# Computational morphology. Day 3. Real-world morphology. 

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Computational morphology. Day 3. Real-world morphology.
Finite-state morphology: real-world examples
Day 3 outline

- Real-world linguistic phenomena in FOMA.

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- Morphological tagging: problem setting.


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- Morphological tagging: problem setting.
- N-gram language models.

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- Person: 1, 2, 3 .

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Turkish verbs
Turkish verb conjugation

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## Turkish verb conjugation

- Input format: infinitive+Voice+Tense+Person+Number.
- +Voice: +Pass/+Act.
- +Tense: +Aor/+Cont.
- +Person: $+1 /+2 /+3$.
- +Number: $+\mathrm{Sg} /+\mathrm{Pl}$.


## Turkish verb conjugation

- Input format: infinitive+Voice+Tense+Person+Number.
- +Voice: +Pass/+Act.
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- +Person: $+1 /+2 /+3$.
- +Number: $+\mathrm{Sg} /+\mathrm{PI}$.
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$$
\langle\text { stem }\rangle\langle\text { VoiceSuf }\rangle\langle\text { Tense }\rangle\langle\text { PersNumSuf }\rangle
$$

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- Aorist suffix:
- $-r$ after vowels.
- -Ir after consonants in polysyllabic stems.
- -Ar after consonants in monosyllabic stems.
- -Ir after 13 monosyllabic exceptions.


## Turkish verb conjugation

- Verb form structure: $\langle$ stem $\rangle\langle$ VoiceSuf $\rangle\langle$ Tense $\rangle\langle$ PersNumSuf $\rangle$.
- Passive voice suffix: -n after vowels, -In after I, -II otherwise.
- Aorist suffix:
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- Progressive suffix:
- -Iyor after consonants.
- -yor after u, ü, i, ı.
- -Iyor after vowels, the vowel is removed.
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- Verb ending ( $\langle$ PersNumSuf $\rangle$ ):

| Number | Person | 1 | 2 |
| :--- | :--- | :--- | :--- |
|  | 3 |  |  |
| Singular | $-\operatorname{Im}$ | $-s \ln$ | $-\varnothing$ |
| Plural | -Iz | $-\operatorname{sln} \mathrm{lz}$ | -IAr |

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## Turkish verb conjugation

```
1 step: defining slots
define Voice "+Act" | "+Pass" ;
define Tense "+Aor" | "+Prog";
define Number "+Sg" | "+PI" ;
define Person "+1" | "+2" | "+3" ;
define Input Infinitive Voice Tense Person Number;
\# deleting -mAk and defining slots
define MarkerInsertion [..] -> "!" || _m [a | e] k Voice ;
define InfinitiveDeletion m [a|e]k \(->\) "" || "!"
define TensePattern [ [..] -> "!AorSuffix!" || "!" - ?+ "+Aor" ] .o. [ [..] -> "!ProgSuffix!"
    || "!" _ ?+ "+Prog" ];
define PassivePattern [..] -> "!PassSuffix!" || "!" _ ?+ "+Pass" ;
define Cleanup [ Voice | Tense | "!" ] -> "" ;
```

| \$ flookup -i -w "" turkish_diacr.bin < test.in |  |
| :--- | :--- |
| okumak+Pass+Prog+1+Pl | oku!PassSuffix!!ProgSuffix!+1+Pl |
| gelmek+Pass+Aor+2+Sg | gel!PassSuffix!!AorSuffix!+2+Sg |
| uyumak+Act+Prog+3+Pl | uyu!ProgSuffix!+3+Pl |
| izlemek+Act+Prog+3+Pl | izle!ProgSuffix!+3+Pl |
| bilmek+Act+Aor+2+Pl | bil!AorSuffix!+2+Pl |
| görmek+Act+Aor+2+Pl | gör!AorSuffix!+2+Pl |

## Turkish verb conjugation

```
2 step: filling voice
## passive suffix filling
define Passive1 "!PassSuffix!" -> II|[ Consonant - I ] _ ;
define Passive2 "!PassSuffix!" -> | n || I
define Passive3 "!PassSuffix!" -> n || Vowel
define PassiveSuffix Passive1 .o. Passive2 .o. Passive3;
```

| \$ flookup -i -w "" turkish_diacr.bin < test.in |  |
| :--- | :--- |
| okumak+Pass+Prog+1+Pl | okun!ProgSuffix!+1+Pl |
| gelmek+Pass+Aor+2+Sg | gelIn!AorSuffix!+2+Sg |
| uyumak+Act+Prog+3+Pl | uyu!ProgSuffix!+3+Pl |
| izlemek+Act+Prog+3+Pl | izle!ProgSuffix!+3+Pl |
| bilmek+Act+Aor+2+Pl | bil!AorSuffix!+2+Pl |
| görmek+Act+Aor+2+Pl | gör!AorSuffix!+2+Pl |

## Turkish verb conjugation

## 3 step: filling aorist

```
## aorist suffix filling
define PseudoVowel Vowel|||A;
read lexc aor exception.lexc
define AorException;
define Monosyllable Consonant* Vowel Consonant* ;
define AorSuffix0 "!AorSuffix!" -> I r || .#. AorException
```

$\qquad$

```
define AorSuffix1 "!AorSuffix!" -> r || PseudoVowel
define AorSuffix2 "!AorSuffix!" -> A r || .#. Monosyllable
```

$\qquad$

```
define AorSuffix3 "!AorSuffix!" -> I r || _;
define AorSuffix AorSuffix0 .o. AorSuffix1 .o. AorSuffix2 .o. AorSuffix3;
```

\$ flookup -i -w "" turkish_diacr.bin < test.in
okumak+Pass+Prog+1+Pl okun!ProgSuffix!+1+Pl
gelmek+Pass+Aor+2+Sg gelInIr+2+Sg
uyumak+Act+Prog+3+Pl
uyu!ProgSuffix!+3+Pl
izlemek+Act+Prog+3+Pl
izle! ProgSuffix!+3+Pl
bilmek+Act+Aor+2+Pl billr+2+Pl
görmek+Act+Aor+2+Pl görAr+2+Pl

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## Turkish verb conjugation

## 4 step: filling progressive

```
## progressive suffix filling
define ProgSuffix0 "!ProgSuffix!" -> "!" I y o r || _
## after i, ı, u, ü
define ProgSuffixVowel0 "!" I -> "" || [u | ü| i| |]_ ;
## other vowels
define ProgSuffixVowel1 [ a | o | e | ö] "!" -> "" || _ ;
## demek, yemek
define ProgDemek e "!" I -> i || .#. [ d | y ] _ ;
## sonorization
define ProgSonor t >> d ||.#. [g i|e|t a ]_ "!" ;
define ProgCleanup "!" -> "" || ;
define ProgSuffix ProgSuffix0 .o. ProgSuffixVowel0 .o. ProgSuffixVowel1 .o. ProgDemek
    o. ProgSonor .o. ProgCleanup ;
```

\$ flookup -i -w "" turkish_diacr.bin < test.in
okumak+Pass+Prog+1+Pl okunIyor+1+Pl
gelmek + Pass + Aor $+2+$ Sg gelInIr $+2+$ Sg
uyumak+Act+Prog+3+Pl uyuyor $+3+\mathrm{Pl}$
izlemek+Act+Prog+3+Pl izllyor+3+Pl
bilmek+Act+Aor+2+Pl bilIr+2+Pl
görmek+Act+Aor+2+Pl görAr+2+Pl

## Turkish verb conjugation

```
5 step: verbal endings
\#\# ending filling
define Ending1s "+1" "+Sg" -> | m ||
define Ending2s " +2 " " + Sg" \(->\) s I n ||
define Ending3s "+3" "+Sg" -> "" ||
define Ending1p "+1" "+PI" -> | z || _ ;
define Ending2p "+2" "+PI" \(->\) s | n | z ||
define Ending3p "+3" "+PI" \(->\) I A r ||
define Ending Ending1s .o. Ending2s .o. Ending3s .o. Ending1p .o. Ending2p .o.
    Ending3p ;
```

```
$ flookup -i -w "" turkish_diacr.bin < test.in
okumak+Pass+Prog+1+Pl okunIyorIz
gelmek+Pass+Aor+2+Sg gelInIrsIn
uyumak+Act+Prog+3+Pl uyuyorlAr
izlemek+Act+Prog+3+Pl izllyorlAr
bilmek+Act+Aor+2+Pl bilIrsInIz
görmek+Act+Aor+2+Pl görArsInIz
```


## Turkish verb conjugation

## 6 step: vowel harmony

```
## Vowel Harmony (left context on output size)
define VowelHarmony [A -> a // LastVowelHard
                        I -> I// LastVowelHardStraight _ ,, I -> i //
        A -> e // LastVowelSoft
```

$\qquad$

``` ,,
LastVowelSoftStraight
``` \(\qquad\)
``` ,' I \(\rightarrow>\) u // LastVowelHardRound _ ,, I \(->\) ü// LastVowelSoftRound _] ;
define Fill PassiveSuffix .o. AorSuffix .o. ProgSuffix .o. Ending .o. VowelHarmony ; define Grammar Input .o. Pattern .o. Fill ;
```

\$ flookup -i -w "" turkish_diacr.bin < test.in okumak+Pass+Prog+1+Pl okunuyoruz
gelmek+Pass+Aor+2+Sg gelinirsin
uyumak+Act+Prog+3+Pl uyuyorlar
izlemek+Act+Prog+3+Pl izliyorlar
bilmek+Act+Aor+2+Pl bilirsiniz
görmek+Act+Aor+2+P1 görersiniz

## General model

- Spanish verb conjugation is rather simple:

| Number | Person | -ar (tomar) | -er (comer) | -ir (escribir) |
| :--- | :---: | :--- | :--- | :--- |
| Singular | 1 | tomo | como | escribo |
|  | 2 | tomas | comes | escribes |
|  | 3 | toma | come | escribe |
| Plural | 1 | tomamos | comemos | escribimos |
|  | 2 | tomáis | coméis | escribís |
|  | 3 | toman | comen | escriben |

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- There are several morphonetic alterations:
- In $+1+\operatorname{Sg} g$ becomes $j$ before -er: emerger $\rightarrow$ emerjo.


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- There are several morphonetic alterations:
- In $+1+\operatorname{Sg} g$ becomes $j$ before -er: emerger $\rightarrow$ emerjo.
- In $+1+\operatorname{Sg} c$ turns to $z c$ before -er/-ir and after vowel: conducir $\rightarrow$ conduzco, agradecer $\rightarrow$ agradezco (though mecer $\rightarrow$ mezo).


## Model alterations

- Spanish verb conjugation is rather simple.
- But model vowel alterations exist:

| Number | Person | $-o-/-u e-$ <br> contar | -e-/-ie- <br> sentir | $-e-/-i-$ <br> servir |
| :--- | :---: | :--- | :--- | :--- |
| Singular | 2 | cuento | siento | sirvo |
|  | 3 | cuentas | sientes | sirves |
|  | 1 | contamos | sentimos | sirve |
|  | 2 | contáis | sentís | servís |
|  | 3 | cuentan | sienten | sirven |

## Spanish verb: present tense

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|  | 3 | cuentas | sientes | sirves |
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- These classes include much more verbs:
- -o-/-ue-: morir, dormir, soler, soñar, ...
- -e-/-ie-: pensar, entender, perder, preferir, ...


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|  | 3 | cuentas | sientes | sirves |
|  | siente | sirve |  |  |
| Plural | 1 | contamos | sentimos | servimos |
|  | 2 | contáis | sentís | servís <br> suentan |
|  | sirven |  |  |  |

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- -o-/-ue-: morir, dormir, soler, soñar, ...
- -e-/-ie-: pensar, entender, perder, preferir, ...
- -e-/-i-: pedir, vestir, elegir, expedir, ...


## Model alterations

- Also Spanish has some irregular verbs:

| Number | Person | estar | ser | haber |
| :--- | :---: | :--- | :--- | :--- |
| Singular | 1 | estoy | soy | he |
|  | 2 | estás | eres | has |
|  | 3 | está | es | ha |
| Plural | 1 | estamos | somos | hemos |
|  | 2 | estáis | sois | habéis |
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- There are some more irregular verbs: decir, dar, ver, ...
- Some verbs just have irregular $+1+\mathrm{Sg}$ forms:
- traer $\rightarrow$ traigo (also caer).
- valer $\rightarrow$ valgo (also salir, poner).
- saber $\rightarrow$ sé, caber $\rightarrow$ quepo.


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- How to model that all properly?

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## Finite-state morphology: real-world examples

Spanish verb: present tense

## Regular model

## First, model regular verbs (with regular phonetic alterations):

```
define Vowel e |i |é| i| a | u | o |á| ú| ó;
```



```
define Letter Cons | Vowel:
define Stem Letter* Vowel Letter* ;
define InfSuffix [a|i|e]r
define Infinitive Stem InfSuffix:
define Number "+Sg" | "+PI" ;
define Person "+1" | "+2" | "+3" ;
define Input Infinitive Number Person;
## phonetic alterations
define ChangeEndCons1 c -> z c || Vowel _ [ e | i ] r "+Sg" "+1";
define ChangeEndCons2 c -> z || [ Cons - z ] _ [ e | i ] r "+Sg" "+1" ;
define ChangeEndCons3 g m, gu m g, qu uc c|_ [e|i]r "+Sg" "+1";
define UIR [..] -> y || [ Letter - q ] u _ir [ "+Sg" | "+PI" "+3" ];
define ChangeEnd ChangeEndCons1 .o. ChangeEndCons2 o. ChangeEndCons3 o. UIR ;
## endings
define ielnfSuffix[i|e]r:
define PresEnding1s InfSuffix }->>0||_"+Sg" "+1
define PresEnding2s a r -> a s, ielnfSuffix -> es || _ "+Sg" "+2" ;
define PresEnding3s a r m a, ielnfSuffix }->>\mathrm{ e || _ "+'Sg" "+3" ;
define PresEnding1p r -> mos || _ "+PI" "+1";
define PresEnding2p a r >> ái s, e }\overline{r}->\mathrm{ éi s, ir r >> is || _"+PI" "+2";
define PresEnding3p a r m a n, ielnfSuffix >> en || _ "+PI" "+3"
define PresEnding PresEnding1s .o. PresEnding2s .o. PresEnding3s .o. PresEnding1p .o. PresEnding2p .o. PresEnding3p
## combining all
define CleanUp [ Person | Number ] -> "" || _ ;
define Regular [ Input .o. ChangeEnd .o. PresEnding ]
define Grammar [ IrregularForm .P. Regular ] .o. CleanUp ;
```

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## Finite-state morphology: real-world examples

## Lexicon file

Exceptions are listed in the lexicon file:
Multichar_Symbols +Sg +PI +1 +2 +3

## LEXICON Root

Verb; Sg1Verb;
LEXICON Verb
estar $+\mathrm{Sg}+1$ :estoy \#; estar+Sg+2:estás \#; estar $+\mathrm{Sg}+3$ :está \#; estar $+\mathrm{PI}+3$ : están \#;
ser+Sg+1:soy \#; ser $+\mathrm{Sg}+2$ :eres \#;
ser+Sg+3:es \#;
ser+PI+1:somos \#;
ser $+\mathrm{PI}+2$ :sois \#;
ser+PI+3:son \#;

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Spanish verb: present tense

## Spanish: stem alterations

## Regular model: application

\$ flookup -i -w "" spanish.bin < spanish_test.in

| caer + Sg +1 | caigo | comer + Sg +3 | come |
| :--- | :--- | :--- | :--- |
| ser $+\mathrm{Pl}+1$ | somos | correr $+\mathrm{Pl}+2$ | corréis |
| ser $+\mathrm{Pl}+2$ | sois | vender+Pl+3 | venden |
| ser+Sg+1 | soy | escribir+Sg+2 | escribes |
| estar+Pl+3 | están | surgir+Pl+1 | surgimos |
| estar+Sg+2 | estás | destruir+Pl+3 | destruyen |
| estar+Sg+3 | está | instruir+Sg+2 | instruyes |
| hablar+Sg+1 | hablo | cojer+Sg+1 | cojo |
| hablar+Sg+2 | hablas | distinguir+Sg+1 | distingo |
| cantar+Pl+1 | cantamos | conducir $+S g+1$ | conduzco |

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- Moreover, after stem alterations stems are subject to usual phonological rules:
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- seguir $+\mathrm{Sg}+1 \rightarrow$ sigo (not *siguo).


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- This is lenient composition:

$$
X . O . Y=(X . o . Y) . P . Y
$$

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- This is lenient composition:

$$
X . O . Y=(X . o . Y) . P . Y
$$

- But we use priority union instead.


## Spanish: stem alterations

- We have two alteration branches:
- First inserts -(i)g-before ending of exceptional $+\mathrm{Sg}+1$ forms: (caer $+\mathrm{Sg}+1 \rightarrow$ caigo, salir $+\mathrm{Sg}+1 \rightarrow$ salgo).
- Second deals with stem vowel change (-o-/-ue-, -e-/-ie-, -e-/-i-).
- First branch has higher priority: $($ tener $+S g+1 \rightarrow$ tengo, but tener $+S g+2 \rightarrow$ tienes, tener $+S g+3 \rightarrow$ tiene $)$.


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- Not to deal with pseudoforms as *traiger we replace ending with special symbol:

```
!!!first stem.lexc!!!
LEXICON Root
traer:traiG%!Ending2%! #;
salir:salG%!Ending3%! #;
```


## Spanish: stem alterations

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!!!first_stem.lexc!!!
LEXICON Root
traer:traiG\%! Ending2\%! \#;
salir:salG\%!Ending3\%! \#;
- Analogously for second branch (dorm- $\rightarrow$ duerm-):
!!!second stem.lexc!!!
LEXICON Root
tener:tien\%!Ending2\%! \#;
pedir:pid\%!Ending2\%! \#;


## Spanish: stem alterations

- Verb endings are replaced by markers (rules are changed accordingly):

$$
\begin{aligned}
& \text { define Marker [ a r ] -> "!Ending1!" , [ e r ] -> "!Ending2!" , } \\
& \text { [ i r ] -> "!Ending3!" || _ Number ; }
\end{aligned}
$$

- Stem transformations are read from lexicons:
\#\# lexicon for stem changes
read lexc first_stem.lexc
define FirstStem ;
define FirstStemChange FirstStem " + Sg" " +1 " ;
read lexc second_stem.lexc
define SecondStem ;
define SecondStemChange SecondStem ["+Sg" ? | "+PI" "+3" ];
define IrregularStemChange FirstStemChange .P. SecondStemChange;


## Spanish: stem alterations

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define SecondStem ;
define SecondStemChange SecondStem ["+Sg" ? | "+PI" "+3" ];
define IrregularStemChange FirstStemChange .P. SecondStemChange;
- In the end everything is combined by priority union:
define Regular [ Input .o. [IrregularStemChange .P. Marker ] .o. ChangeEnd .o. PresEnding ] ;

Computational morphology. Day 3. Real-world morphology.
Finite-state morphology: real-world examples
Spanish verb: present tense

## Spanish: stem alterations

- Stem alterations work indeed:

| \$ flookup -i | -w | "" spanish_full.bin < spanish_stem.in |  |
| :--- | :--- | :--- | :--- |
|  |  |  |  |
| detraer+Sg+1 | detraigo | pensar+Pl+1 | pensamos |
| tener+Pl+1 | tenemos | morir+Sg+3 | muere |
| tener+Pl+2 | tenéis | morir+Pl+2 | moris |
| tener+Sg+1 | tengo | pedir+Pl+3 | piden |
| dormir+Pl+3 | duermen | pedir+Sg+2 | pides |
| dormir+Sg+2 | duermes | preferir+Pl+1 | preferimos |
| hacer+Sg+1 | hago | preferir+Pl+3 | prefieren |
| hacer+Sg+3 | hace | preferir+Sg+1 | prefiero |
| pensar+Sg+1 | pienso | decir+Sg+3 | dice |
| pensar+Sg+2 | piensas | preferir+Sg+1 | prefiero |

## Spanish: stem alterations

- Stem alterations work indeed:

```
$ flookup -i -w "" spanish_full.bin < spanish_stem.in
detraer+Sg+1 detraigo pensar+Pl+1 pensamos
tener+Pl+1 tenemos
tener+Pl+2 tenéis
tener+Sg+1 tengo
dormir+Pl+3 duermen
dormir+Sg+2 duermes
hacer+Sg+1 hago
hacer+Sg+3 hace
pensar+Sg+1 pienso
pensar+Sg+2 piensas
```

```
morir+Sg+3 muere
```

morir+Sg+3 muere
morir+Pl+2 moris
morir+Pl+2 moris
pedir+Pl+3 piden
pedir+Pl+3 piden
pedir+Sg+2 pides
pedir+Sg+2 pides
preferir+Pl+1 preferimos
preferir+Pl+1 preferimos
preferir+Pl+3 prefieren
preferir+Pl+3 prefieren
preferir+Sg+1 prefiero
preferir+Sg+1 prefiero
decir+Sg+3 dice
decir+Sg+3 dice
preferir+Sg+1 prefiero

```
preferir+Sg+1 prefiero
```

- Should be added: derivatonal prefixes.
- tener $\rightarrow$ contener, mantener, detener, ...
- hacer $\rightarrow$ rehacer, deshacer, ...


## Spanish: fusion

- $+1+\mathrm{Sg}$ form once more:

| Infinitive | $+1+$ Sg | gerund |
| :--- | :--- | :--- |
| partir | parto | partiendo |
| imbuir | imbuyo | imbuyendo |
| destruir | destruyo | destruyendo |
| delinquir | delinco | delinquiendo |
| distinguir | distingo | distinguiendo |
| coger | cojo | cogiendo |
| agradecer | agradezco | agradeciendo |
| mecer | mezo | meciendo |

## Spanish: fusion

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| coger | cojo | cogiendo |
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- Personal ending fuses with the stem on morpheme boundary.
- That could be carefully modeled with context "phonetic" rules.

Computational morphology. Day 3. Real-world morphology.
Finite-state morphology: real-world examples
Arabic: root-and-pattern morphology
Arabic: root-and-pattern morphology

- So far morpheme structure was linear.


## Arabic: root-and-pattern morphology

- So far morpheme structure was linear.
- That is not true for Semitic languages (e.g. Arabic):
kataba "(he) wrote+Perf"
kattabat "(she intensively) wrote+Perf"
yaktubu "(he) was written+Imp"
takattibu "(she) was (intensively) written+Imp"


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- Vowels reflect grammatical information.


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takattibu "(she) was (intensively) written+Imp"
- Root $k-t-b$ consists of consonants (usually 3 ).
- Vowels reflect grammatical information.
- Different verb classes have different vowel patterns:

| marida "(he became) ill+Perf" |  |
| :--- | :--- |
| marradat | "(she intensively became) ill+Perf" |
| yamradu | "(he) was made ill+Imp" |
| tamarridu "(she) was (intensively) made ill+Imp" |  |

Computational morphology. Day 3. Real-world morphology.
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Arabic: root-and-pattern morphology

## Arabic: simple example

- We want to model something like:
$\langle$ stem $\rangle\langle$ Type $\rangle\langle$ Voice $\rangle\langle$ Aspect $\rangle\langle$ Person $\rangle\langle$ Gender $\rangle \mapsto\langle$ wordForm $\rangle$


## Arabic: simple example

- We want to model something like:
$\langle$ stem $\rangle\langle$ Type $\rangle\langle$ Voice $\rangle\langle$ Aspect $\rangle\langle$ Person $\rangle\langle$ Gender $\rangle \mapsto\langle$ wordForm $\rangle$
- Possible values:
- $\langle$ Type $\rangle \in\{I, I I\}$,
- $\langle$ Voice $\rangle \in\{$ Act, Pass $\}$,
- $\langle$ Aspect $\rangle \in\{$ Perf, Imperf $\}$,
- $\langle$ Person $\rangle \in\{3\}$,
- $\langle$ Gender $\rangle \in\{\mathrm{M}, \mathrm{F}\}$.
- 16 variants.


## Arabic: simple example

- We want to model something like:
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- Possible values:
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- $\langle$ Aspect $\rangle \in\{$ Perf, Imperf $\}$,
- $\langle$ Person $\rangle \in\{3\}$,
- $\langle$ Gender $\rangle \in\{\mathrm{M}, \mathrm{F}\}$.
- 16 variants.
- We model only one class (of the verb $K T B$ "to write").


## Arabic: word formation

- Word formation in Arabic (A. A. Zalizniak's handout):
- Stem variants:

| Type | Pattern | Example |
| :--- | :--- | :--- |
| I (basic) | K-T-B | kataba "to write" |
| II (intensive) | K-TT-B | kattaba "to write a lot" |

- Prefix/suffix variants:

| Person+Gender | Perf. suffix | Imp. prefix-suffix |
| :--- | :--- | :--- |
| $+3+$ Masc | -a | ya- $-\mathbf{u}$ |
| $+3+$ Fem | -at | ta- $-\mathbf{u}$ |

- Vowel filler variants:

| Aspect | Voice | Prefix | Filler I | Filler II |
| :--- | :--- | :--- | :--- | :--- |
| Perfect | Active |  | $\mathrm{a}-\mathrm{a}$ | $\mathrm{a}-\mathrm{a}$ |
| Perfect | Passive |  | $\mathrm{u}-\mathrm{i}$ | $\mathrm{u}-\mathrm{i}$ |
| Imperfect | Active | ya- | $\varnothing-\mathrm{u}$ | $\mathrm{a}-\mathrm{i}$ |
| Imperfect | Passive | yu- | $\varnothing-\mathrm{a}$ | $\mathrm{a}-\mathrm{a}$ |

Computational morphology. Day 3. Real-world morphology.
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Arabic: root-and-pattern morphology

## Arabic conjugation in FOMA: input

- Input format:

```
define Vowel [a|i|u ];
define Consonant [k|t|b|z|h|r|s|f|m|d|n|y];
define Letter [ Vowel | Consonant ];
define Stem Consonant Consonant Consonant;
define Type [ "+I" | "+II" ];
define Voice ["+Act" | "+Pass"];
define Aspect ["+Perf" | "+Imperf"];
define Person "+3";
define Gender ["+M" | "+F"];
define Input Stem Type Voice Aspect Person Gender;
```


## Arabic conjugation in FOMA: input

- Input format:

```
define Vowel [a|i|u ];
define Consonant [k|t|b|z|h|r|s|f|m|d|n|y];
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define Stem Consonant Consonant Consonant;
define Type [ "+I" | "+II" ];
define Voice ["+Act" | "+Pass"];
define Aspect ["+Perf" | "+Imperf"];
define Person "+3";
define Gender ["+M" | "+F"];
define Input Stem Type Voice Aspect Person Gender;
```

- Vowel positions are marked with digits:
define Olnsertion [..] -> "0" || .\#. define 1 Insertion [..] -> "1" || "0" Consonant define 2 Insertion [..] $->$ "2" || "1" Consonant define 3Insertion [..] -> "3" || "2" Consonant define PosInsertion Olnsertion .o. 1Insertion .o. $\overline{2}$ Insertion .o. 3Insertion;

Computational morphology. Day 3. Real-world morphology.
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## Arabic conjugation in FOMA: fillers

- Doubling second consonant of intensive:

```
define CheckTypel ? \(*\) " + I" ? \(*\)
define CheckTypell ? \(*\) " + II" ? \(*\);
```




```
    \(->\) [n n] || _ "2";
```

define StemProcessing [ CheckTypel ] | [ CheckTypell .o. TypelIDuplication ];

## Arabic conjugation in FOMA: fillers

- Doubling second consonant of intensive:
define CheckTypel ?* "+।" ?*;
define CheckTypell ? $*$ " + II" ? $*$;
define TypellDuplication $\mathrm{k} \rightarrow>[\mathrm{k} k], \mathrm{b} \rightarrow>[\mathrm{b} \mathrm{b}], \mathrm{t} \rightarrow>[\mathrm{t} \mathrm{t}], \mathrm{z}->[\mathrm{z} \mathrm{z}], \mathrm{h}$ $\rightarrow[\mathrm{h} \mathrm{h}], \mathrm{r} \rightarrow \mathrm{rr}], \mathrm{s} \rightarrow>[\mathrm{s} \mathrm{s}], \mathrm{f} \rightarrow \mathrm{ff} \mathrm{f}], \mathrm{m} \rightarrow$ [m m], d $\rightarrow$ [d d], n $->$ [n n] || _ "2";
define StemProcessing [CheckTypel ] | [CheckTypell .o. TypellDuplication ];
- Defining fillers:

```
define aaFill "1" -> a, "2" -> a;
define aiFill "1" -> a, "2" -> i;
define uiFill "1" -> u, "2" -> i;
define OaFill "1" -> [, "2" -> a;
define 0uFill "1" -> [, "2"-> u;
```


# Arabic conjugation in FOMA: selecting the rule 

- Exhaustive search for appropriate rule:
define PerfectActiveFill aaFill;
define ImperfectActiveFill [ CheckTypel .o. OuFill ] | [ CheckTypell .o. aiFill ];
define ActiveFill [CheckPerf .o. PerfectActiveFill] | [CheckImperf .o.
ImperfectActiveFill];
define PerfectPassiveFill uiFill;
define ImperfectPassiveFill [ CheckTypel .o. OaFill ] | [ CheckTypell .o. aaFill ];
define PassiveFill [CheckPerf .o. PerfectPassiveFill] | [Checklmperf .o.
ImperfectPassiveFill];
define Fill [CheckPass .o. PassiveFill] | [CheckAct .o. ActiveFill] ;


## Arabic conjugation in FOMA: selecting the rule

- Exhaustive search for appropriate rule:
define PerfectActiveFill aaFill;
define ImperfectActiveFill [ CheckTypel .o. OuFill ] | [ CheckTypell .o. aiFill ];
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define PerfectPassiveFill uiFill;
define ImperfectPassiveFill [ CheckTypel .o. OaFill ] | [ CheckTypell .o. aaFill ];
define PassiveFill [CheckPerf .o. PerfectPassiveFill] | [CheckImperf .o.
ImperfectPassiveFill];
define Fill [CheckPass .o. PassiveFill] | [CheckAct .o. ActiveFill] ;
- The same for prefixes (0 marker):
define OPrefix "0" -> [;
define taPrefix "0" $->$ t a;
define yaPrefix "0" -> y a;
define tuPrefix " 0 " $->\mathrm{t} \mathbf{u}$;
define yuPrefix "0" -> y u;
define PerfectPrefix OPrefix;
define ImperfectActivePrefix [CheckMasc .o. yaPrefix] | [CheckFem .o. taPrefix] ;
define ImperfectPassivePrefix [CheckMasc .o. yuPrefix] | [CheckFem .o. tuPrefix] ;
define ImperfectPrefix [CheckAct .o. ImperfectActivePrefix] | [CheckPass .o.
ImperfectPassivePrefix] ;
define Prefix [CheckPerf .o. PerfectPrefix] | [CheckImperf .o. ImperfectPrefix] ;

Computational morphology. Day 3. Real-world morphology.
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## Arabic conjugation in FOMA: selecting the rule

- Processing the suffixes (3 marker):
define ImperfectSuffix "3" -> u || _ Type;
define PerfectMascSuffix "3" $->$ a $\|$ _ Type;
define PerfectFemSuffix "3" -> a t || _ Type;
define PerfectSuffix [ CheckMasc .o. PerfectMascSuffix ] | [CheckFem .o.
PerfectFemSuffix ] ;
define Suffix [ CheckPerf .o. PerfectSuffix ] | [ CheckImperf .o. ImperfectSuffix ];


## Arabic conjugation in FOMA: selecting the rule

- Processing the suffixes (3 marker):
define ImperfectSuffix "3" -> u || _ Type;
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define PerfectFemSuffix "3" -> a t || _ Type;
define PerfectSuffix [ CheckMasc .o. PerfectMascSuffix ] | [CheckFem .o.
PerfectFemSuffix ] ;
define Suffix [ CheckPerf .o. PerfectSuffix ] | [ CheckImperf .o. ImperfectSuffix ];
- Combining all stages together:
define Cleanup Type | Voice | Aspect | Person | Gender -> [] ; define Grammar Input .o. PosInsertion .o. StemProcessing .o. Fill .o. Prefix .o. Suffix .o. Cleanup;


## Arabic conjugation in FOMA: selecting the rule

- Processing the suffixes (3 marker):
define ImperfectSuffix "3" $->$ u || Type;
define PerfectMascSuffix "3" -> a $\overline{1} \quad$ Type;
define PerfectFemSuffix "3" -> a t || _ Type;
define PerfectSuffix [ CheckMasc .o. PerfectMascSuffix ] | [CheckFem .o.
PerfectFemSuffix ] ;
define Suffix [ CheckPerf .o. PerfectSuffix ] | [ CheckImperf .o. ImperfectSuffix ];
- Combining all stages together:
define Cleanup Type | Voice | Aspect | Person | Gender $->$ []; define Grammar Input .o. PosInsertion .o. StemProcessing .o. Fill .o. Prefix .o. Suffix .o. Cleanup;
- Real Arabic morphology is much more complex.


## Arabic conjugation in FOMA: selecting the rule

- Processing the suffixes ( 3 marker):

```
define ImperfectSuffix "3" -> u || _ Type;
define PerfectMascSuffix "3" -> a || _ Type;
define PerfectFemSuffix "3" -> a t || _ Type;
define PerfectSuffix [ CheckMasc .o. PerfectMascSuffix ] | [CheckFem .o.
    PerfectFemSuffix ] ;
define Suffix [ CheckPerf .o. PerfectSuffix ] | [ CheckImperf .o. ImperfectSuffix ];
```

- Combining all stages together:
define Cleanup Type | Voice | Aspect | Person | Gender $->$ [] ; define Grammar Input .o. PosInsertion .o. StemProcessing .o. Fill .o. Prefix .o. Suffix .o. Cleanup;
- Real Arabic morphology is much more complex.
- But it was one of the first languages to obtain a transducer grammar (Beesley, 1990).

Computational morphology. Day 3. Real-world morphology.
Morphological tagging

## Morphological tagging: example

- The main task of computational morphology: morphological tagging.
- Tagging assigns morphological labels to words.

| DT | JJ | NN | VBD | DT | JJ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| NN |  |  |  |  |  |
| The baseball |  |  |  |  |  |
| player | made | a | home | run |  |

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| The baseball player | made | a | home | run |  |

- The most difficult problem: homonymy.

| PRP | VB | RB | TO | VB | NN |
| :---: | :---: | :---: | :---: | :---: | :---: |
| l | run | home | to | play | baseball |

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- Some words have several tags:
- baseball: NN, JJ
- run: VB, VBN, NN
- home: NN, JJ, RB


## Morphological tagging: example

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| :---: | :---: | :---: | :---: | :---: | :---: |
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- run: VB, VBN, NN
- home: NN, JJ, RB
- How to discriminate between possible variants?


## Morphological tagging: example

- The main task of computational morphology: morphological tagging.
- Tagging assigns morphological labels to words.

| DT JJ | NN | VBD | DT | JJ | NN |
| :--- | :---: | :---: | :---: | :---: | :---: |
| The baseball | player | made | a | home | run |

- The most difficult problem: homonymy.

| PRP | VB | RB | TO | VB | NN |
| :---: | :---: | :---: | :---: | :---: | :---: |
| I | run | home | to | play | baseball |

- Some words have several tags:
- baseball: NN, JJ
- run: VB, VBN, NN
- home: NN, JJ, RB
- How to discriminate between possible variants?
- Other problem: tagging of unknown words.

Computational morphology. Day 3. Real-world morphology.
Morphological tagging

## Morphological tagging: variants

- Two variants of morphological tagging.
- Coarse (POS-tagging): only part-of-speech labels (about 10-15 labels).

baseball NN

## Morphological tagging: variants

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## baseball NN

- Fine-grained: full morphological description.
- Feature-based description:
kupila "(she) bought" VERB Mood=Ind, Tense=Past, Aspect=Perf, Voice=Active, Number=Sing, Gender=Fem


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## Morphological tagging: variants

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- Positional description:
kupila Vmis-sfa-e-
- For English: no coarse tags, extended set of POS-tags.
- For inflectional languages: large number of complex tags (up to 1000 for Russian or Czech).


## Morphological tagging standards

- Oldest standard — Penn treebank (Marcus et al., 1993). 36 POStags for English with no inner structure (https://www.ling. upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html):

| 12. | NN | Noun, singular or mass |
| :--- | :--- | :--- |
| 13. | NNS | Noun, plural |
| 14. | NNP | Proper noun, singular |
| 15. | NNPS | Proper noun, plural |

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- Positional tagset (Multext-East project for Slavic languages).


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- For inflectional languages, two basic approaches:
- Positional tagset (Multext-East project for Slavic languages).
- Feature-based tagset (Universal Dependencies project).

Computational morphology. Day 3. Real-world morphology.
Morphological tagging

## Positional tagsets

- Used in Multext-East project for Slavic languages (http://nl.ijs.si/ME/).
- Each tag is a sequence of letters.


## Positional tagsets

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- Other smallcase letters reflect features:

| Ncmsny | common noun, masculine, singular, <br> neuter, animate (yes). |
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- Disadvantage: tags are language- and specification-dependent.


## Feature-based tagsets

- Tags are specified accoriding to CONLL-U format http://universaldependencies.org/format.html.
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- 17 universal POS labels:

| ADJ | adjective | INTJ | interjection | PUNCT | punctuation |
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| ADP | adposition | NOUN | noun | SCONJ | subordinating <br> conjunction |
| ADV | adverb | NUM | numeral | SYM | symbol |
| AUX | auxiliary <br> CCONJ | PART <br> condinating | PRON | particle |  |
| pronoun | VERB | verb |  |  |  |
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- 21 features: 6 lexical and 15 inflectional (Gender, Number, etc.).
- Is a general standard for corpora in different languages (50 languages in version 2.0, March, 2017).

Computational morphology. Day 3. Real-world morphology.
N -gram models
N-gram models: motivation

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- But how to calculate the probability $p(\mathbf{t} \mid \mathbf{w})$ ?
- For now we cannot estimate even $p(\mathbf{t})$.


## Probability of sequence

- By chain rule, $p\left(t_{1} \ldots t_{N}\right)$ is

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p\left(t_{1} \ldots t_{N}\right)=p\left(t_{1}\right) p\left(t_{2} \mid t_{1}\right) p\left(t_{3} \mid t_{1} t_{2}\right) \ldots p\left(t_{N} \mid t_{1} \ldots t_{N-1}\right)
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$c\left(t_{1} t_{2} t_{3}\right)$ - number of $t_{1} t_{2} t_{3}$ occurrences, $c\left(t_{1} t_{2} \odot\right)-$ number of times something occurs after $t_{1} t_{2}$.

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- Solution: every n -gram additionally occurs $\alpha$ times.

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p\left(t_{3} \mid t_{1} t_{2}\right)=\frac{c\left(t_{1} t_{2} t_{3}\right)+\alpha}{c\left(t_{1} t_{2} \odot\right)+\alpha|D|},|D|-\text { size of dictionary. }
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## Estimating $n$-gram probabilities

- additive (Laplace) smoothing - add $\alpha$ to all the counts:

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- How to choose $\alpha$ ? It should depend on n-gram order, size of dictionary, corpus size...
- With improper $\alpha$ : inadequate.
- Selection of proper $\alpha$ : too complicated (used only for unigram models).


## Backoff smoothing

- Sometimes trigram counts are too sparse (data from Europarl corpus):

| new scientific fact | 0 |
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| scientific fact | 12 |
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p_{l}\left(t_{n} \mid \mathbf{t}_{1, n-1}\right) & =\lambda p_{c}\left(t_{n} \mid \mathbf{t}_{1, n-1}\right)+(1-\lambda) p_{l}\left(t_{n} \mid \mathbf{t}_{2, n-1}\right) \\
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- We do it when:
- $t_{1} \ldots t_{n-1}$ occurs enough times.
- $t_{1} \ldots t_{n-1}$ has not much continuations.


## Witten-Bell smoothing

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p_{l}\left(t_{n} \mid \mathbf{t}_{1, n-1}\right) & =\lambda p_{c}\left(t_{n} \mid \mathbf{t}_{1, n-1}\right)+(1-\lambda) p_{l}\left(t_{n} \mid \mathbf{t}_{2, n-1}\right) \\
\lambda & =c\left(t_{1} \ldots t_{n-1} \odot\right) c\left(t_{1} \ldots t_{n-1} \odot\right)+N_{1+}\left(t_{1} \ldots t_{n-1}\right) \\
N_{1+}\left(t_{1} \ldots t_{n-1}\right) & =\mid\left\{t \mid c\left(t_{1} \ldots t_{n-1} t\right)>0\right\} \\
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\end{aligned}
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- Example (BNC corpus):

| $w_{1}$ | $c\left(w_{1} \odot\right)$ | $N_{1+}\left(w_{1}\right)$ | $N_{3+}\left(w_{1}\right)$ | $\lambda\left(w_{1}\right)$ | $1-\lambda\left(w_{1}\right)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| spite | 2899 | 59 | 15 | $\frac{2899}{2899+59}=0.980$ | 0.02 |
| stupid | 2898 | 602 | 117 | $\frac{2898}{2898+602}=0.828$ | 0.172 |

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- Example (BNC corpus):

| $w_{1}$ | $c\left(w_{1} \odot\right)$ | $N_{1+}\left(w_{1}\right)$ | $N_{3+}\left(w_{1}\right)$ | $\lambda\left(w_{1}\right)$ | $1-\lambda\left(w_{1}\right)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| spite | 2899 | 59 | 15 | $\frac{2899}{2899+59}=0.980$ | 0.02 |
| stupid | 2898 | 602 | 117 | $\frac{2898}{2898+602}=0.828$ | 0.172 |

- Unigram counts for stupid are 86 times more valuable than for spite.
- The more continuations we have, the less is $\lambda$.

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N -gram models

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p_{B O}\left(t_{n}\right) & =\frac{N_{+1}\left(t_{n}\right)}{\sum_{t} N_{+1}(t)} \\
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- More powerful methods:
- Deleted interpolation.
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- Also non-ngram language model (factored models, neural netbased, etc.).

