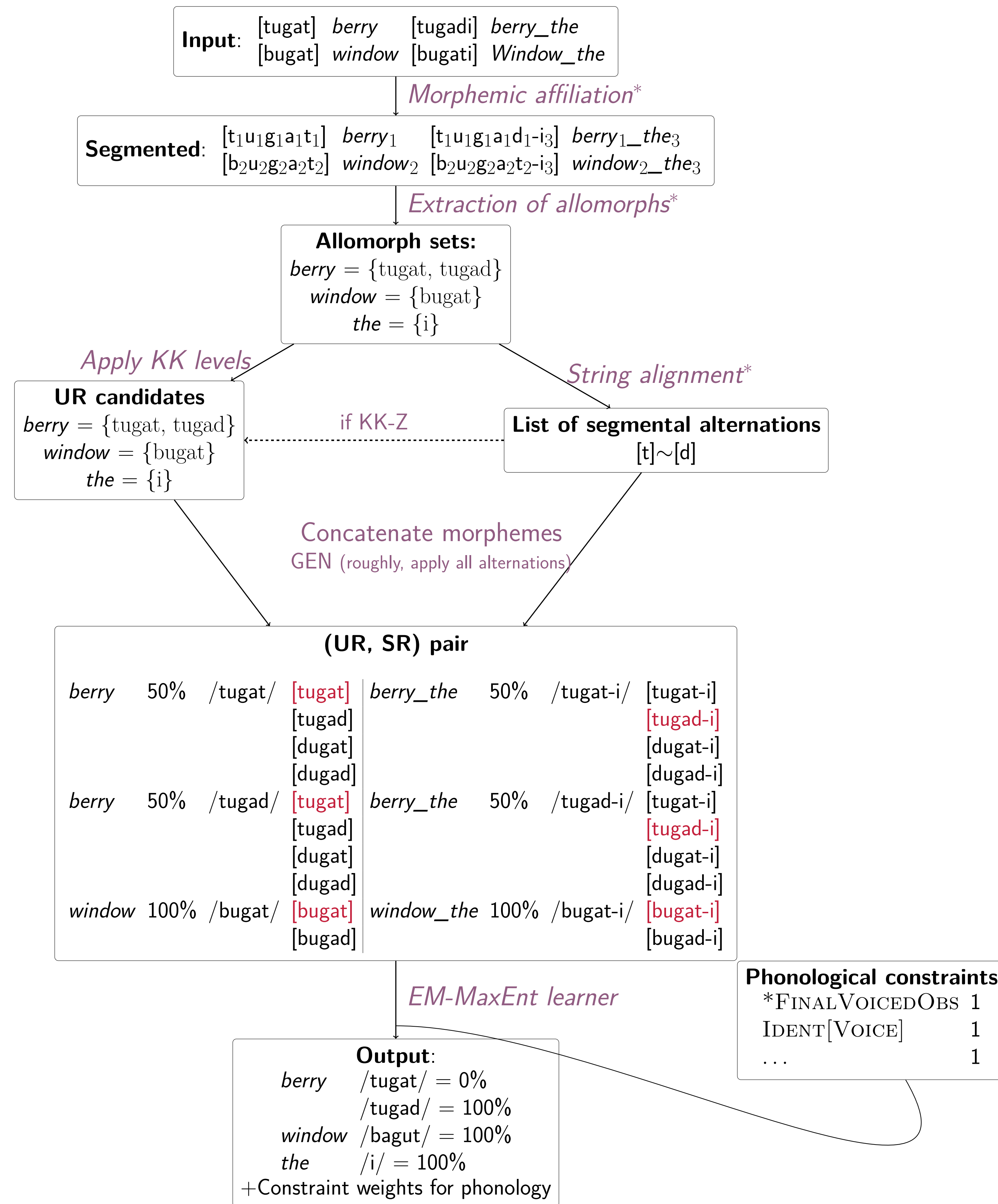


### 1. Setting

- We return to the classical **UR-learning problem** (e.g. Tesar et al., 2003; Jarosz, 2006; Merchant, 2008; Pater et al., 2012; Tesar, 2014; Cotterell et al., 2015; Jarosz, 2015; Rasin and Katzir, 2016; Rasin et al., 2021; O'Hara, 2017; Nelson, 2019; Hua et al. 2021, Hua and Jardine 2021, Tan 2022, Ellis et al. 2022)
- Goals
  - Scale up learning simulations, to the size of first-year problem sets.
  - Readdress the **Abstractness Controversy** in computational terms

### 2. The proposed learning system: Architecture

Any procedure marked with \* is omitted. For details, see the full paper. Feel free to ask!



### 3. Example Language: Tangale (Kidda 1985)

Target UR	Noun	'the N'	'your N'	Gloss
/tugad/	tugat	tugad-i	tugad-go	'berry'
/bugat/	bugat	bugat-i	bugat-ko	'window'
/wudo/	wudo	wud-i	wud-go	'tooth'
/lutu/	lutu	lut-i	lut-ko	'bag'

(+ 8 more stems, 2 more paradigm slots)

<b>Word final obstruent devoicing</b>	/tugad/ → [tugat]; cf. [tugad-i] Compare: [bugat] ~ [bugat-i] with invariant [t]
<b>Stem-final (short) vowel syncope before any suffix</b>	/wudo-i/ → [wud-i] cf. [wudo]
<b>Progressive voicing assimilation</b>	/bugat-go/ → [bugat-ko] /lutu-go/ → lutgo → [lut-ko]

### 4. Constructing the UR candidates: the KK hierarchy

**KK-hierarchy** : Kenstowicz and Kisseberth (1977, ch 1)

- Key insight: the candidate URs can be projected from the set of surface allomorphs.
- Higher levels → a larger set of UR candidates

Level	Meaning	e.g. Tangale 'berry'
B"	Single surface base hypothesis Albright 2002	If base = isolation form, */tugat/
C	UR is some surface allomorph	✓ /tugat/, */tugat/
D & E	(omitted here)	
Z	Apply all attested alternations to all attested allomorphs	/tugat/, /tugat/, /tgad/, /dukat/ +28 others

- The learning task: select the right UR among the candidates, and learn phonology simultaneously.

### 5. Learning Tangale phonology: Modeling

- Data: 60 word forms, exemplified as before
- Initialization: all UR candidates for each morpheme are **equiprobable**, all weights initialized as **1** for each weight optimization procedure
- Convergence criterion:  $\Delta(\log \text{likelihood}) < 10^{-5}$

### 6. Results

- Constraint set with weights fitted under both models:

Constraint	KK-C	KK-Z
*V]X	65.9	67.6
*FINAL VOICED OBS	35.9	17.9
AGREE[VOICE]	45.1	48.4
IDENT[VOICE]	4.4	5.26
IDENT[VOICE] <sub>STEM</sub>	17.7	22.4
MAX	24.8	27.31
DEP	36.7	0
...	...	...
<b>Log-likelihood</b>	$-5.2 \times 10^{-4}$	-4.5

#### Successful learning under KK-C

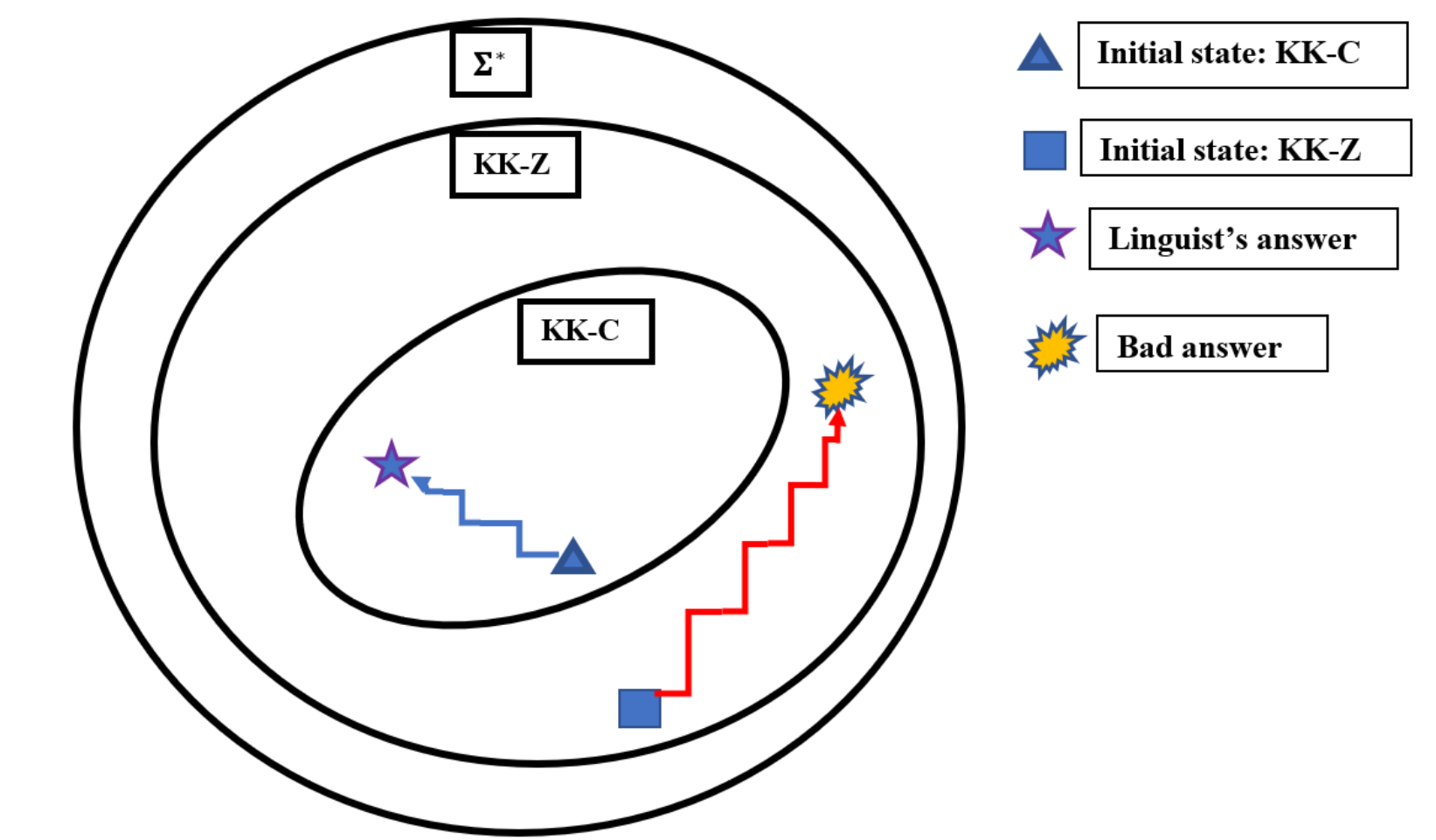
- the linguist's answer
- ... consensus UR's
- ... near-perfect output accuracy.

#### Failed learning with KK-Z

- ... in URs: learnt erroneous \*/tgat/, \*/tugat/
- ... thus in outputs:  
P('your berry', \*[tugatko])=25% ([tugadgo])  
P('berry', \*[tugado])=75% ([tugat])

### 7. Diagnosis of KK-Z failure

- The system gets trapped in a **local maximum**



- Partial diagnosis: the KK-Z UR candidate /tgat/ → [tugat] forces the system to consider an epenthesis grammar → low weights to DEP → terminal confusion
- This doesn't happen when the initial state has a more reasonable candidate set.

### 8. Summary & Conclusions

- The need to scale up:** We worked on scaling up to problem-set size. Other languages: Catalan, Lamba, Seediq, English plurals, Indonesian
  - Exploring abstractness**
    - The abstract debate long ago (1970's): whether abstract phonology is learnable.
    - Computational phonology can address such claims concretely: try the same learning system with different degrees of abstractness permitted.
- Too-abstract UR → large search space → fatal local maxima
- All of this is tentative, pending additional research :
    - in learning algorithms
    - in psycholinguistics: what URs are actually learnt

#### Appendix 1. the Objective

The log-likelihood of the observed data (cf. O'Hara 2017)

$$\ln(P(D|\theta, W)) = \sum_{(s, \omega) \in D} f(s, \omega) \ln \left( \sum_{u_\omega} P(s | u_\omega, W) P(u_\omega | \omega, \theta) \right) \quad (1)$$

where

$$p(s | u_\omega, W) = \frac{\exp(-\sum_i W_i C_i(u_\omega, s))}{\sum_{s' \in \text{GEN}(u_\omega)} \exp(-\sum_i W_i C_i(u_\omega, s'))} \quad (2)$$

$$P(u_\omega | \omega, \theta) = \prod_{i=1}^n \theta_{(\mu_i, u_i)} \text{ if } u_\omega = u_1 u_2 u_3 \dots u_n \text{ and } \omega = \mu_1 \mu_2 \mu_3 \dots \mu_n \quad (3)$$

#### Appendix 2. Searching with Expectation Maximization

Given  $D = \{(s, \omega)\}$  (SR, Word) pairs, the learner conducts an iterative search, maximizing the likelihood.

**Input:** D, maxIteration,  $\theta^0$ ,  $W^0$   
**Output:**  $\theta^f$ ,  $W^f$

**Function EM-MaxEnt Learner:**

```

1 iter = 0
2 Repeat until converge
3   E = E-step( $W^t$ ,  $\theta^t$ )
4    $W^{t+1}$  = M-stepW(E)
5   E' = E-step( $W^{t+1}$ ,  $\theta^t$ )
6    $\theta^{t+1}$  = M-stepθ(E')
7   iter += 1
8 while iter ≤ maxIteration
9   return  $W$ 
10 Function M-stepW(E):
11    $W = \arg\max_W \sum_{(s, \omega) \in D} \sum_{u_\omega} E(u_\omega, s, \omega) \ln(p(s|u_\omega, W))$ 
12   return W
13 Function E-step( $W$ ,  $\theta$ ):
14   for  $(s, \omega) \in D$  do
15     for  $u_\omega \in U_\omega$  do
16        $P_{u_\omega} = \frac{P(s | u_\omega, W) P(u_\omega | \omega, \theta)}{\sum_{u' \in U_\omega} P(s | u', W) P(u' | \omega, \theta)}$ 
17       E( $u_\omega, s, \omega$ ) =  $P_{u_\omega} \cdot f(s, \omega)$ 
18   return E
19 Function M-stepθ(E):
20   M ← set of word forms containing  $\mu$ 
21    $\theta_{(\mu, u)} = \frac{\sum_{(s, \omega) \in M} \sum_{u_\omega} E(u_\omega, s, \omega)}{\sum_{u' \in U_\omega} \sum_{(s, \omega) \in M} \sum_{u_\omega} E(u_\omega, s, \omega)}$ 
22   return  $\theta$ 

```

Download draft paper (still in progress) and references

References can be obtained by looking at the draft paper, downloadable by scanning the QR code.

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