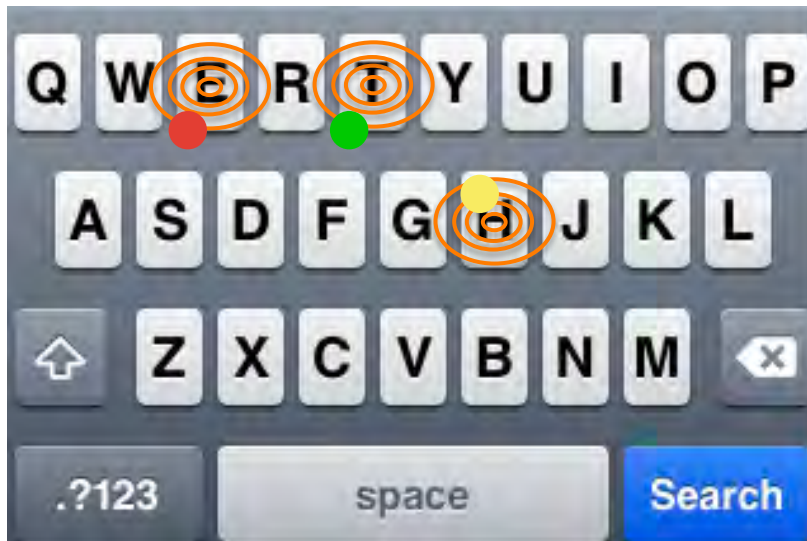
- Entry and error rate
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# Touch modelling



*2D Gaussians centered at each key.  
Separate variances in the x- and y-dimensions.*

$$P(\text{Letters}|\text{Taps}) \propto \underbrace{P(\text{Taps}|\text{Letters})}_{\text{touch model}} \underbrace{P(\text{Letters})}_{\text{language model}}$$

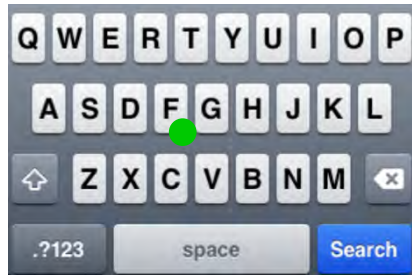
Vertanen, K., Memmi, H., Emge, J., Reyat, S. and Kristensson, P.O. 2015. VelociTap: investigating fast mobile text entry using sentence-based decoding of touchscreen keyboard input. *In Proceedings of the 33rd ACM Conference on Human Factors in Computing Systems (CHI 2015)*. ACM Press: 659-668.

# Language modelling

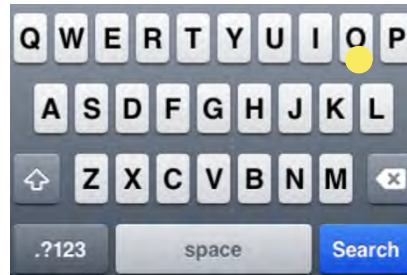
- Language models:
  - **12-gram letter** model
  - **4-gram word** model with unknown word
  - Trained on **billions of words** of data
    - Twitter, blog, social media, Usenet, and web data
  - Optimized for **short email-like messages**
  - Letter + word language model = ~4 GB memory

Vertanen, K., Memmi, H., Emge, J., Reyal, S. and Kristensson, P.O. 2015. VelociTap: investigating fast mobile text entry using sentence-based decoding of touchscreen keyboard input. *In Proceedings of the 33rd ACM Conference on Human Factors in Computing Systems (CHI 2015)*. ACM Press: 659-668.

# Decoding



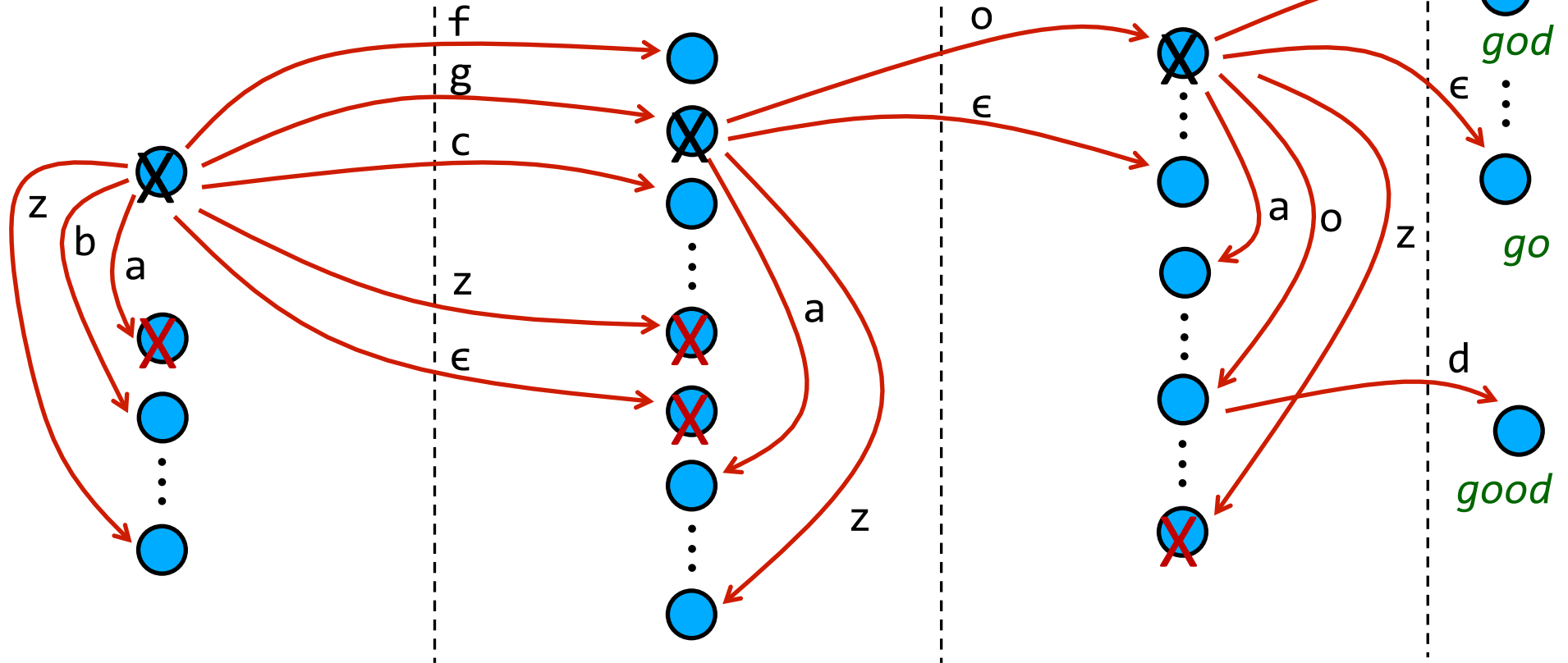
Observation 1



Observation 2



Observation 3

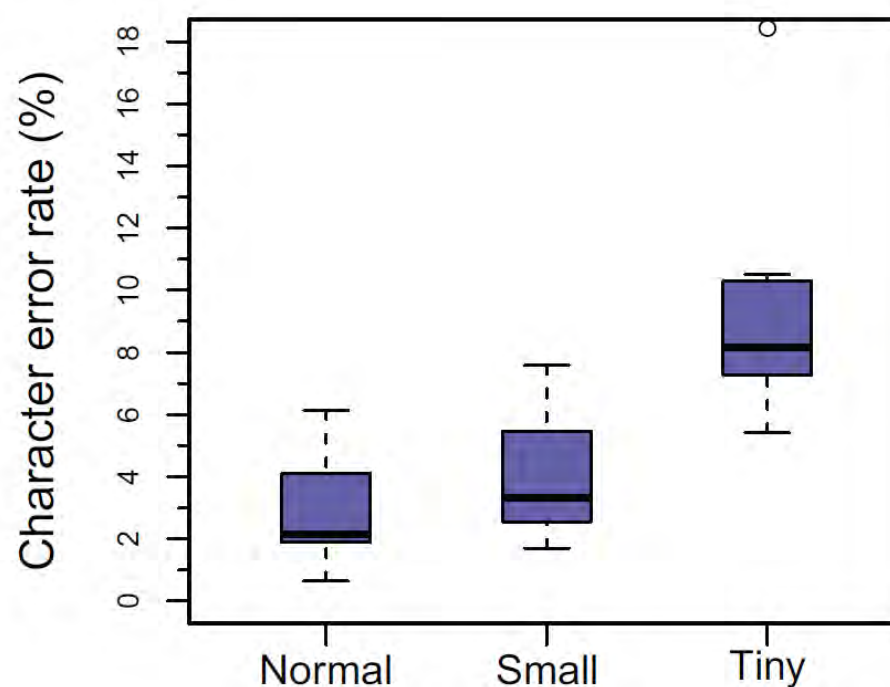
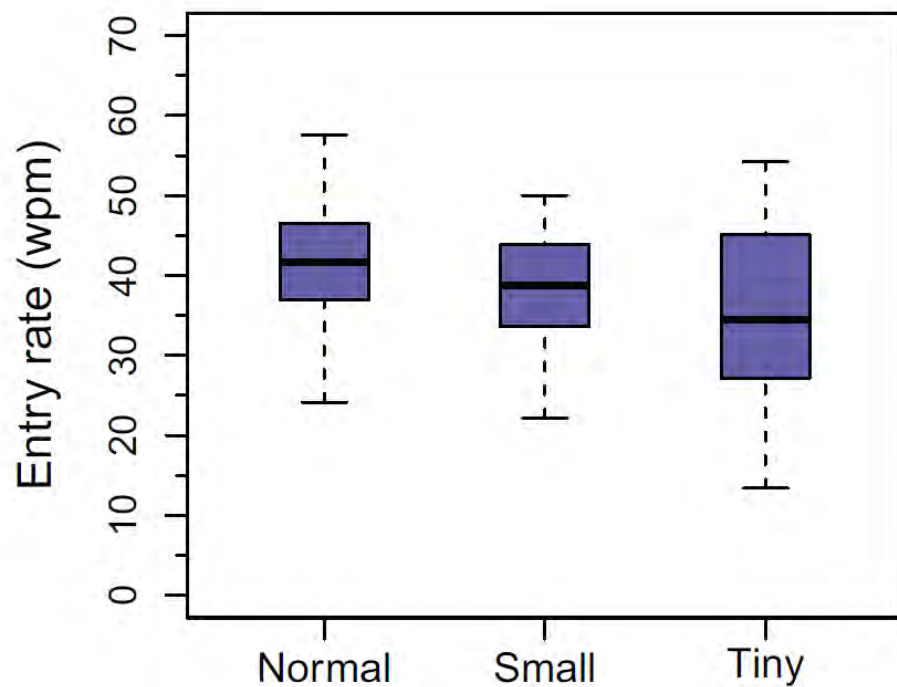
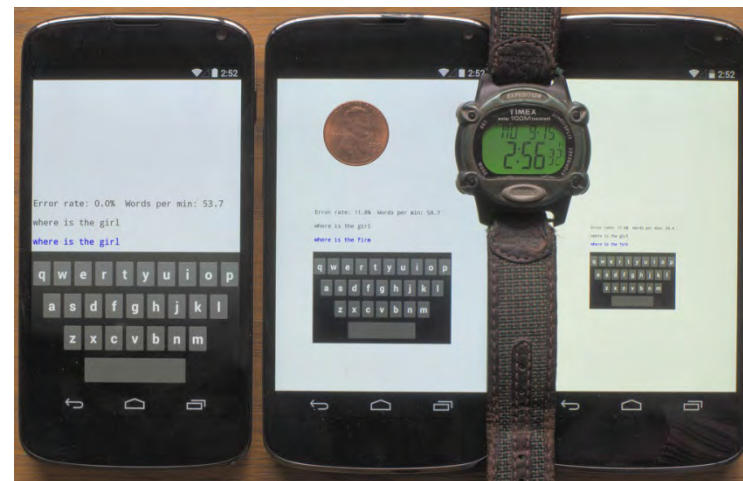


Tokens track: probability, LM context, traceback

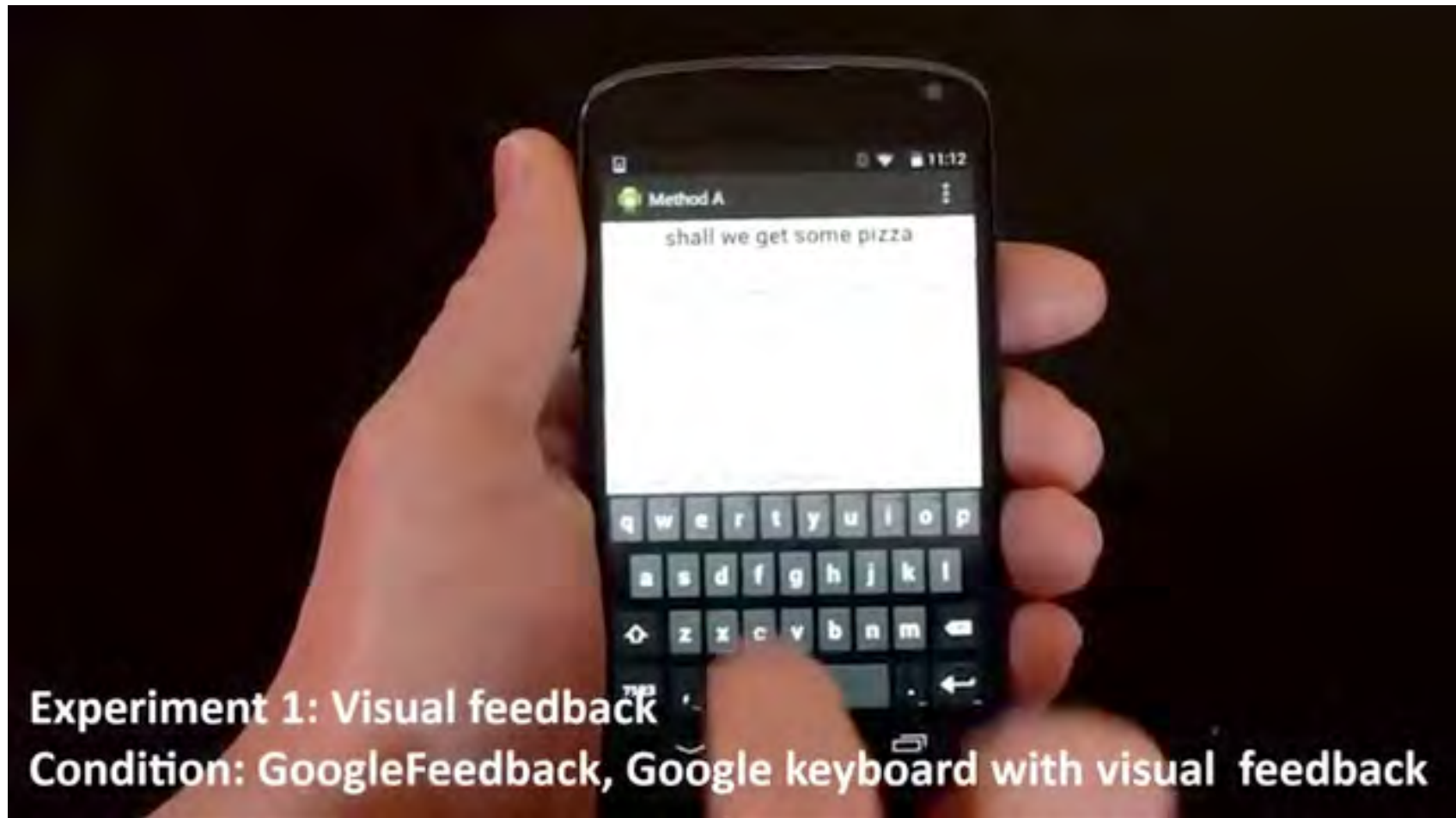
Beam prune to keep tractable

# Entry and error rate

Condition	
Normal	Standard portrait keyboard, 60mm wide
Small	Big smartwatch, 40mm wide
Tiny	Small smartwatch, 25mm wide



# Typing on a tiny keyboard



Experiment 1: Visual feedback

Condition: GoogleFeedback, Google keyboard with visual feedback

**Flexibility**

# Speech recognition error correction: the standard method

- User: “the cat sat”



# Speech recognition error correction: the standard method

- User: “the cat sat”
- System: “the bat sat”

# Speech recognition error correction: the standard method

- User: “the cat sat”
- System: “the bat sat”
- User: “select bat”

# Speech recognition error correction: the standard method

- User: “the cat sat”
- System: “the bat sat”
- User: “select bat”
- System: “the bat sat dissect rat”

# Speech recognition error correction: the standard method

- User: “the cat sat”
- System: “the bat sat”
- User: “select bat”
- System: “the bat sat dissect rat”
- (User: “I hate this...”)

# The flexible multimodal fusion approach

- User speaks: “the cat sat”

# The flexible multimodal fusion approach

- User speaks: “the cat sat”
- System: “the bat sat”

# The flexible multimodal fusion approach

- User speaks: “the cat sat”
- System: “the bat sat”
- User gestures the word: “cat”

# The flexible multimodal fusion approach

- User speaks: “the cat sat”
- System: “the bat sat”
- User gestures the word: “cat”
- System: “the cat sat”



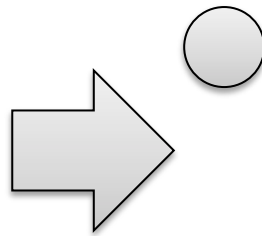
# The flexible multimodal fusion approach

- User speaks: “the cat sat”
- System: “the bat sat”
- User gestures the word: “cat”
- System: “the cat sat”
  
- The system automatically identifies the error location and corrects the error

Kristensson, P.O. and Vertanen, K. 2011. Asynchronous multimodal text entry using speech and gesture keyboards. *In Proceedings of the 12th Annual Conference of the International Speech Communication Association (Interspeech 2011)*. ISCA: 581-584.

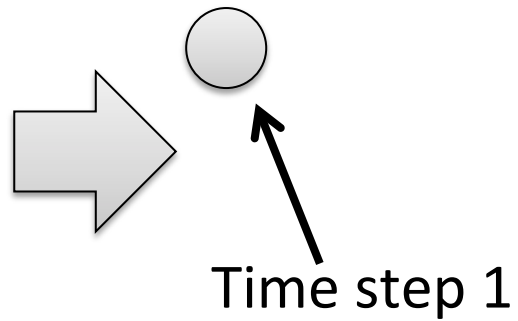
# Output from a text entry modality

Gesture  
keyboard



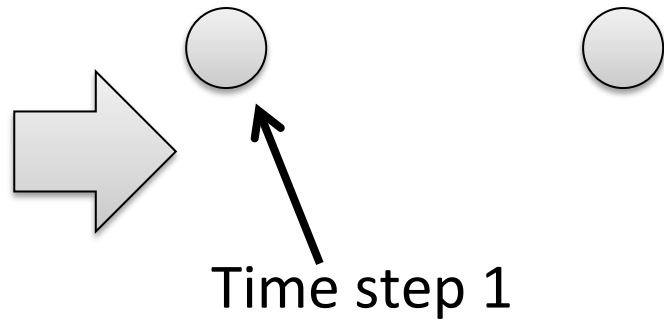
# Output from a text entry modality

Gesture  
keyboard



# Output from a text entry modality

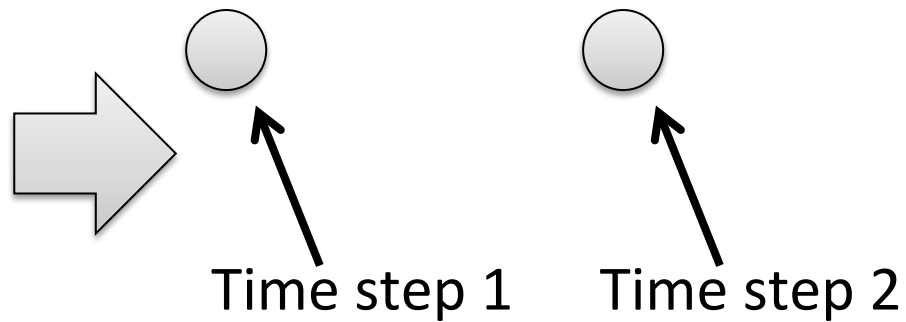
Gesture  
keyboard



Time step 1

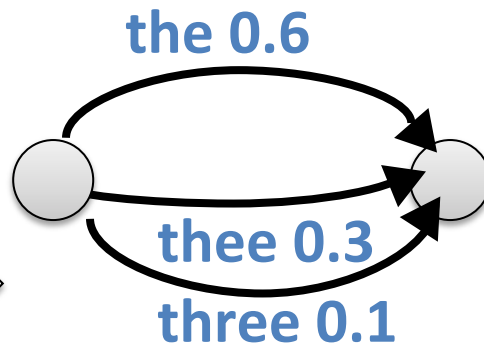
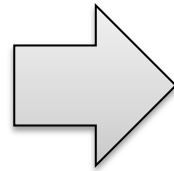
# Output from a text entry modality

Gesture  
keyboard



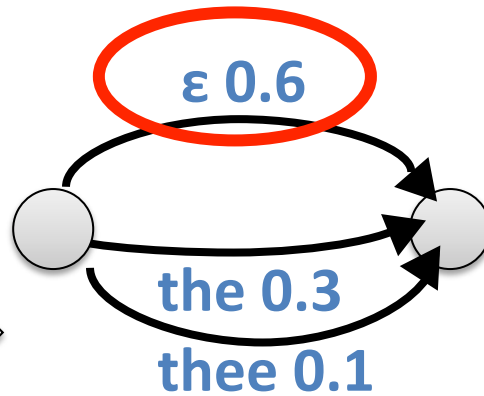
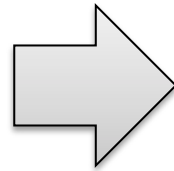
# Output from a text entry modality

Gesture  
keyboard



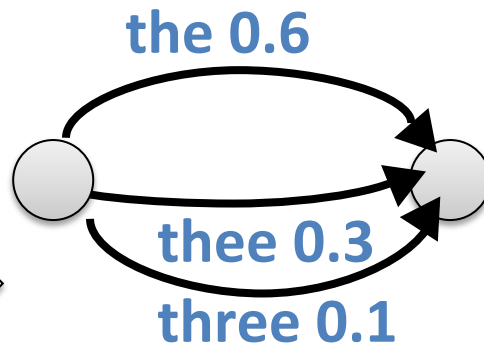
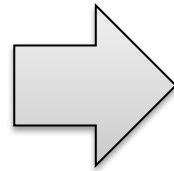
# Output from a text entry modality

Gesture  
keyboard



# Output from a text entry modality

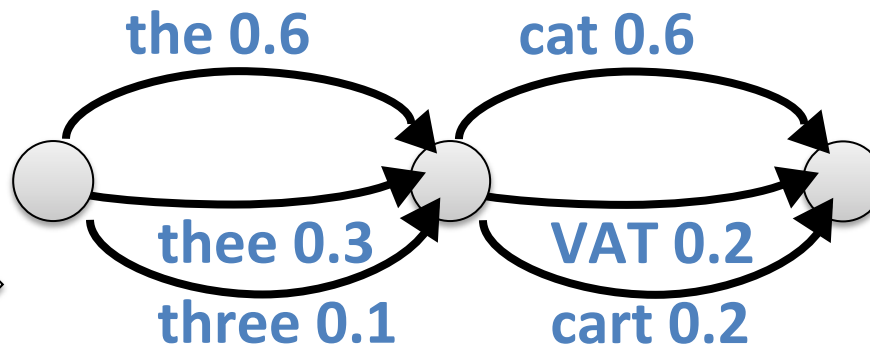
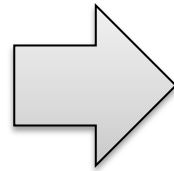
Gesture  
keyboard



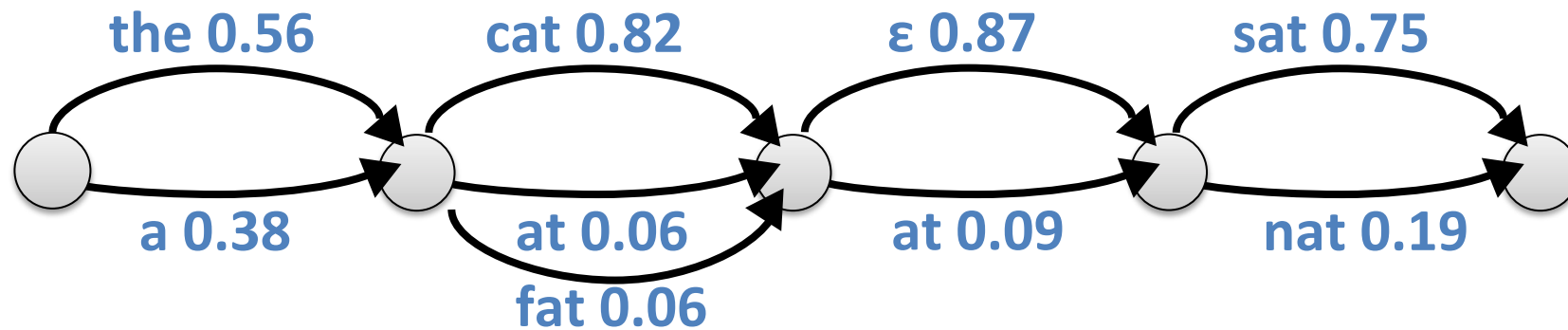
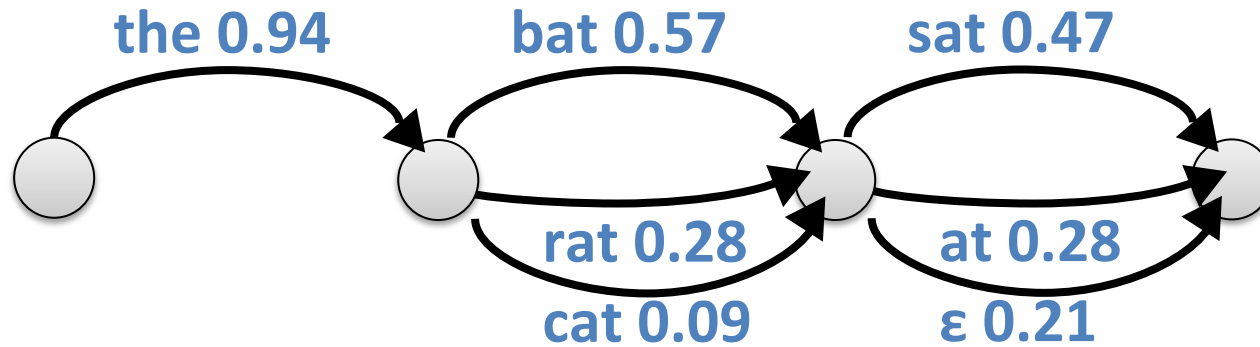


# Output from a text entry modality

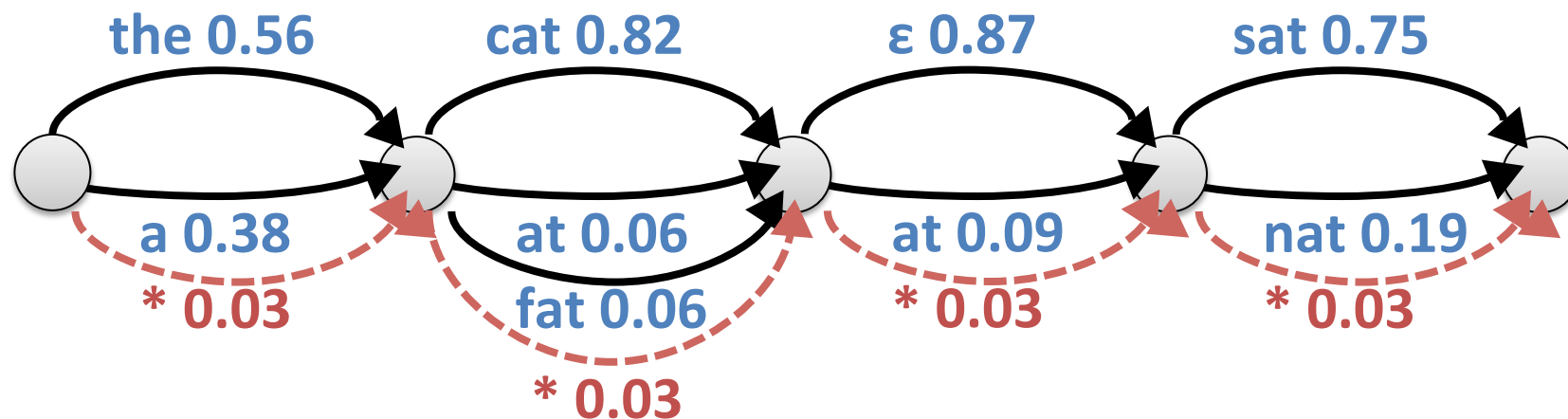
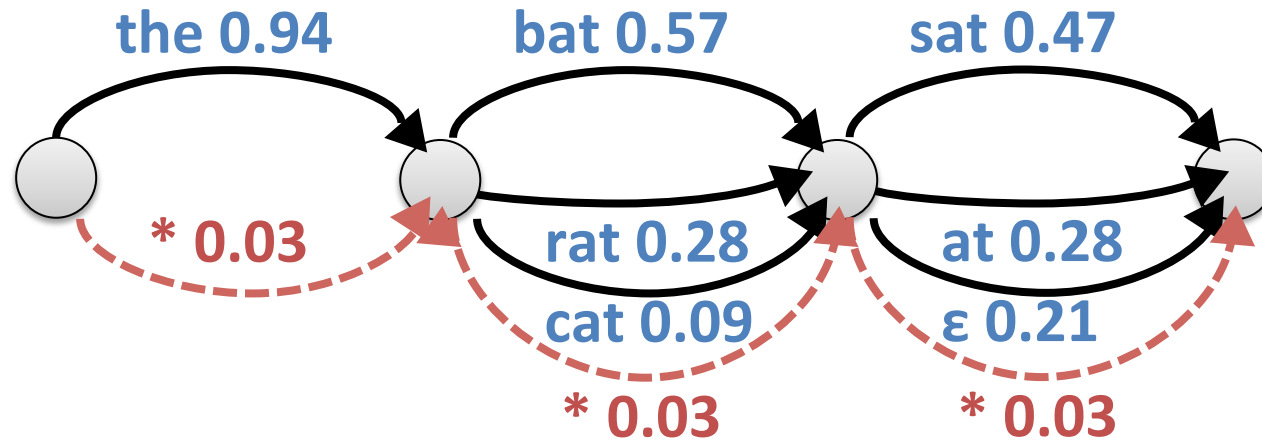
Gesture  
keyboard



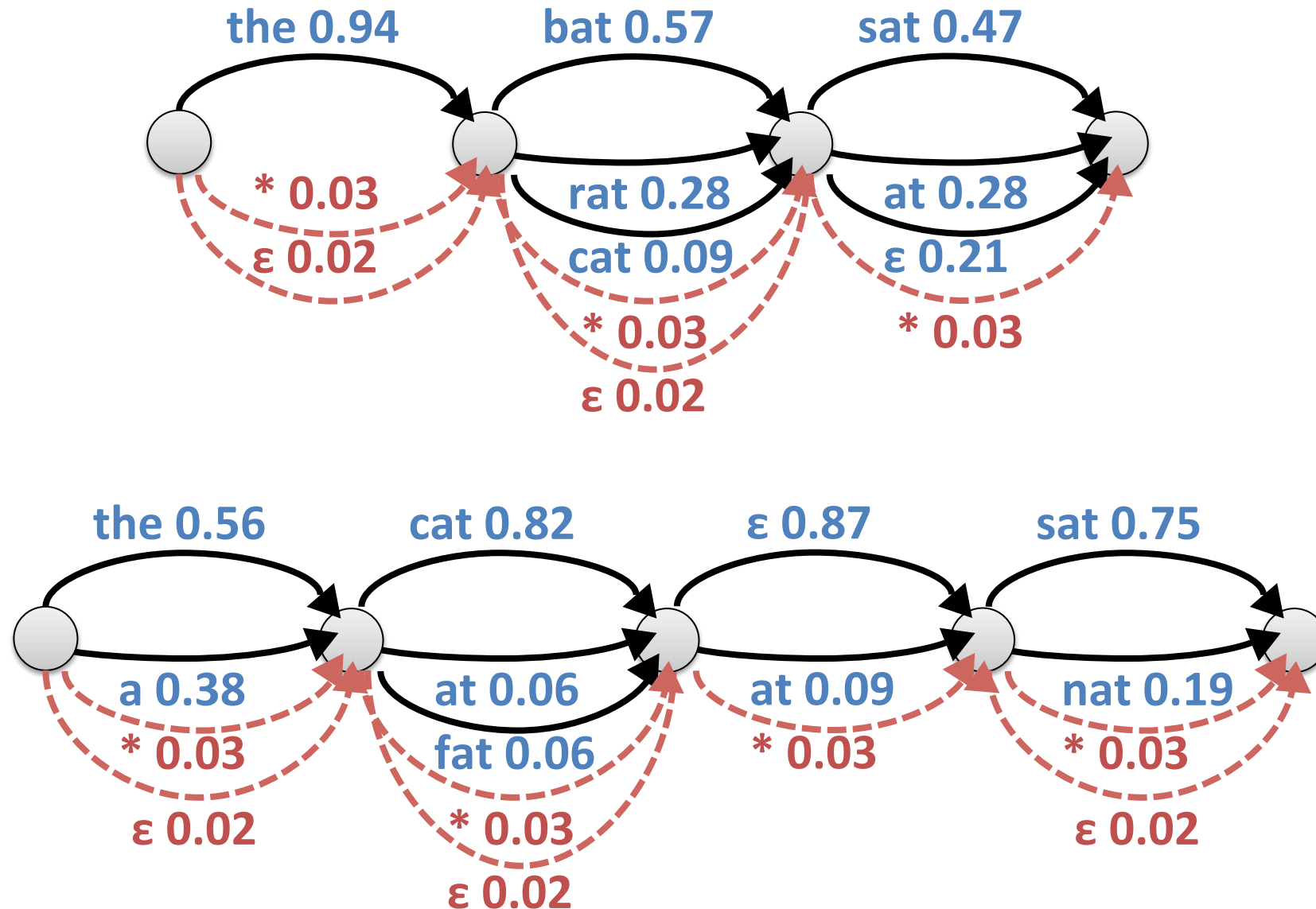
# Output from two text entry modalities



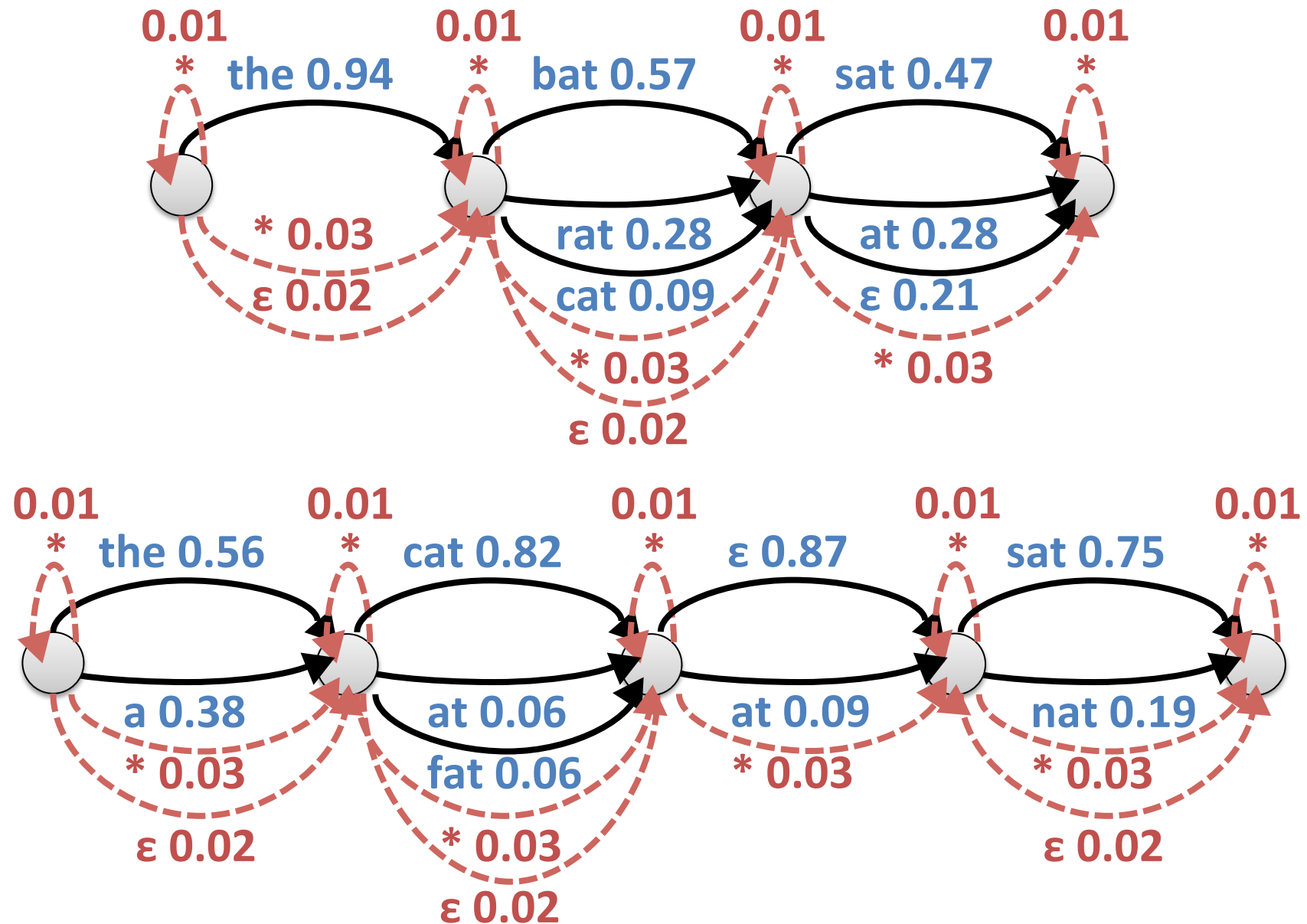
# Softening the word confusion networks: adding **wild-card transitions**



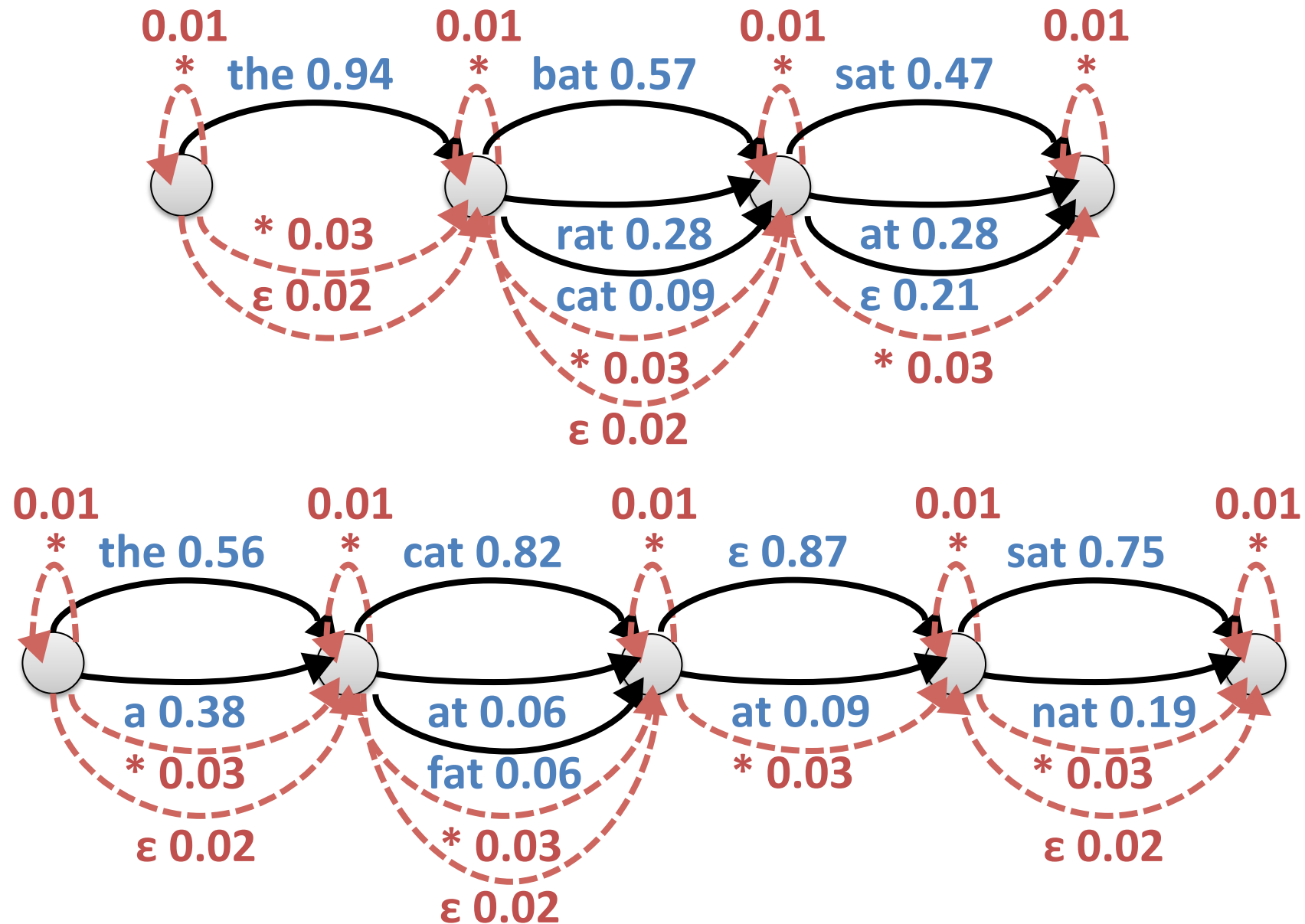
# Softening the word confusion networks: adding **epsilon transitions**



# Softening the word confusion networks: adding **wild-card self-loops**



# Search for the highest joint path in both recognition modalities



# Speech-only flexible repair



# Probabilistic error correction



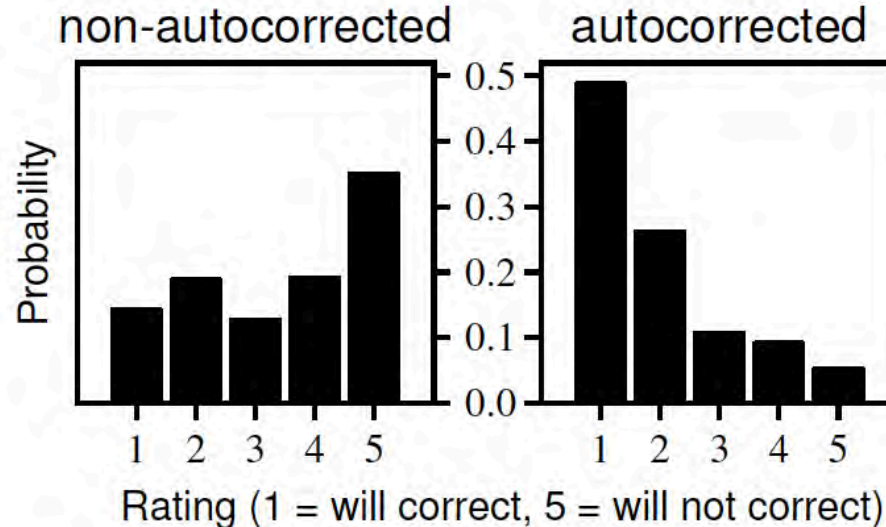
# Probabilistic error correction

- For any probabilistic text entry method...
  - Capable of assigning posterior probability distributions to words
- ...there exists a **hypothesis space**
- The best result is the maximum probability path in this hypothesis space
  - However, it need not be the one the user intended
- By exposing part of the hypothesis space to users, high efficiencies can be gained when users correct words

# Fluid regulation of uncertainty

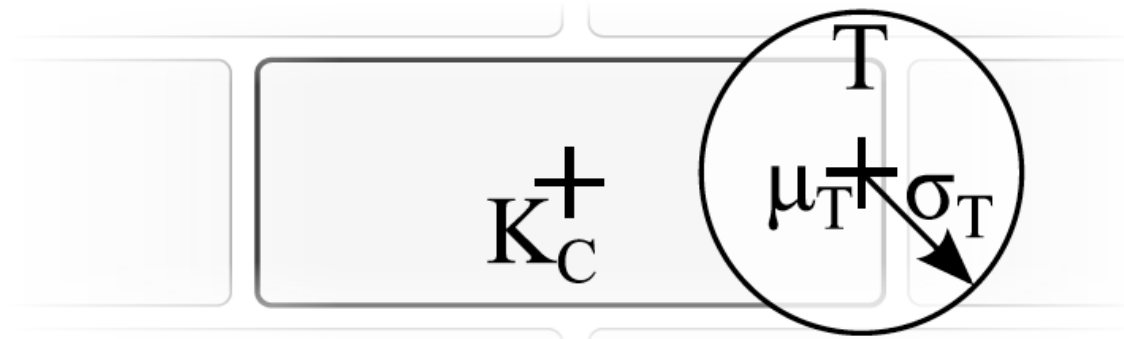
# The auto-correct trap

- Auto-correct is great when it works
- However, when auto-correct fails error correction activities exhibit a high penalty
- The solution is to provide users with more **agency** and allow them to regulate their **certainty**



Weir, D., Pohl, H., Rogers, S., Vertanen, K. and Kristensson, P.O. 2014. Uncertain text entry on mobile devices. In *Proceedings of the 32<sup>nd</sup> ACM Conference on Human Factors in Computing Systems (CHI 2014)*. ACM Press: 2307-2316.

# Pressure-sensitive auto-correct

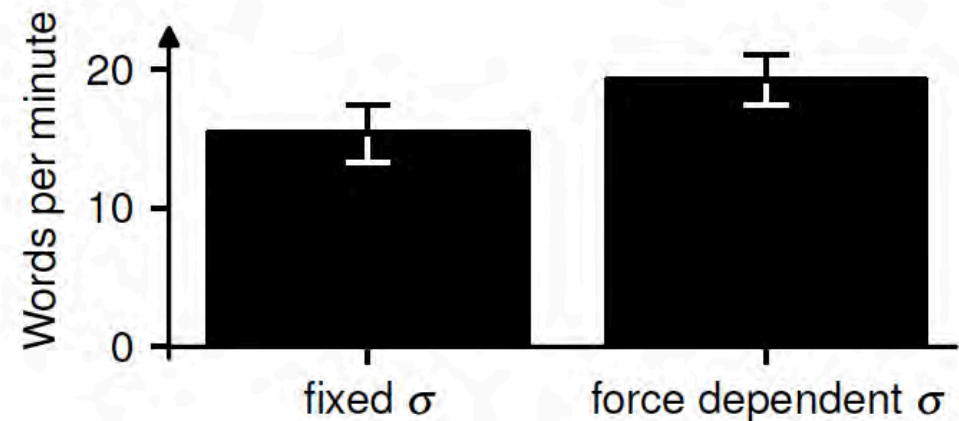


- Likelihood of a Gaussian with standard deviation regulated by pressure
- Standard deviation computed as  $C/\omega_T$ , where  $C$  is a constant and  $\omega_T$  is the pressure for touch  $T$
- Tuned  $C$  so that the pressure of a typical touch had a standard deviation of half a key width

Weir, D., Pohl, H., Rogers, S., Vertanen, K. and Kristensson, P.O. 2014. Uncertain text entry on mobile devices. In *Proceedings of the 32<sup>nd</sup> ACM Conference on Human Factors in Computing Systems (CHI 2014)*. ACM Press: 2307-2316.

# Results

- Enabling users to regulate their certainty by force resulted in a 10% percentage drop in active corrections (fixing a word by backspacing or retyping)
- This improved entry rate by 20%



Efficiency

# Eye-typing

Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Eye-typing


Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			



# Eye-typing

125 ms


Q	W	E	R	T	U	I	O	P
A	S	D	F	G	H	J	K	L
Z	X	C	V	B	N	M		



# Eye-typing

250 ms


Q	W	E	R	T	U	I	O	P
A	S	D	F	G	H	J	K	L
Z	X	C	V	B	N	M		



# Eye-typing

375 ms


Q	W	E	R	T	U	I	O	P
A	S	D	F	G	H	J	K	L
Z	X	C	V	B	N	M		



# Eye-typing

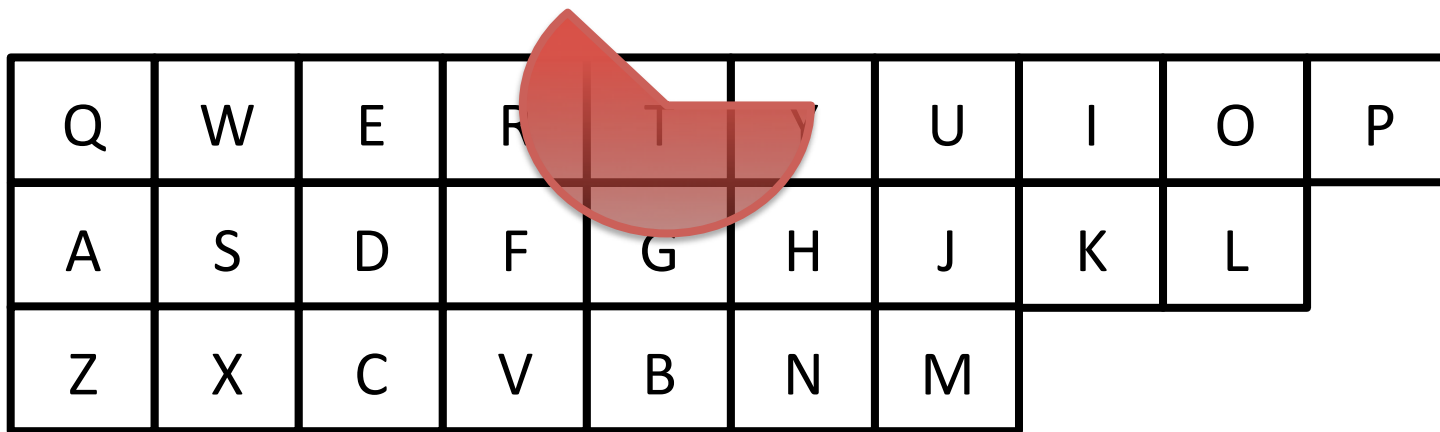
500 ms

Q	W	E	R		U	I	O	P
A	S	D	F	G	H	J	K	L
Z	X	C	V	B	N	M		



# Eye-typing

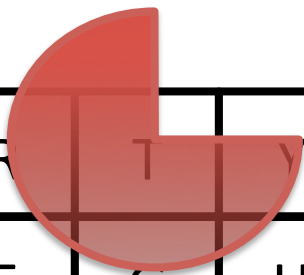
625 ms



Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Eye-typing

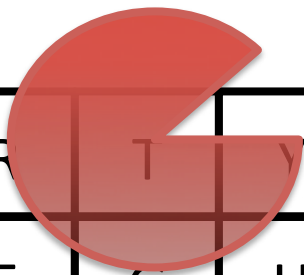
750 ms



Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Eye-typing

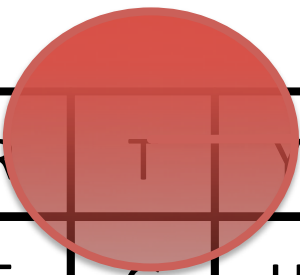
875 ms



Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Eye-typing

1000 ms



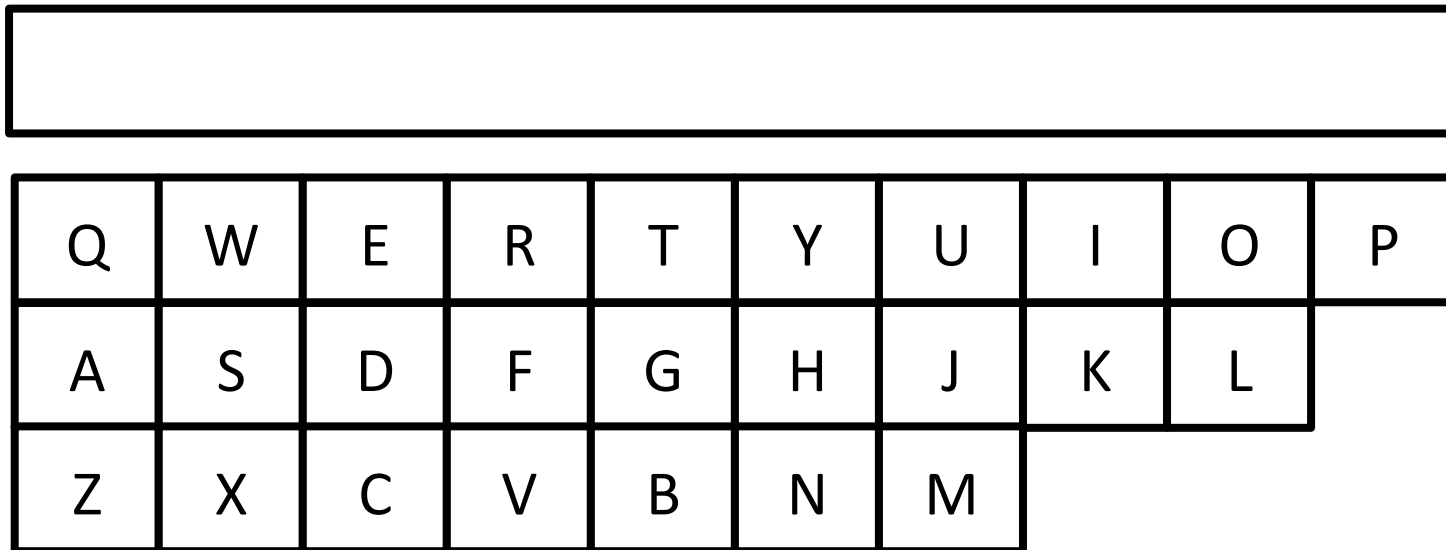
Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			



# Record speeds achieved when writing by gaze

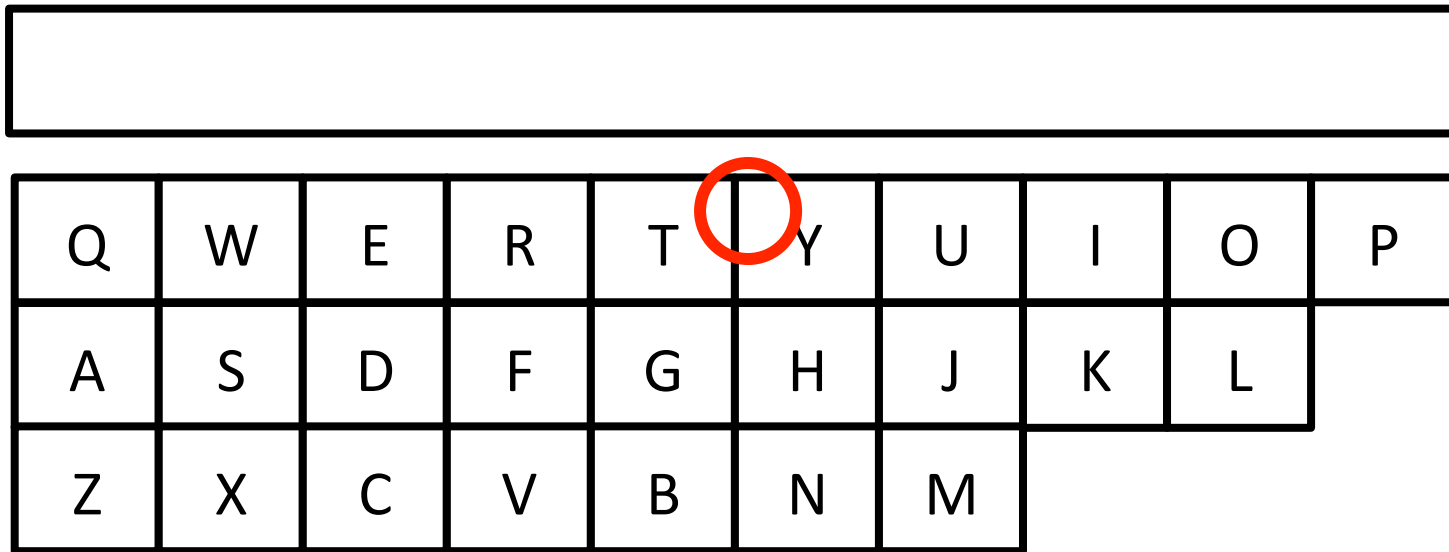
- **Eye-typing**
  - 5–10 wpm (Majaranta and Riih  2002; Rough et al. 2014)
- **Eye-typing with adjustable-dwell**
  - 7-20 wpm (Majaranta et al. 2009; Riih  and Ovaska 2012; Rough et al. 2014)
- **Dasher**
  - 12–26 wpm (Tuisku et al. 2008; Ward and MacKay 2002; Rough et al. 2014)

# Dwell-free eye-typing



Kristensson, P.O. and Vertanen, K. 2012. The potential of dwell-free eye-typing for fast assistive gaze communication. In *Proceedings of the 7th ACM Symposium on Eye-Tracking Research & Applications (ETRA 2012)*. ACM Press: 241-244.

# Dwell-free eye-typing



# Dwell-free eye-typing



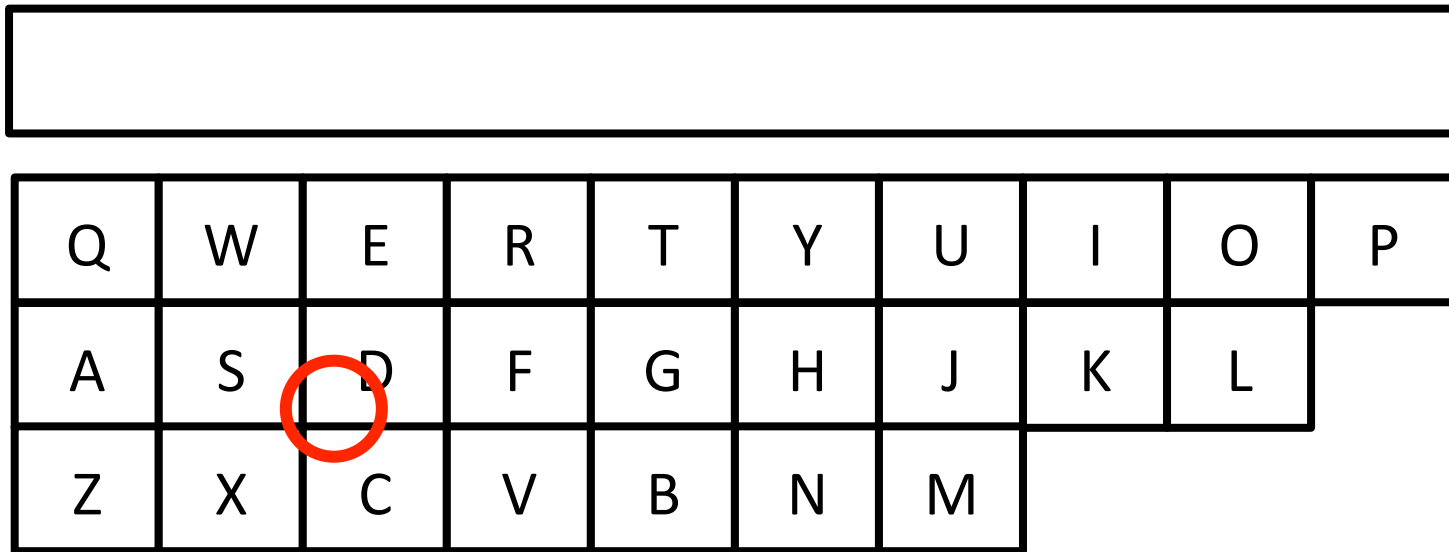
Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Dwell-free eye-typing



Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Dwell-free eye-typing



# Dwell-free eye-typing



Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

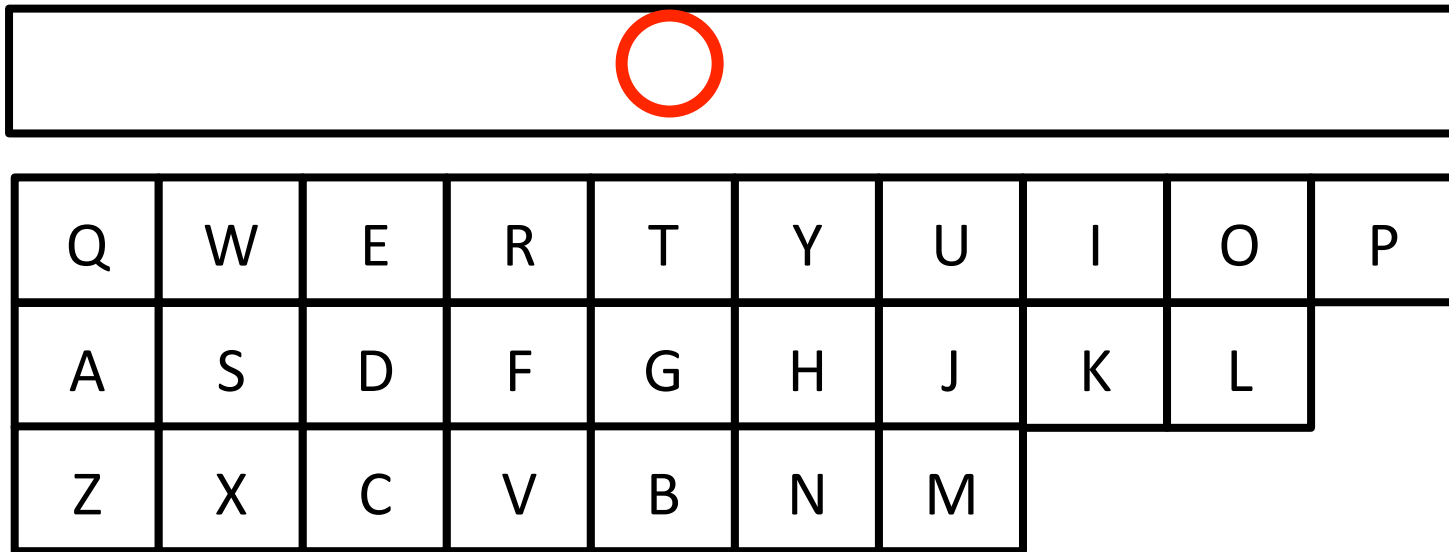
# Dwell-free eye-typing



Q	W	E	R	F	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			



# Dwell-free eye-typing

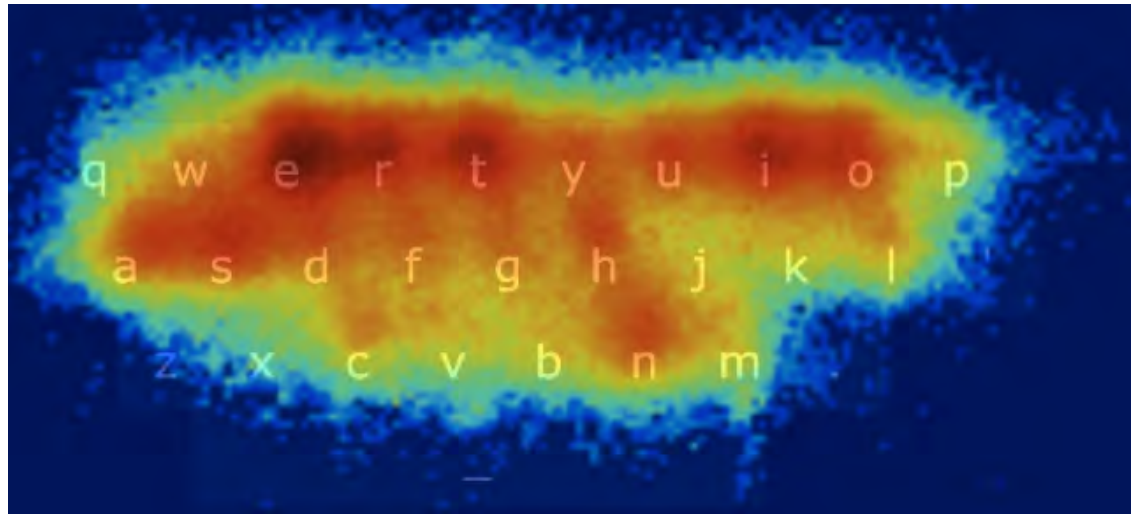


# Dwell-free eye-typing

The cat

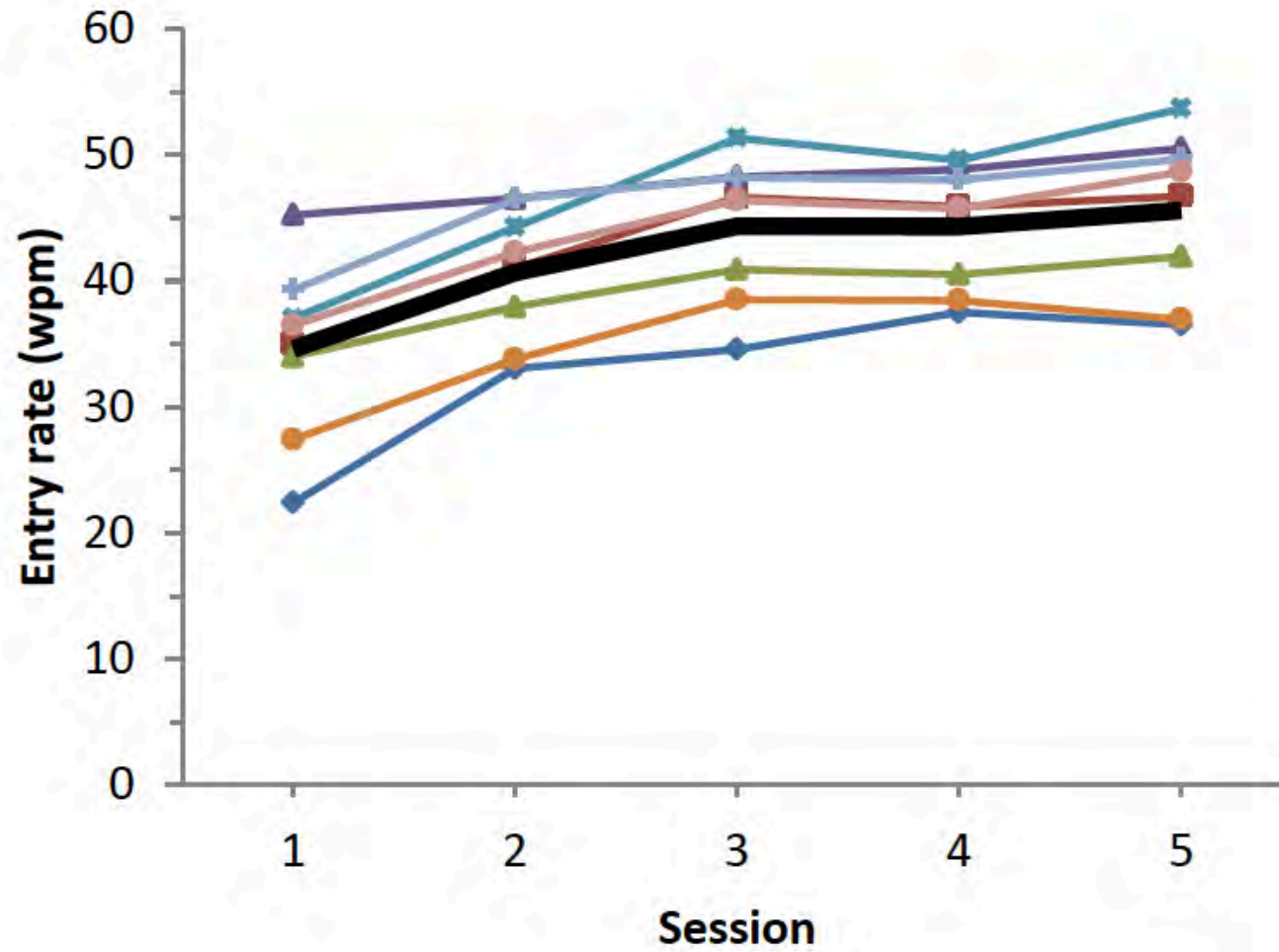
Q	W	E	R	T	Y	U	I	O	P
A	S	D	F	G	H	J	K	L	
Z	X	C	V	B	N	M			

# Human performance estimate of dwell-free eye-typing

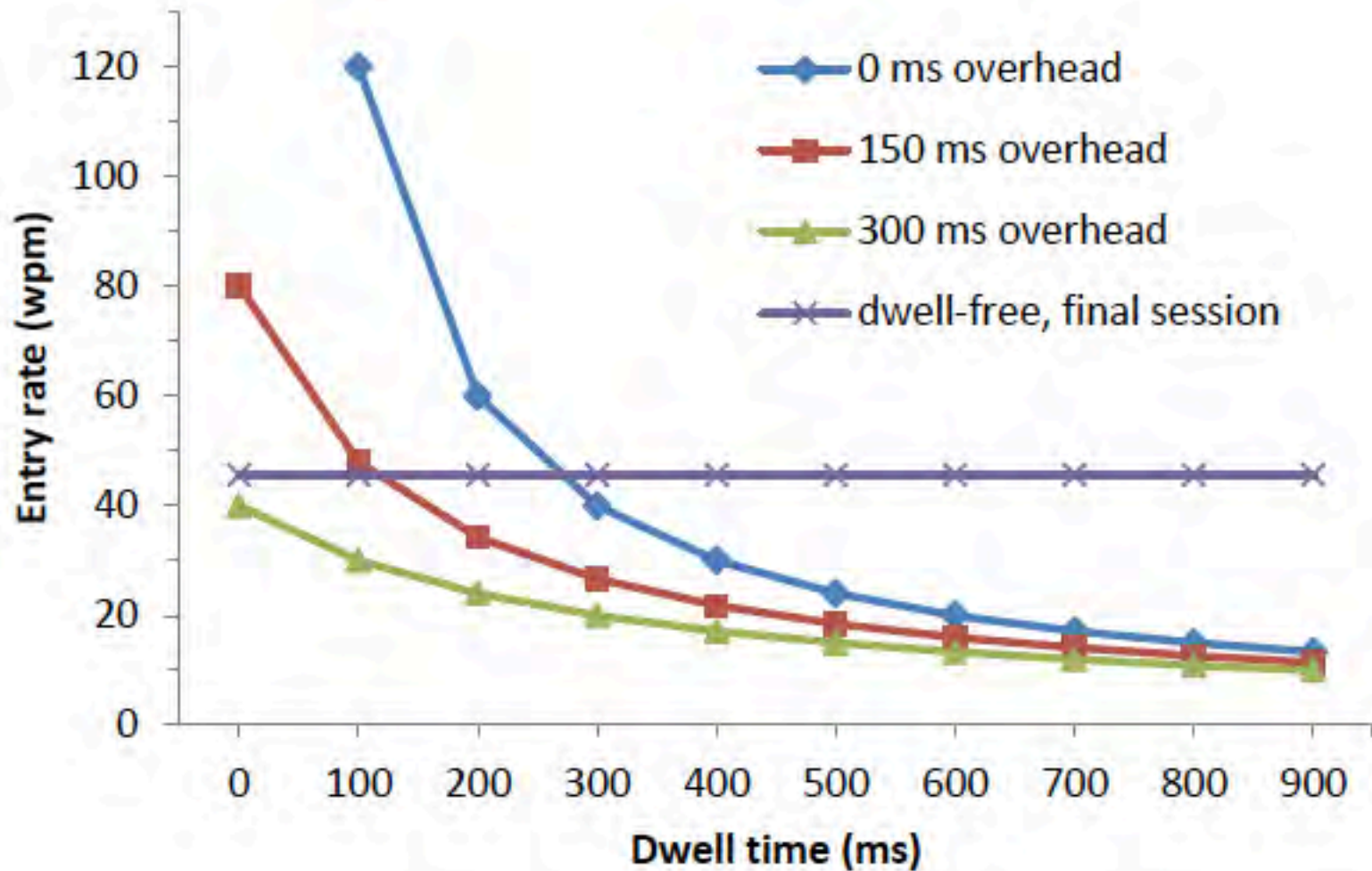


- Recorded 400 minutes of eye-trace data
- Participants entered a total of 2026 phrases
- Participants were prompted phrases and asked to copy them as quickly and as accurately as possible
- Our system knew what the user was supposed to write and verified that the user is gazing at the letter sequence corresponding to the stimulus

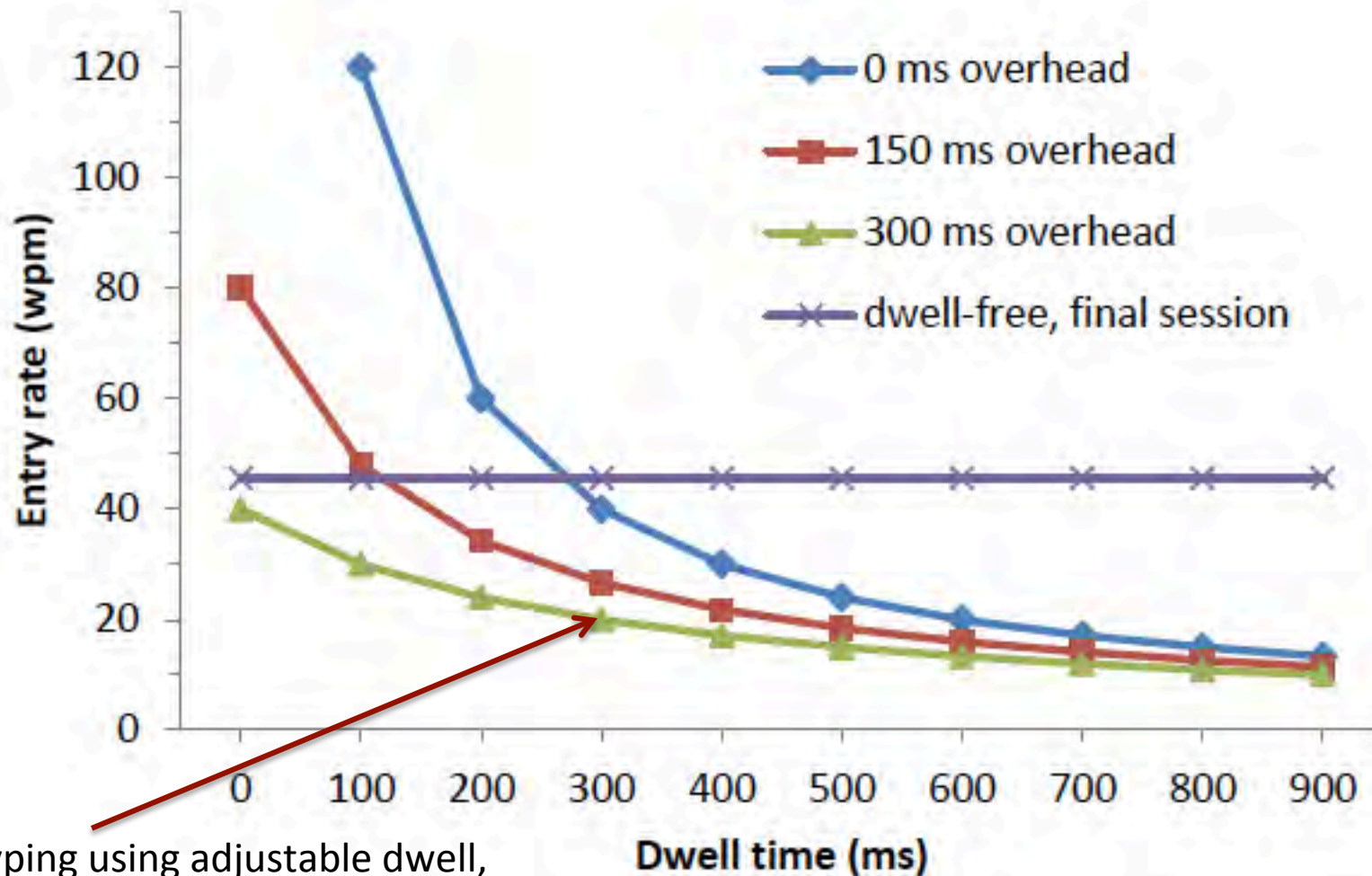
# Entry rate



# Human performance model

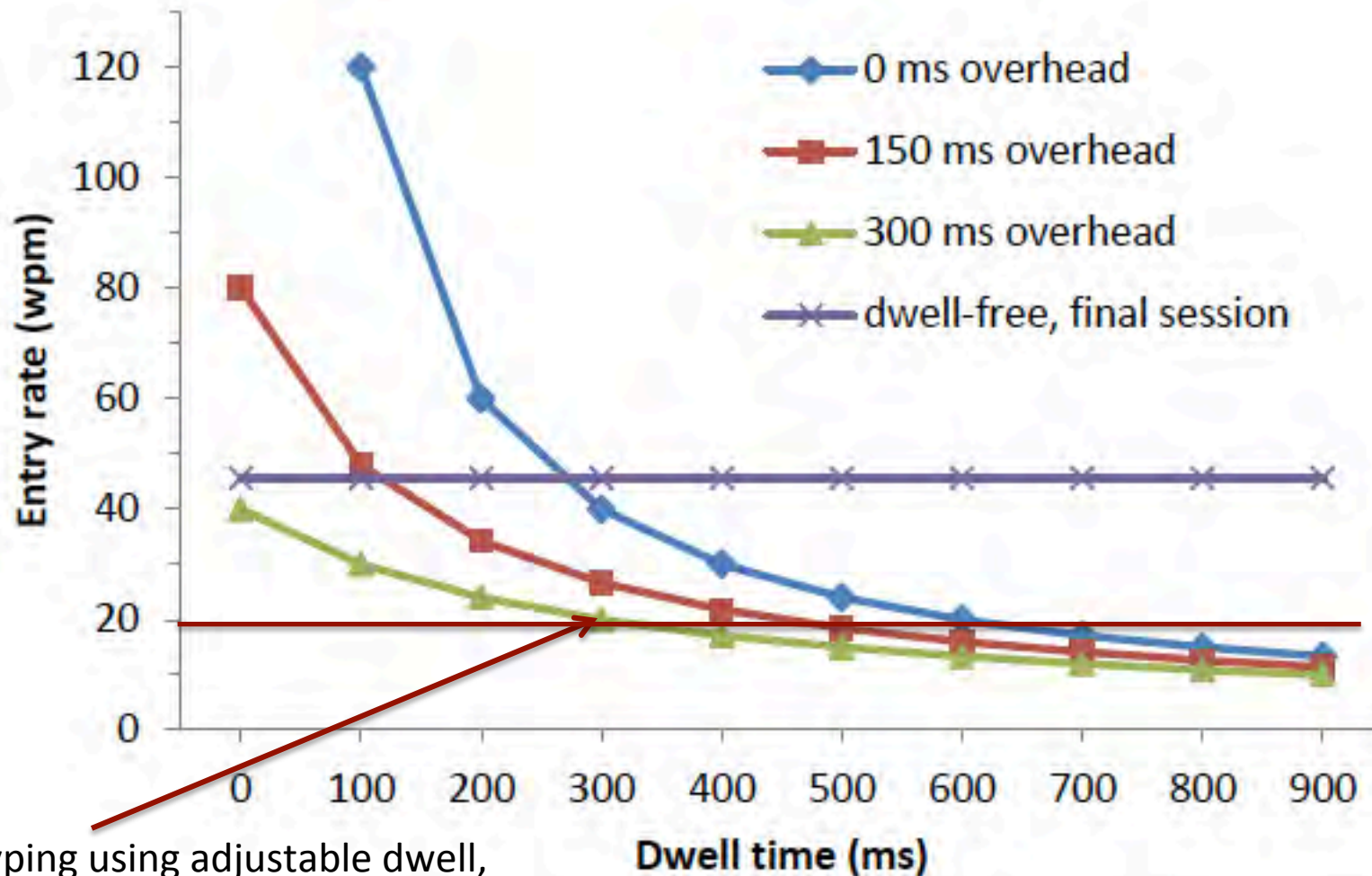


# Human performance model



Eye-typing using adjustable dwell,  
final entry rate (mean = 20 wpm)

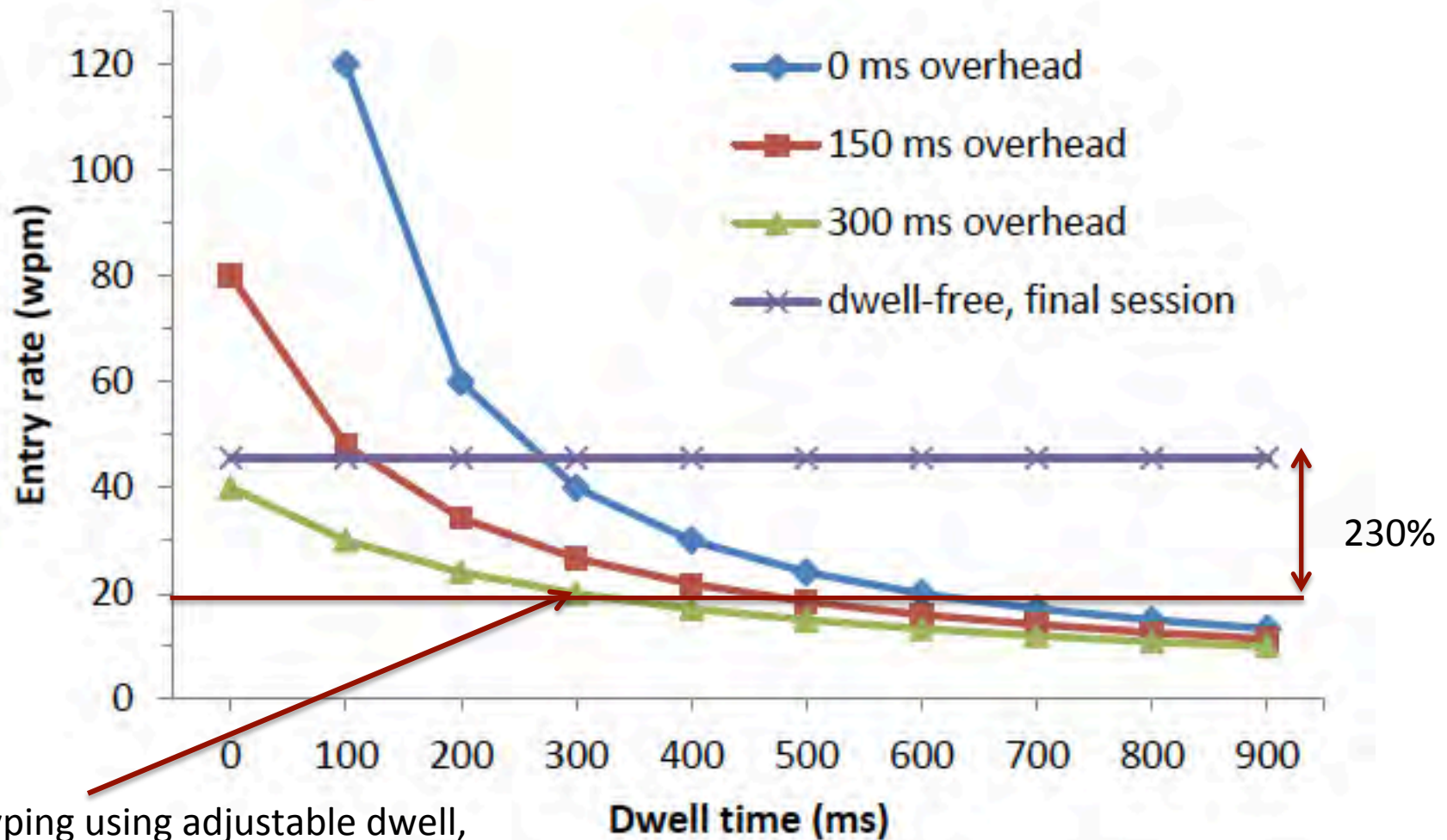
# Human performance model



Eye-typing using adjustable dwell,  
final entry rate (mean = 20 wpm)



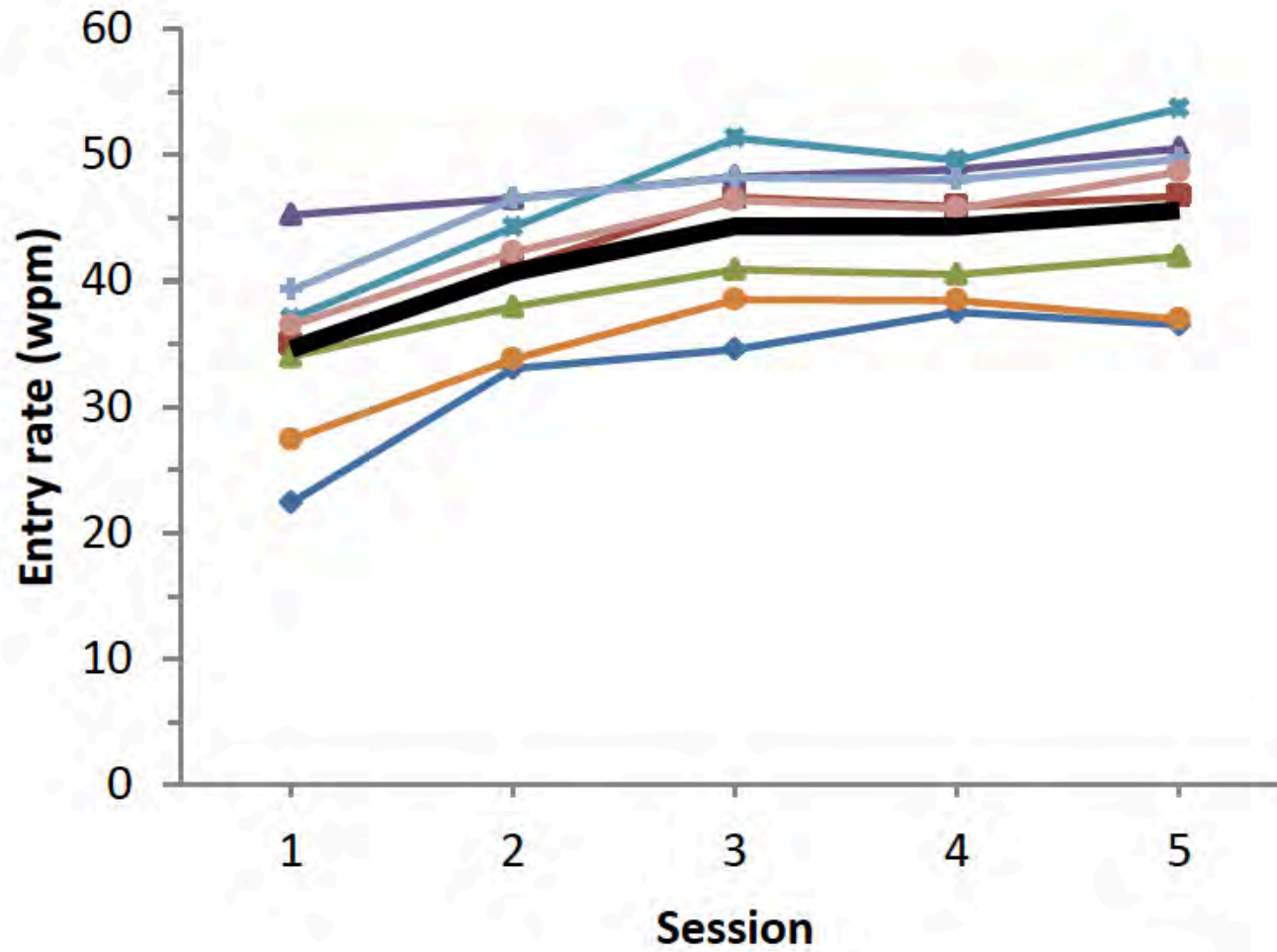
# Human performance model



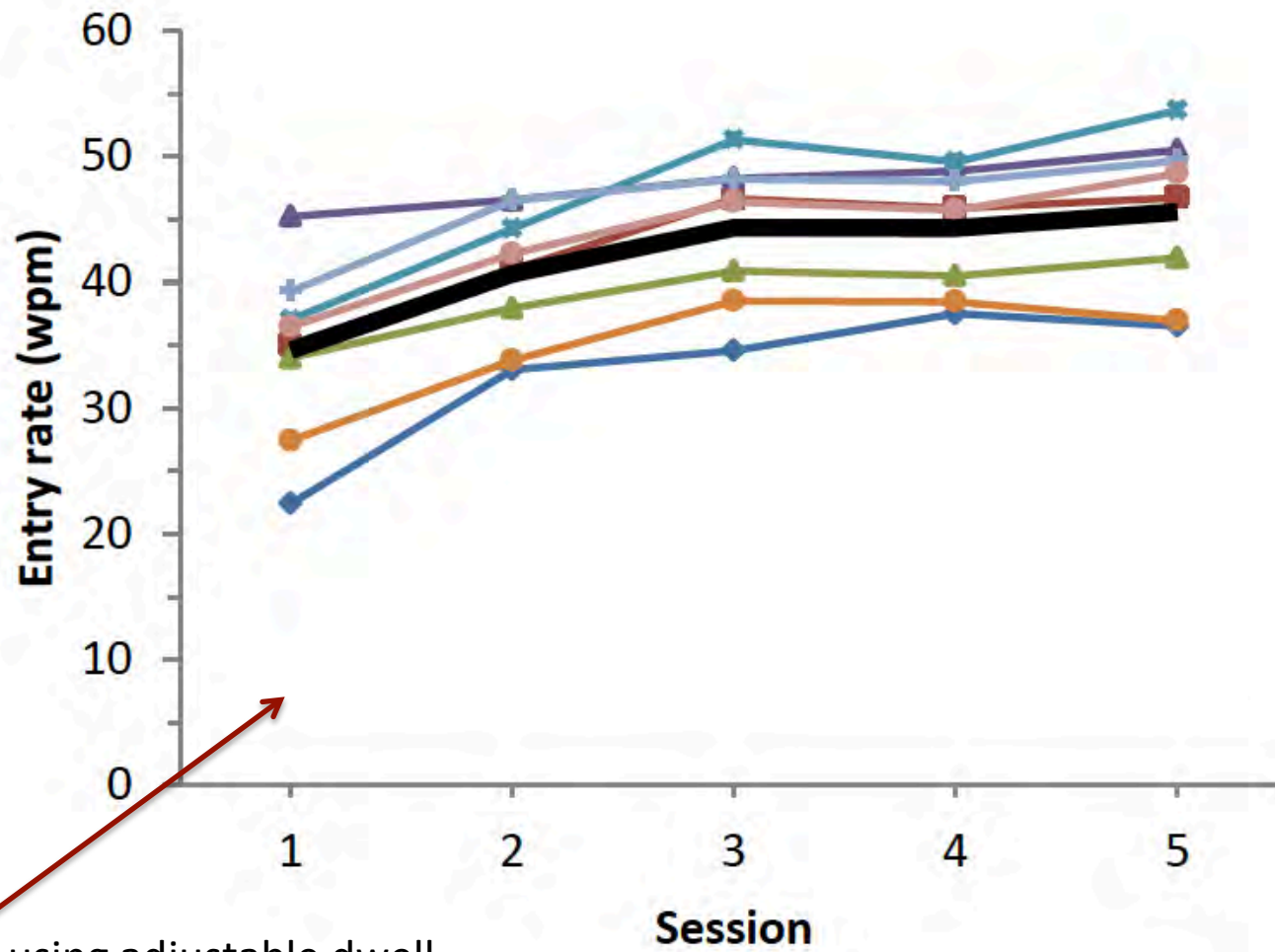
Eye-typing using adjustable dwell,  
final entry rate (mean = 20 wpm)



# Entry rate, first 10-15 minutes

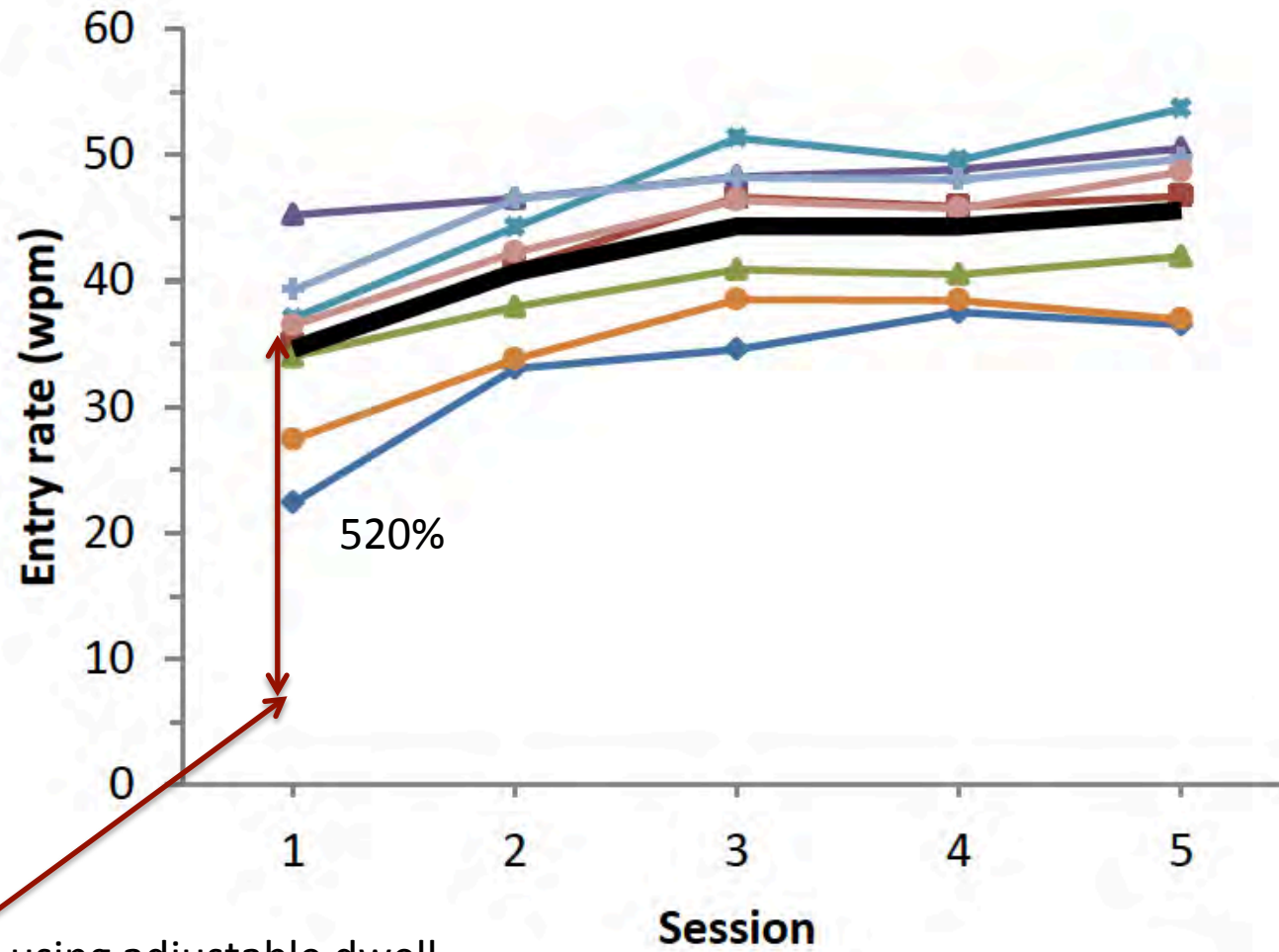


# Entry rate, first 10-15 minutes



Eye-typing using adjustable dwell,  
entry rate in the first session (mean = 6.9 wpm)

# Entry rate, first 10-15 minutes



Eye-typing using adjustable dwell,  
entry rate in the first session (mean = 6.9 wpm)

# A step-change in gaze communication

- **Existing gaze communication solutions**
  - Limited to circa 20 wpm
- **Dwell-free eye-typing**
  - Empirically measured human performance potential: 46 wpm average
- Released as a product: Tobii-Dynavox I-Series+

# Conclusions

- A text entry method likely to be adopted by users is probably similar to existing solutions and at least as fast
- It is still possible to make progress by using a few solution principles:
  - From closed to open-loop
  - Continuous novice-to-expert transition
  - Path dependency
  - Flexibility
  - Probabilistic error correction
  - Fluid regulation of uncertainty
  - Efficiency
- In general, these can be viewed as **solution principles for uncertain interaction**