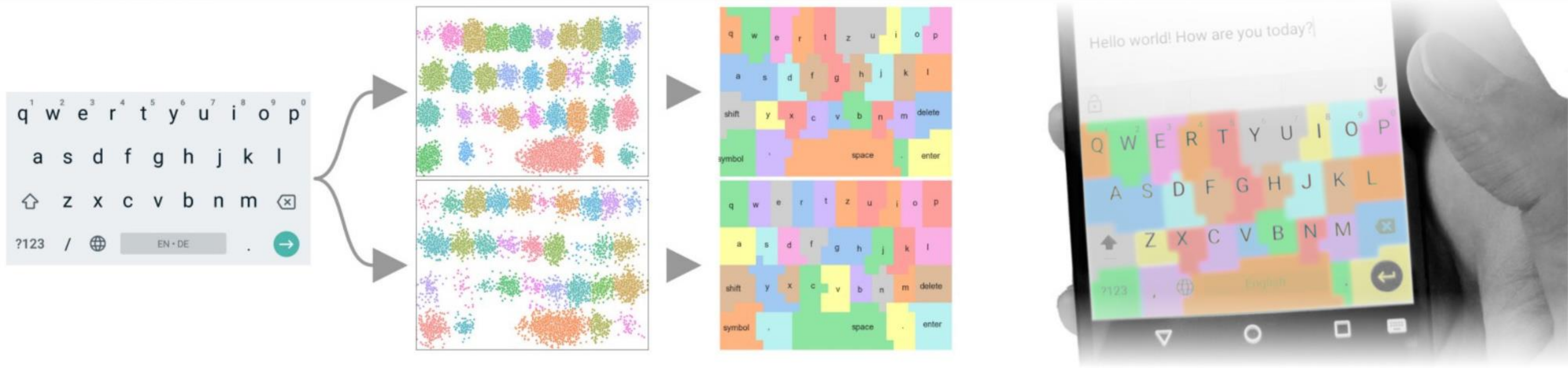


Adaptive and Predictive Keyboards

Daniel Buschek

Learning Goals

- Challenges of mobile touch and typing
- Modelling typing behaviour
- Probabilistic methods for keyboard adaptation and input decoding

Motivation: Fast typing without errors

Here: mobile devices

- „Inviscid entry rate“: Bottleneck is not the text entry UI but coming up with the text
- Estimated as 67 WPM

→ Try to reach this on your phone without errors, e.g. in an online typing speed test.

Text entry method	Highest reported entry rate (wpm)
Estimate of the inviscid entry rate	*67*
Physical thumb keyboards	60 [3]
Gesture keyboards	45 [9]
Optimized on-screen keyboards	45 [12]
QWERTY on-screen keyboards	40 [12]
KALQ thumb keyboard	37 [14]
Half-QWERTY	35 [13]
Twiddler	35 [11]
WalkType	31 [5]
ContextType	28 [6]
Disambiguating keypads	26 [7]
Unconstrained handwriting recognition	25 [8]
Dasher	20 [21]
Mobile speech	18 [18]
Quikwriting	16 [15]
Unistrokes	16 [1]
TiltText	14 [22]
Multi-tap	12 [23]
Graffiti	11[1]
EdgeWrite	7 [24]

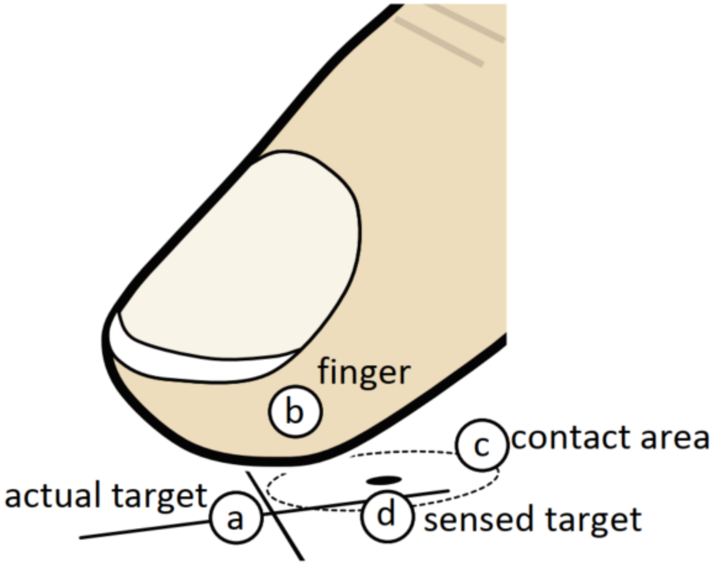
[Kristensson and Vertanen 2014]

Challenges for Mobile Typing

Why is it inaccurate?

Parallax

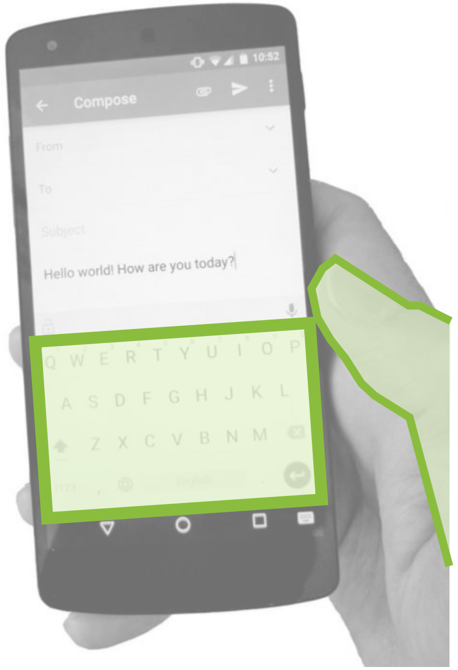
eye – finger - screen



[Holz and Baudisch 2011]

Mobile use

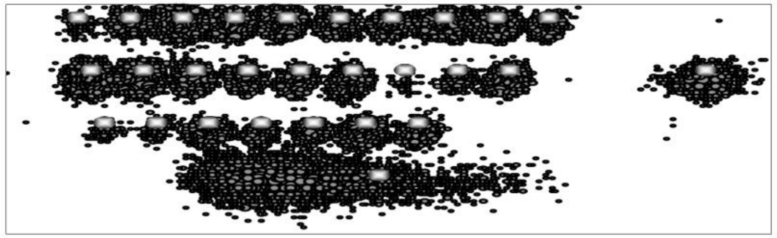
1-2 fingers, small keys, body movement



Variance in Touchscreen Keypresses

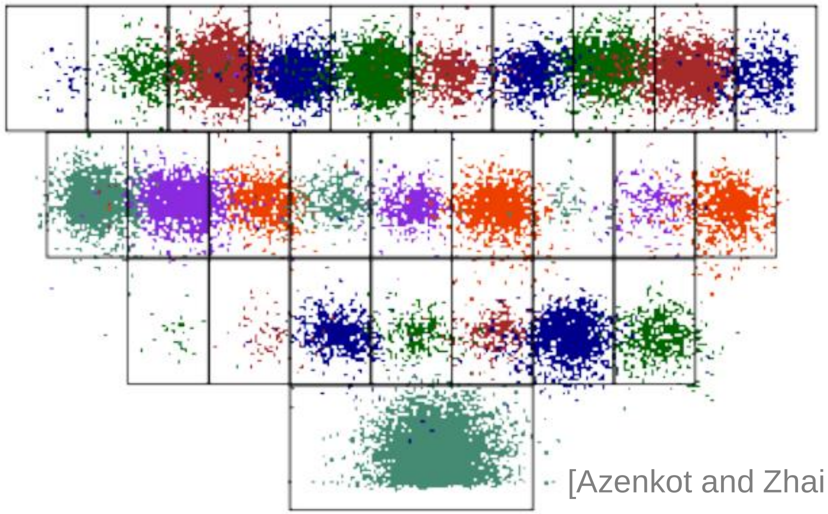
Spread of x,y touch locations around key centres

PDA



[Goodman et al. 2002]

Smartphone

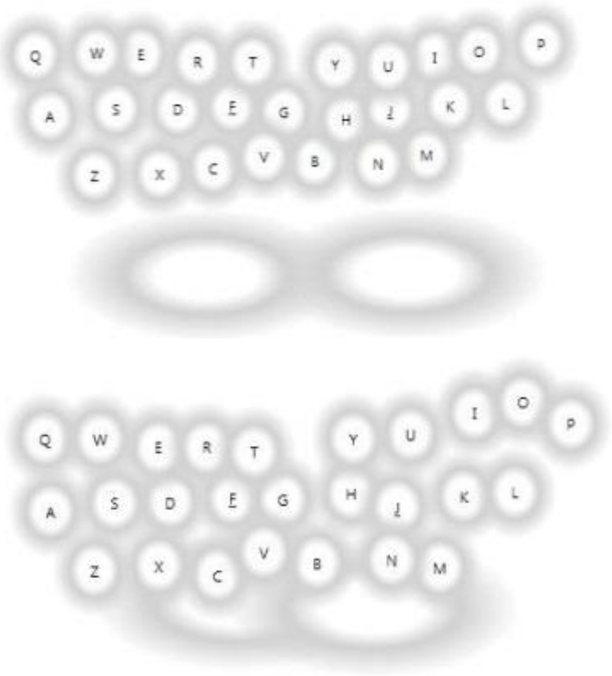


[Azenkot and Zhai 2012]

https://www.microsoft.com/en-us/swiftkey

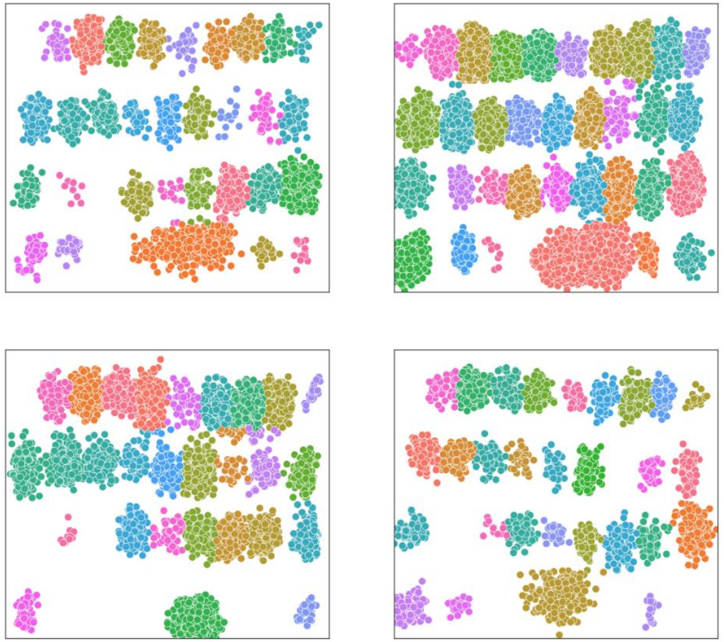
Individual Typing Behaviour

Tabletop



[Findlater and Wobbrock 2012]

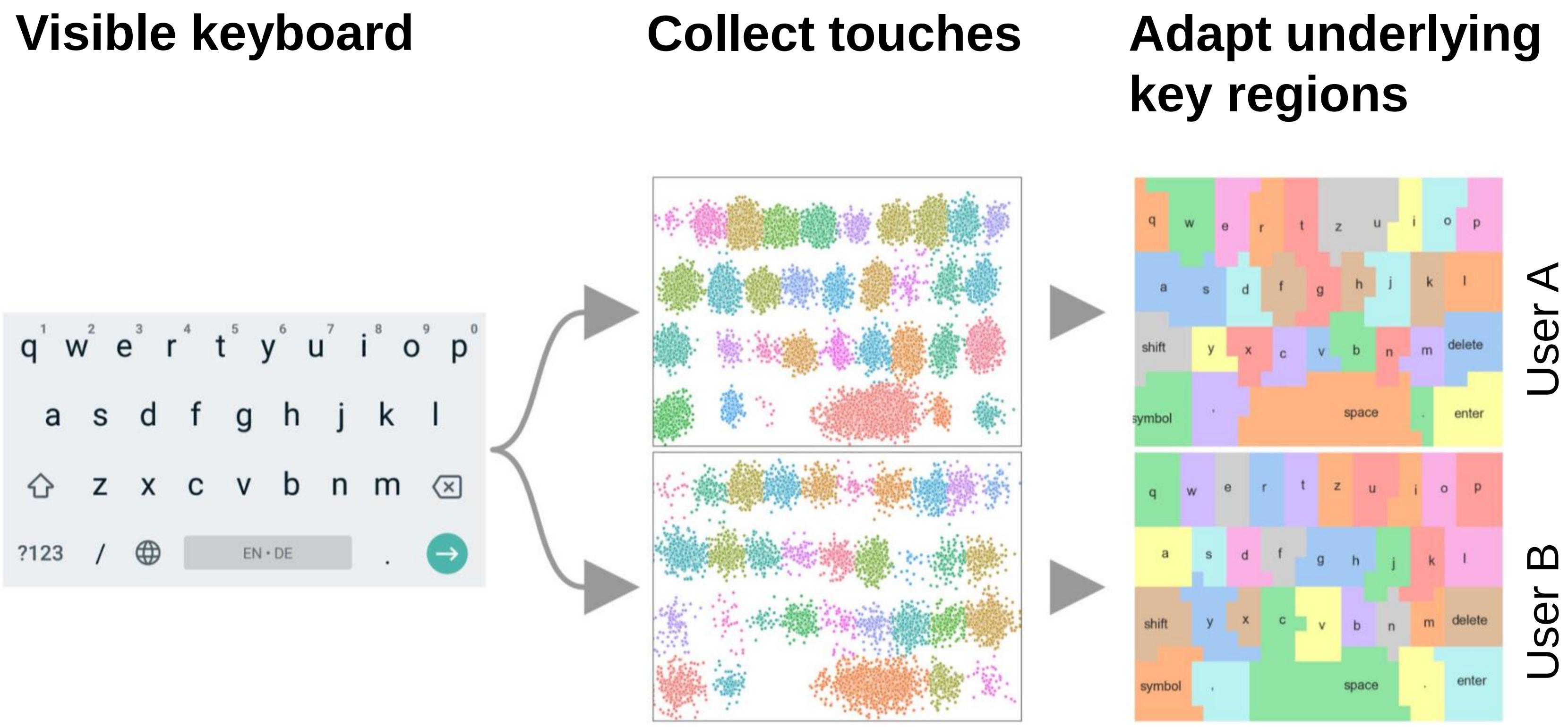
Smartphone



[Buschek et al. 2018]

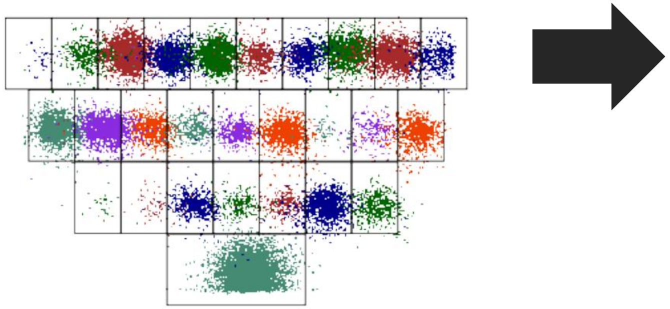
Adapting Keyboards to Typists

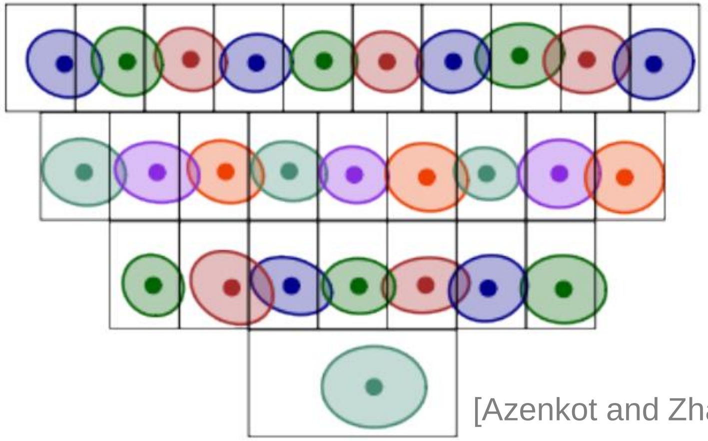
Overview



Modelling Touchscreen Keypresses

From x,y touch points to one Gaussian per key



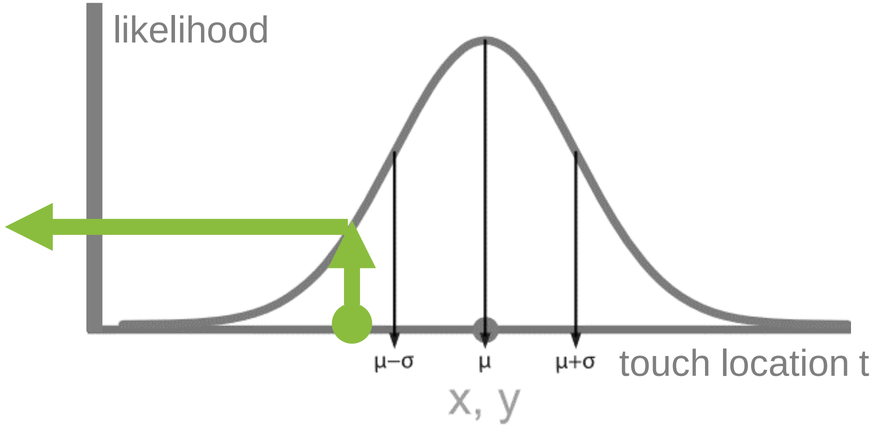


[Azenkot and Zhai 2012]

Gaussian key model:

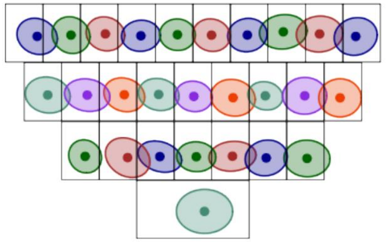
(shown in 1D here)

$$p(t|k) = \mathcal{N}(\mu_k, \sigma_k^2)$$



Probabilistic Keyboard Model

Which key does the user intend to press? i.e. „input decoding“



Gaussian key model

Language model

e.g. based on last five characters:
$p(k_n|k_{n-1}..k_{n-5})$

$$k' = \underset{k \in K}{\operatorname{argmax}} \underbrace{\left(\frac{p(t|k)p(k)}{p(t)} \right)}_{\text{Bayes' rule} = p(k|t)} = \underset{k \in K}{\operatorname{argmax}} \left(p(t|k)p(k) \right)$$

predicted keypress

Evaluate and colour ***k'*** for each pixel

[Yin et al. 2013]

DIY: Probabilistic Keyboard Model

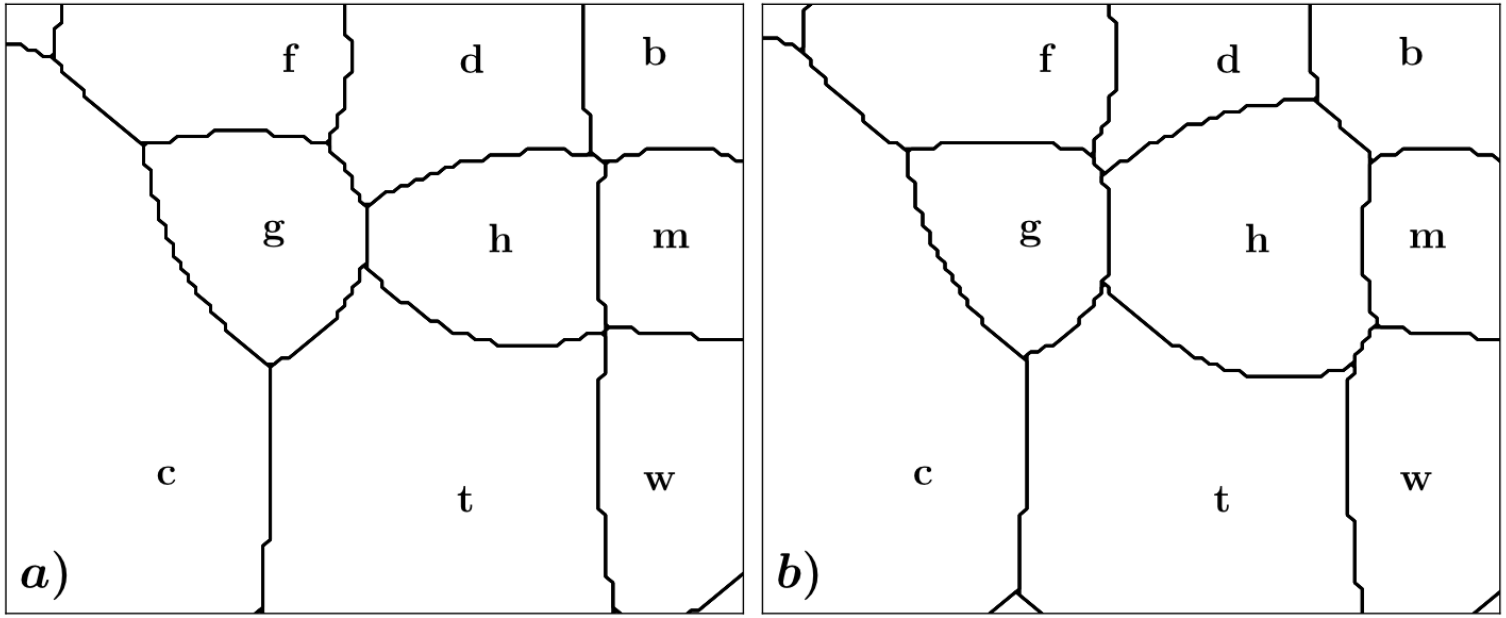
```
touchX = ... // touch X coordinate
touchY = ... // touch Y coordinate
num_keys = ... // number of keys on keyboard
means = [...] // list of all key means (2D key locations)
variances = [...] // list of key variances (real values) or covariances (2x2 matrices)

probs = [] // list to store the likelihoods of each key being pressed
sum = 0 // variable to store sum of likelihoods for normalisation (see below)

for k = 0 to num_keys: // iterate over all keys
    // evaluate touch location under distribution of the key*:
    prob_t_given_k = multinormal_pdf(touchX, touchY, means[k], variances[k])
    // likelihood of key without touch info; uniform (here), or based on language*:
    prob_k = 1/num_keys
    // store product and add it to the sum of all likelihoods*:
    probs[k] = prob_t_given_k * prob_k
    sum = sum + probs[k]

// normalise, so that the likelihoods add up to 1*:
probs = probs / sum //note: "/" is element-wise division

// find most likely key:
pressed_key_index = argmax(probs)
// TODO for adaptation: update means and variances with new touchX and touchY
```

* in real implementation use logarithm and corresponding operations for numerical stability

Language Model Influence

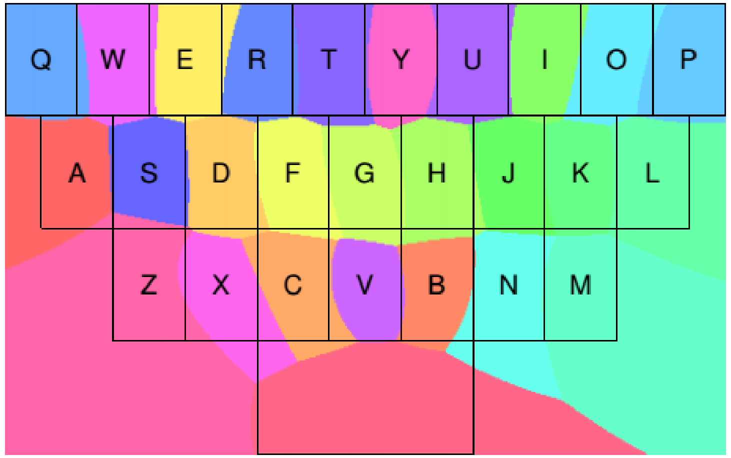
Example: bigram model for English

After „**n**“: After „**t**“:



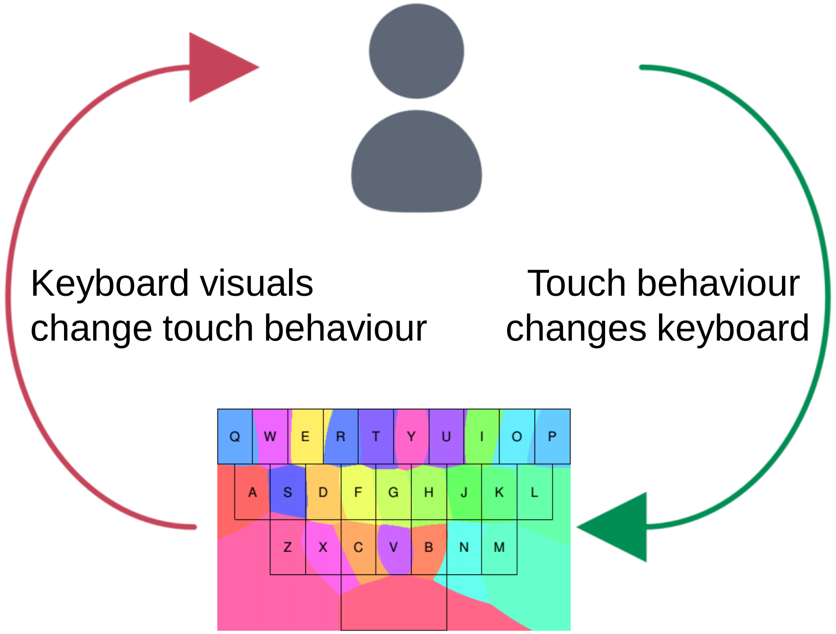
Adaptation in the Background

Why do our keyboards not look like this?



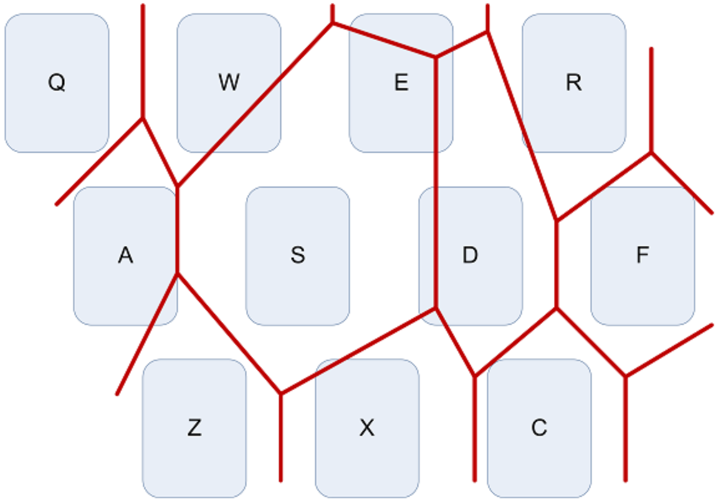
[Yin et al. 2013]

→ Avoid co-adaptation of user and system



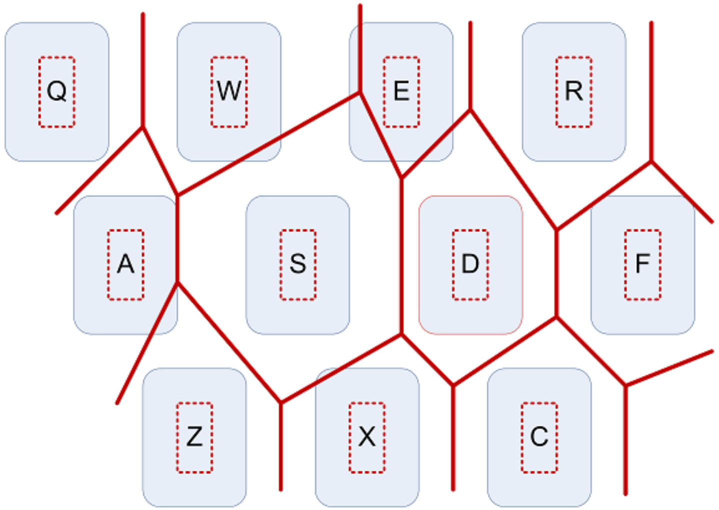
Adaptation vs Distortion

Unlimited adaptation



Here: (almost) impossible to type „e“!

With protected key region



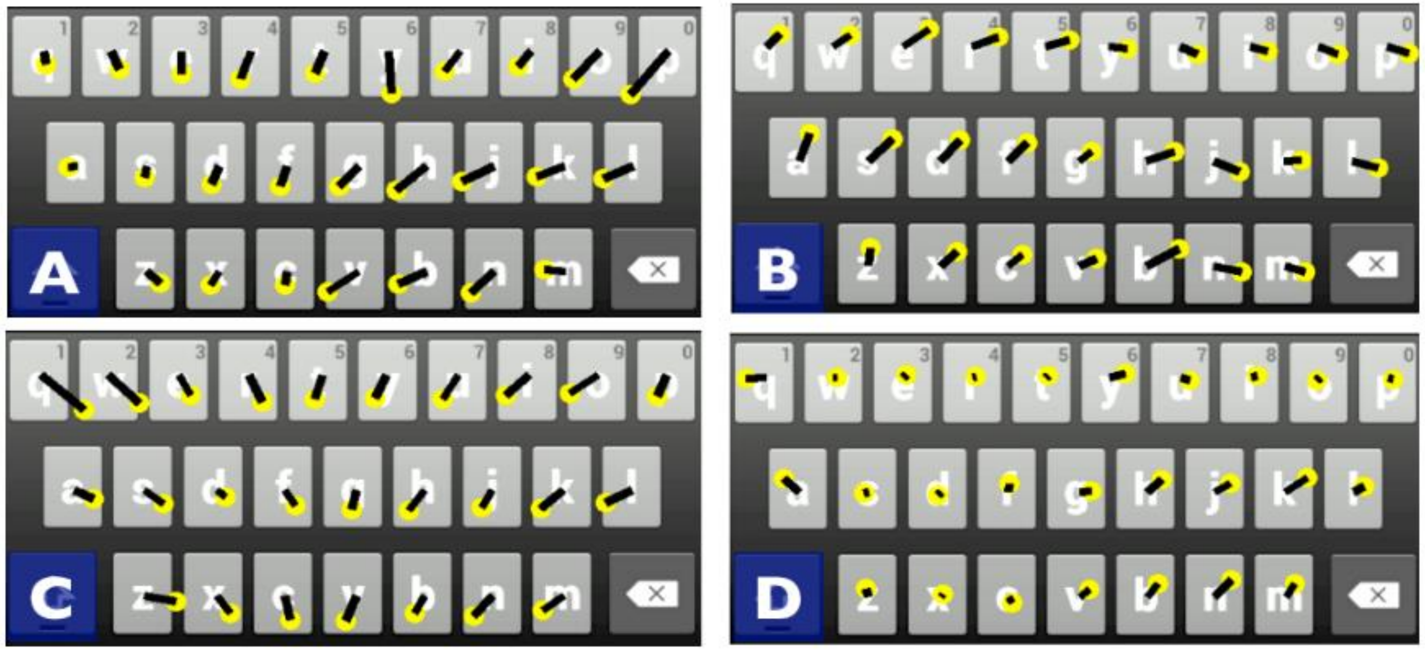
[Gunawardana et al. 2010]

Context Adaptations

e.g. hand posture – „ContextType“, Goel et al. 2013

Left thumb

Right thumb



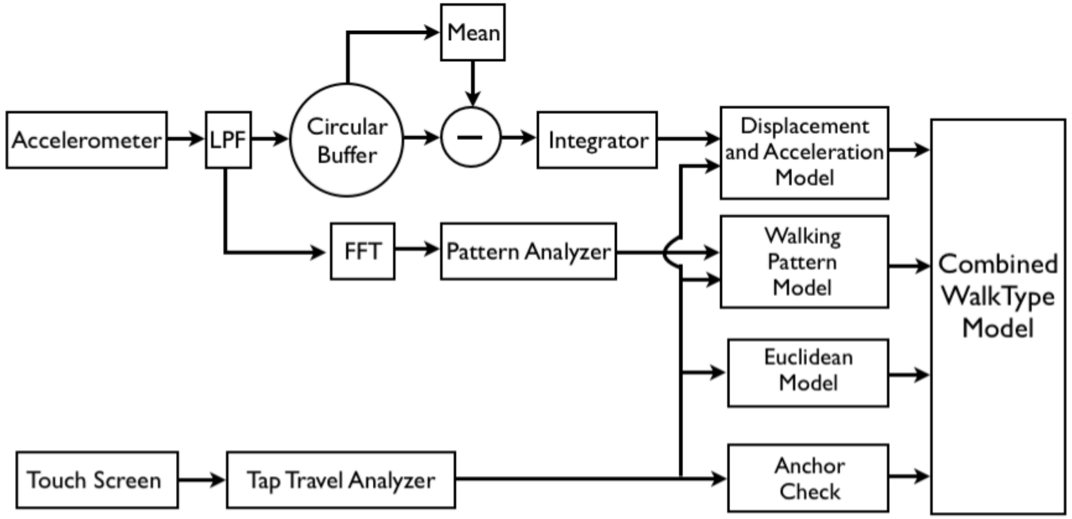
Index finger

Two thumbs

[Goel et al. 2013]

Context Adaptations

e.g. walking – „WalkType“, Goel et al. 2012



[Goel et al. 2012]

Decoding Typing Sequences

- Infer intended input after entering whole word or sentence
  - \+ More evidence for inference
  - \+ No need for user to pay attention to intermediate output
  - − No intermediate feedback

- Example (sentence-based decoding):

„pleaseforwarxmetheatachement“

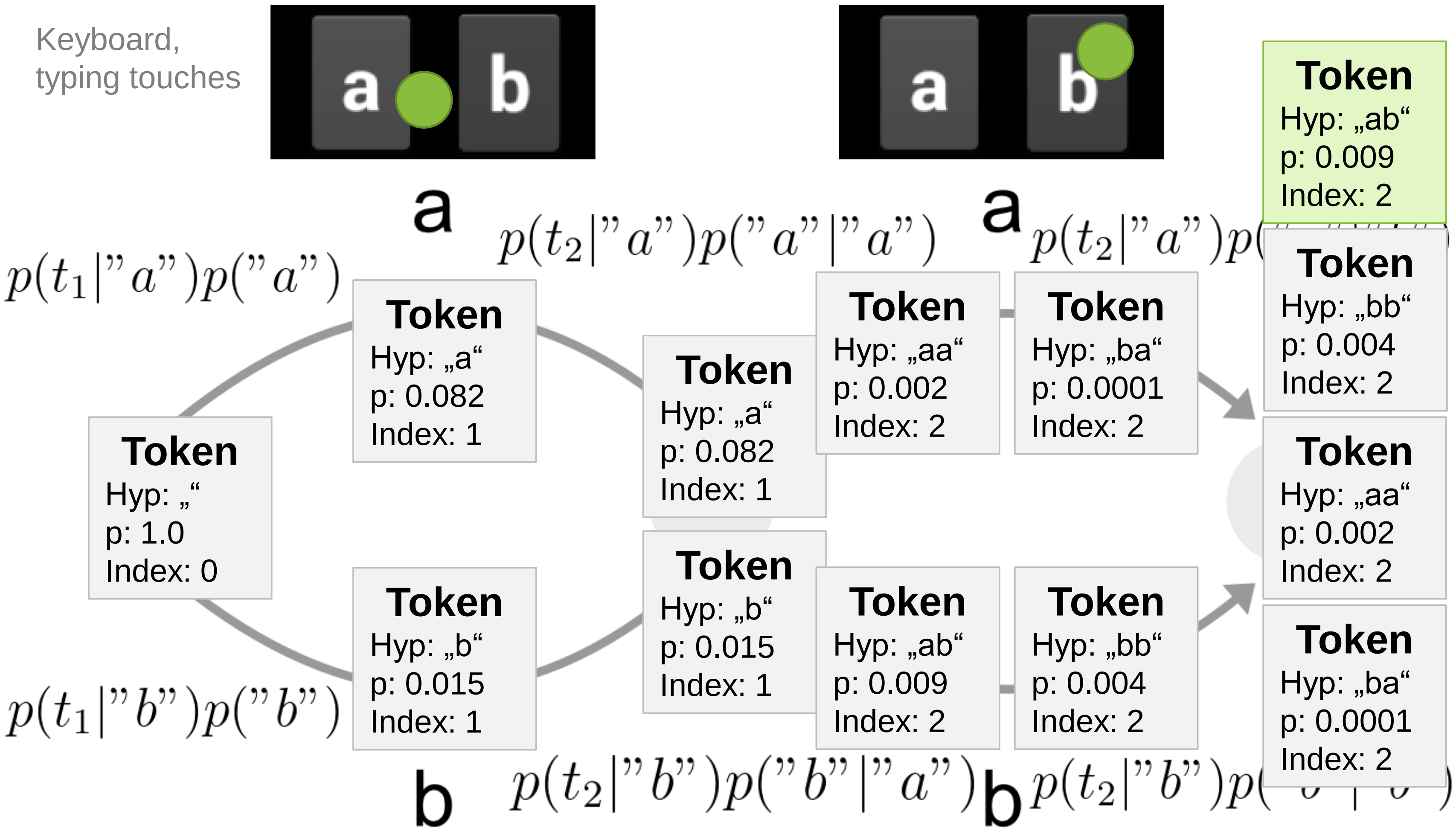
Hit enter ↵

„Please forward me the attachement.“

[Vertanen et al. 2015]

Decoding Typing Sequences

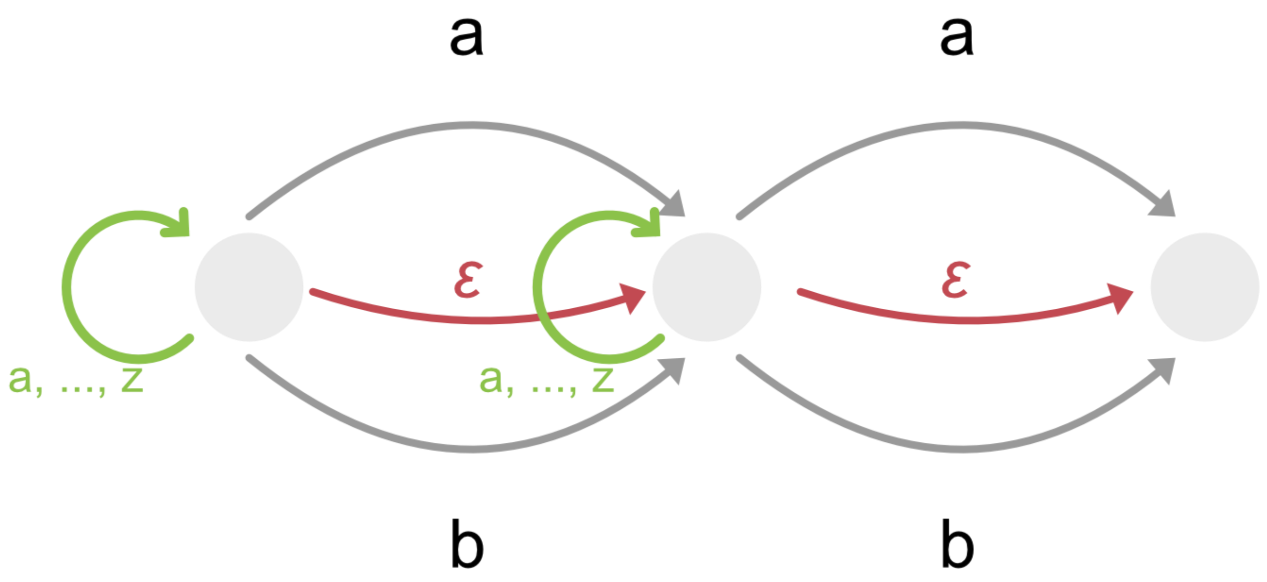
Token passing algorithm



Decoding Typing Sequences

With insertion and deletion

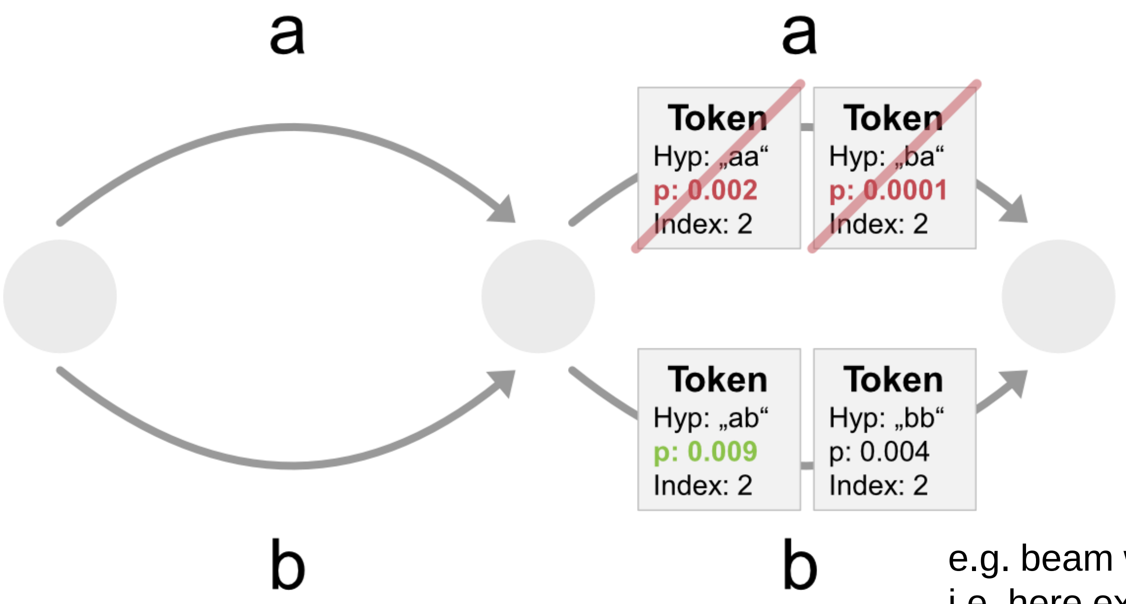
- Previous slide: Substitution-only decoder
- Extensions: **insertion** and **deletion** transitions, with „penalty“



Decoding Typing Sequences

With beam search / pruning

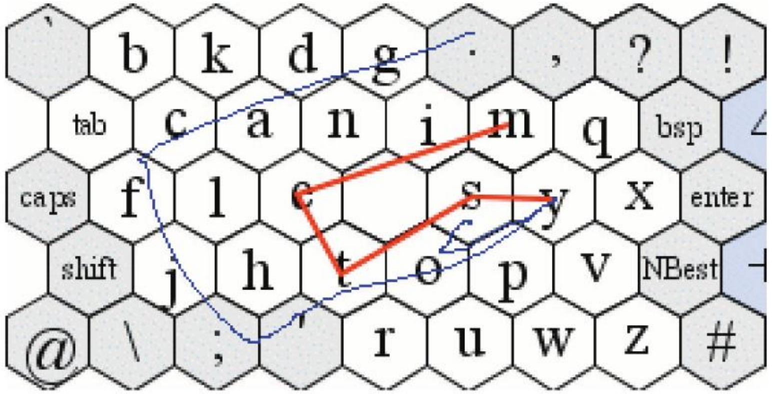
- Problem: Large search space
  Substitution-only → exponential, Insertion → infinite
- Solution: **Beam search / pruning**
  Per index, only propagate tokens that are within a certain range (=„beam width“) of the probability of the most likely token.



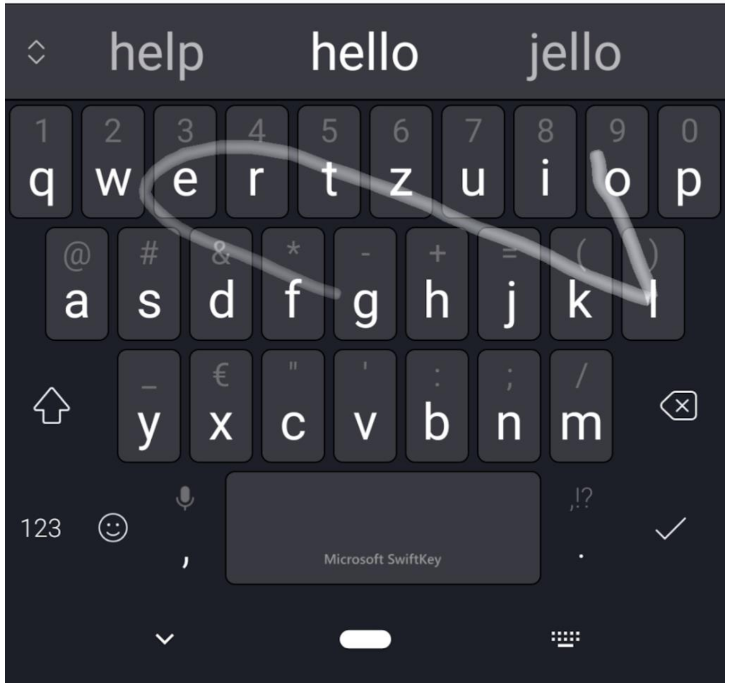
e.g. beam width = 0.005,
i.e. here exclude p < 0.009-0.005=0.004

Gesture-based Decoding

Infer intended word from shape of finger trace on the keyboard



„SHARK2“ [Kristensson and Zhai 2004]



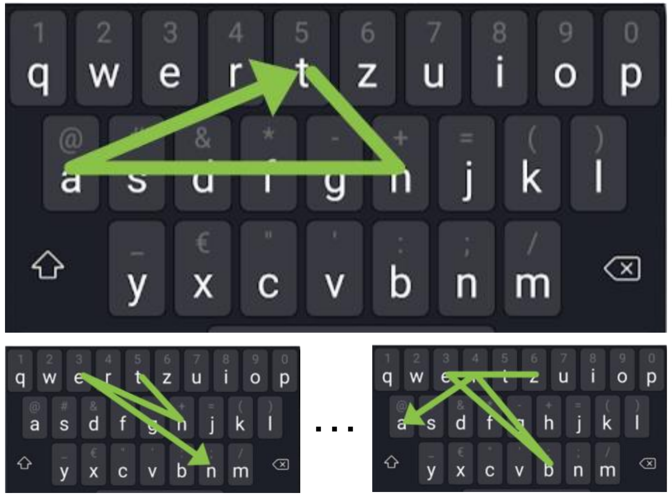
Microsoft SwiftKey (screenshot Nov 2020)

Gesture-based Decoding

Shape model Language model

$$w' = \text{argmax}_{w \in W}(p(trace|w)p(w))$$

Stored template (ideal) shapes for all words in dictionary W



Distance metric

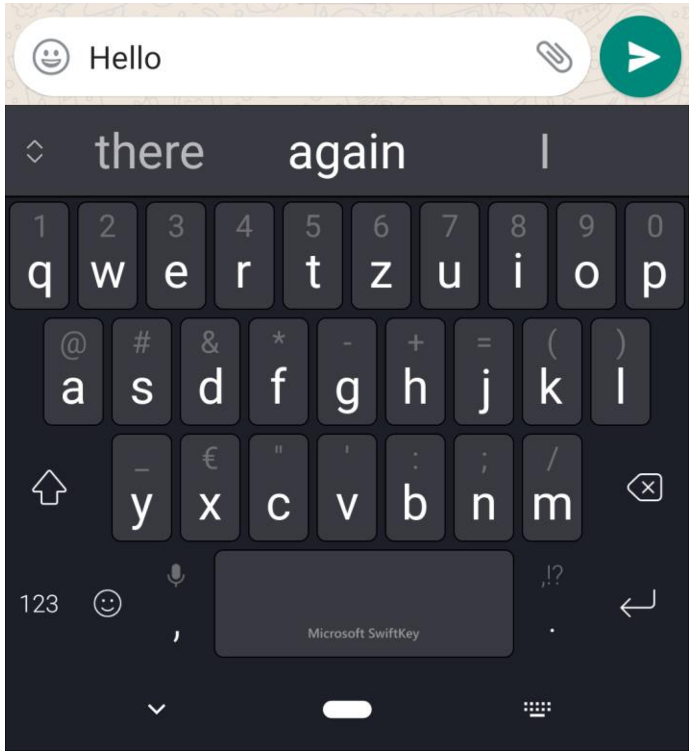
e.g. see Kristensson and Zhai, 2004

User‘s touch trace

Word Prediction

- So far: Inference used touch input
- Now: Predict *next* word that user has not yet started to type, only using language context

$$p(w_t | w_{t-n} \ldots w_{t-1})$$



- E.g. n-gram word models, i.e. context of last n-1 words
- More recently: Deep Learning to include larger context

Summary

- Improving keyboards by probabilistically combining input information with language information

- **Adaptation:**
  - Individual input behaviour → adaptation to typist
  - Further sensors → adaptation to context

- **Prediction/Decoding:**
  - Single touch + language context → current key
  - Touch sequences + language context → current word/sentence
  - Language only → next word(s)

Questions & Discussion

- Which problems do adaptive and predictive keyboards address?
- Explain how touch information and language information can be combined for keyboard adaptation. What effect does this achieve at the pixel level?
- Explain decoding of touch sequences with token passing and beam pruning.

- Are adaptive and predictive keyboards „deceptive“?
- Which (further) factors could be considered for adaptation and word prediction in keyboards?
- Which other UIs beyond keyboards could benefit from similar approaches? What might have to be changed?

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Further Reading:

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