Natural Language Processing

SoSe 2017

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Morphological Parsing

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Morphological parsing

- Breaking down words into components and building a structured representation.

  - English:
    - cats → cat +N +Pl
    - caught → catch +V +Past

  - Spanish:
    - vino (came) → venir +V + Perf +3P + Sg
    - vino (wine) → vino +N + Masc + Sg

Morphological parsing

- Exercise: Give an example of an ambigous word in German and parse two of its meanings into parts.

Morphological parsing

- Exercise: Think of one example of an ambiguous word in German and parse two of its meanings.
  - Weiß:
    - weiß (white) → white + Adj
    - weiß (know) → to know +V + Present +1P/3P + Sg

Morphological parsing

- Surface segmentation: sequence of substrings whose concatenation is the entire word
  - achievability → achiev + abil + ity

- Canonical segmentation: sequence of standardized segments
  - achievability → achieve + able + ity

Stemming vs. Lemmatization

- Stemming: stripping off word endings (rule-based)
  - foxes → fox
  - going → go

- Lemmatization: mapping the word to its lemma (lexicon-based)
  - sang, sung → sing
  - going, went, goes → go

Motivation for morphological parsing

- Information retrieval
  - Normalize verb tenses, plurals, grammar cases

- Machine translation
  - Translation based on the stem

Morphological parsing

- Resources
  - Lexicon
    - List of all stems and affixes
  - Morphotactics
  - Ortographic rules

Morphological parsing

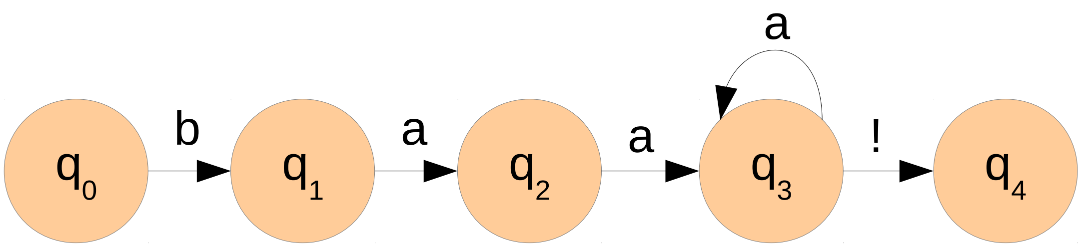
- Resources
  - Lexicon
  - Morphotactics
    - A model of morpheme ordering in a word
    - e.g., plurals are suffixes in English
  - Ortographic rules

Morphological parsing

- Resources
  - Lexicon
  - Morphotactics
  - Ortographic rules
    - Rules for changing in the words when combining morphemes
    - e.g., city → cities

Finite-state automata (FSA)

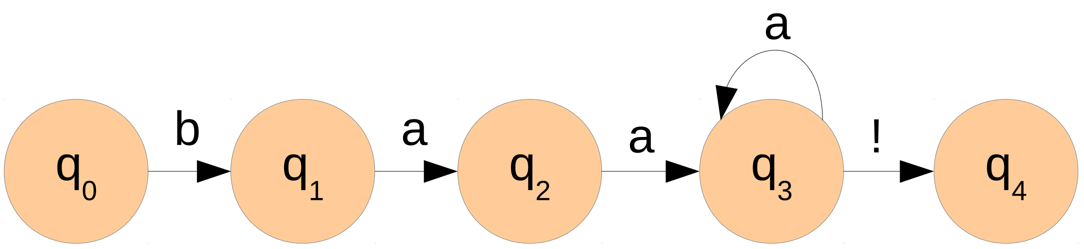
- FSAs are composed of
  - Vertices (nodes)
  - Arcs (links)



string?

Finite-state automata (FSA)

- FSAs are composed of
  - Vertices (nodes)
  - Arcs (links)

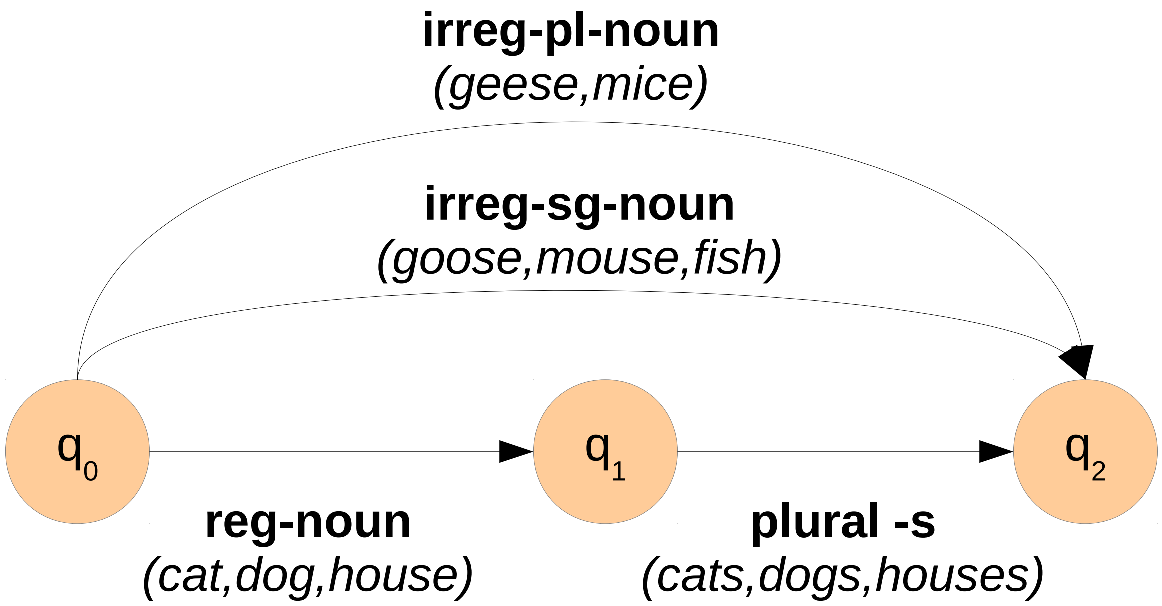


baa!
baaa!
baaaa!
…

/baa+!/

Finite-state lexicon

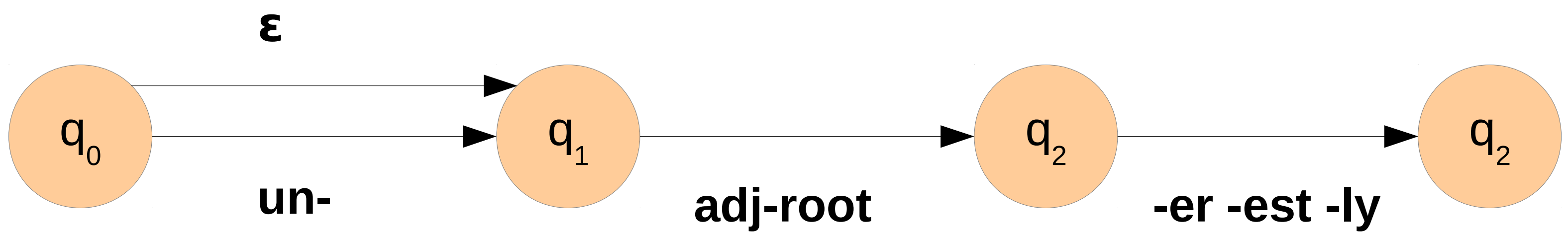
- Finite state automata (FSA) for English nominal inflection (same word category)



(Check example for verbal inflections in Jurafski & Martin book.)

Finite-state lexicon

- FSA for derivational morphology (distinct word categories)



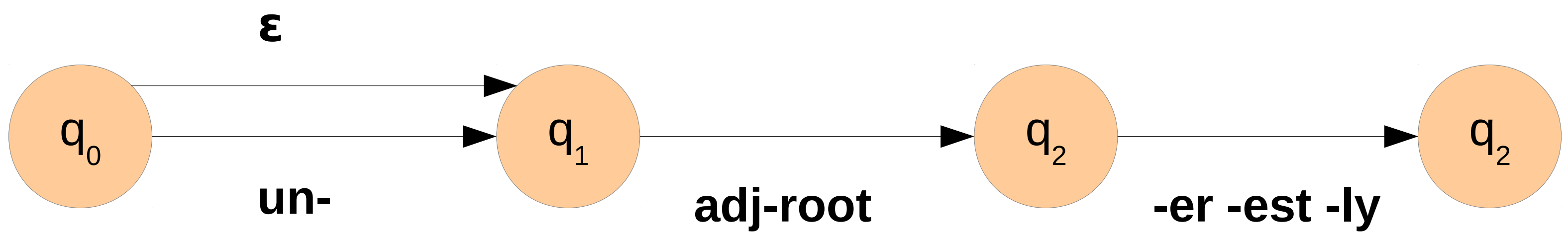
Adjectives:
- cool-er
- small-er
- un-usual-ly
...

Finite-state lexicon

- Exercise: Is it possible to create adjectives that do not exist?

Finite-state lexicon

- Exercise: Is it possible to create adjectives that do not exist?

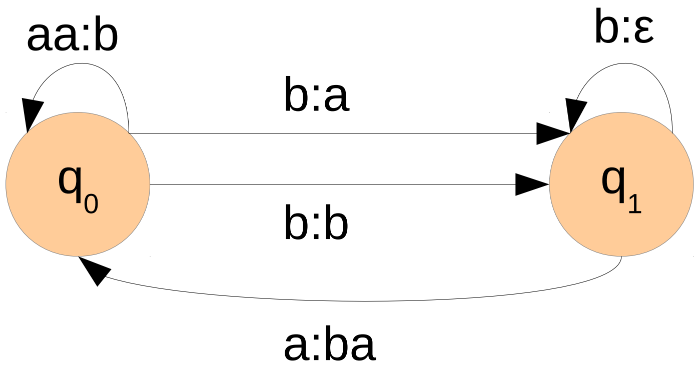


Incorrect adjectives:
- un-small-er
- orange-er
- small-ly

Solution: classes of roots (**adj-root$_1$**, **adj-root$_2$**, etc.)

Finite-state transducers (FST)

- FST is a type of FSA which maps between two sets of symbols.
- It is a two-tape automaton that recognizes or generates pairs of strings, one from each type.
- FST defines relations between sets of strings.



Finite-state transducers for NLP

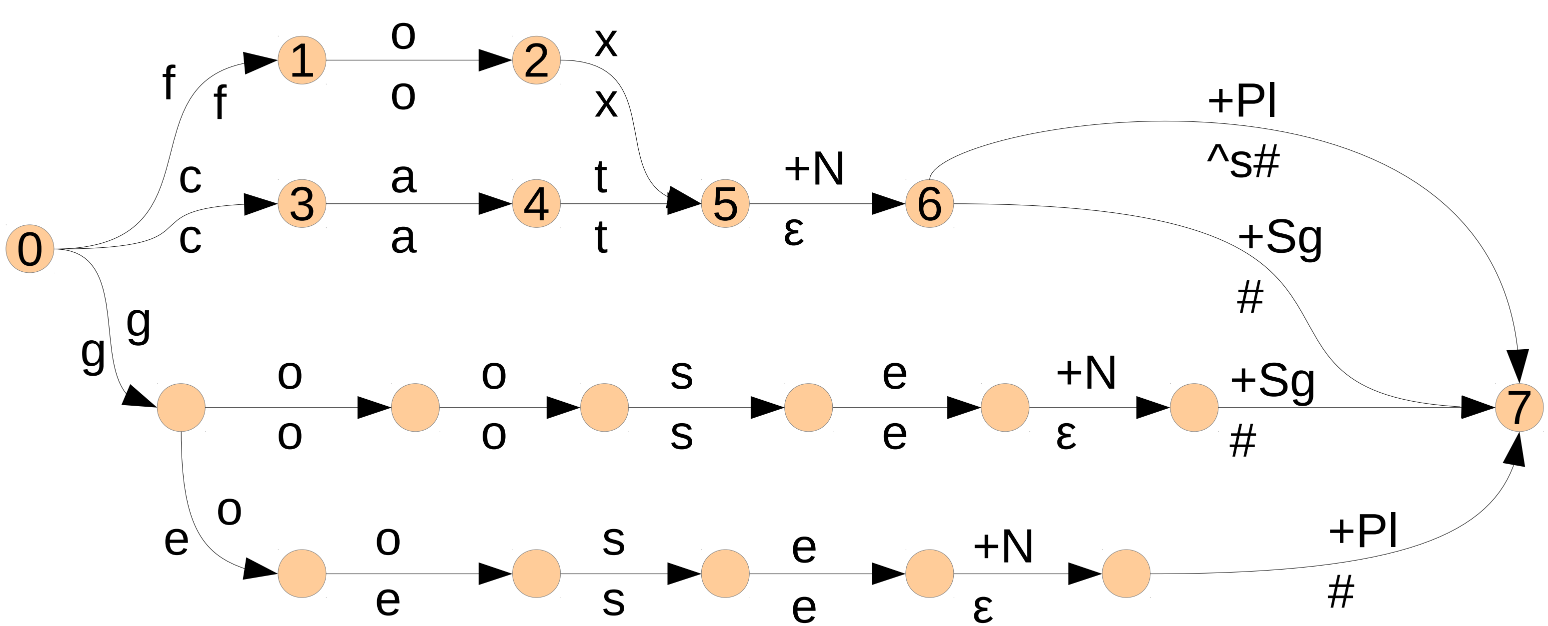
- FST as recognizer
  - Takes a pair of strings and accepts or rejects them
- FST as generator
  - Outputs a pair of strings for a language
- FST as translator
  - Reads a string and outputs another string
  - Morphological parsing: letters (input); morphemes (output)
- FST as relater
  - Computes relations between sets

FST for morphological parsing

- Two tapes
  - Upper (lexical) tape: input alphabet Σ
    - cat +N +Pl
  - Lower (surface) tape: output alphabet Δ
    - cats

FST for morphological parsing

- goose/geese: g:g o:e o:e s:s e:e
  - Feasible pairs (e.g., o:e) vs. default pairs (g:g)



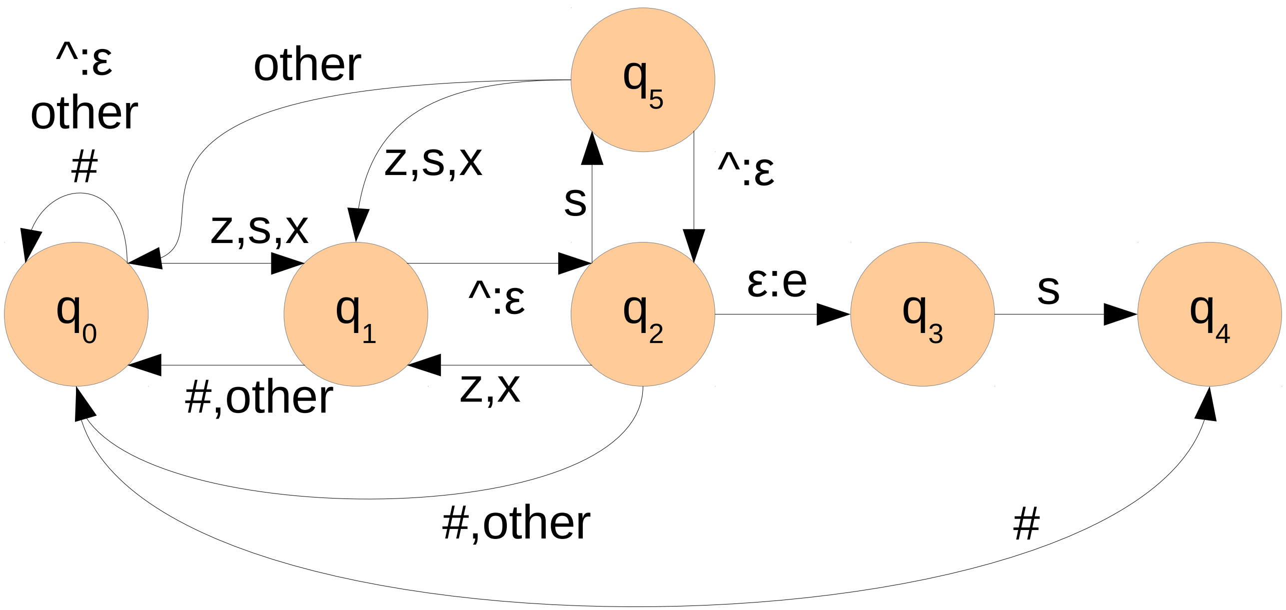
FST and ortographical rules

- Plural of „fox“ is „foxes“ not „foxs“

- Consonant double: beg/begging
- E deletion: make/making
- E insertion: watch/watches
- Y replacement: try/tries
- K insertion: panic/panicked

FST and ortographical rules

- Lexical: foxes +N +Pl
- Intermediate: fox^s#
- Surface: foxes



Combination of FST lexicon and rules for generation

Lexical → fox +N +Pl

↕

LEXICON-FST

↕

Intermediate → fox^s#

↕

$FST_1 \ldots FST_n$ (ortographical rules)

↕

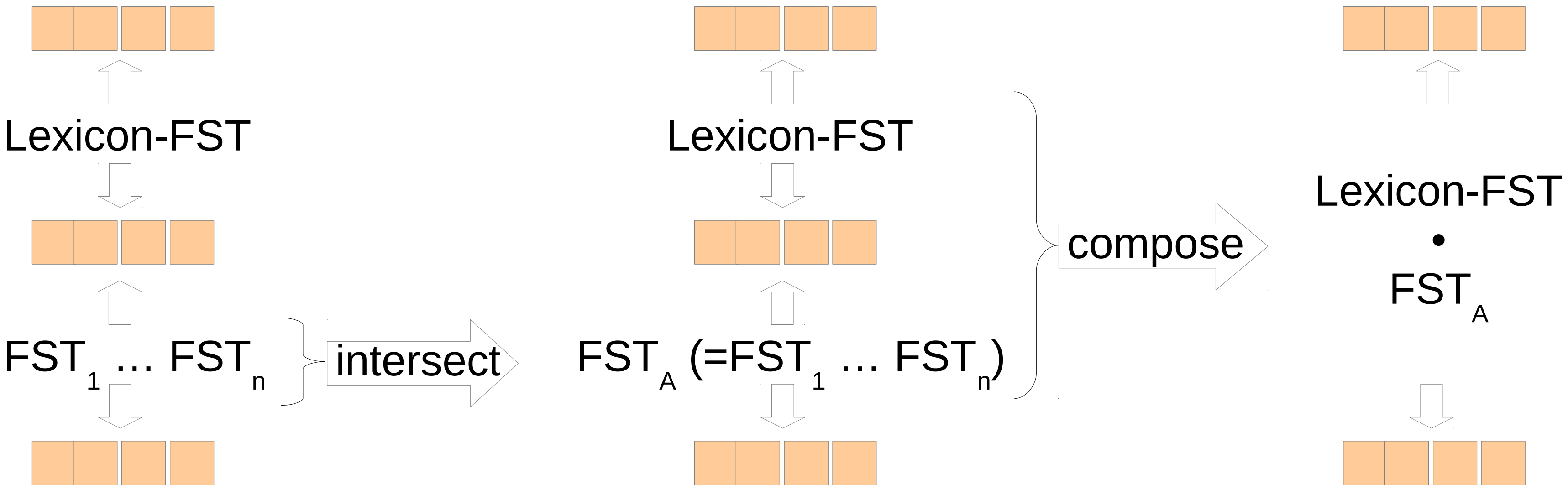
Surface → foxes

FST lexicon and rules

- Disambiguation
  - For some cases, it requires external evidences:
    - I saw two foxes yesterday. (fox +N +Pl)
    - That trickster foxes me every time! (fox +V +3SG)
  - But it can handle local ambiguity (intersection & composition)
    - „asses“ vs. „assess“

FST lexicon and rules

- Intersection & Composition



Porter Stemmer (Lexicon-Free FST)

- Popular for information retrieval and text categorization tasks
- It is based on a series of simple cascade rules
  - ATIONAL → ATE (relational → relate)
  - ING → ε (motoring → motor)
  - SSES → SS (grasses → grass)
- But it commits many errors:
  - ORGANIZATION → ORGAN
  - DOING → DOE

(http://tartarus.org/martin/PorterStemmer/)

WordNet lemmatizer

- Uses WordNet to find the stem of a word.

WordNet
A lexical database for English

Noun

- S: (n) **small** (the slender part of the back)
- S: (n) **small** (a garment size for a small person)

Adjective

- S: (adj) **small**, little (limited or below average in number or quantity or magnitude or extent) *"a little dining room"; "a little house"; "a small car"; "a little (or small) group"*
- S: (adj) minor, modest, **small**, small-scale, pocket-size, pocket-sized (relatively moderate, limited, or small) *"a small business"; "a newspaper with a modest circulation"; "small-scale plans"; "a pocket-size country"*
- S: (adj) little, **small** ((of children and animals) young, immature) *"what a big little boy you are"; "small children"*
- S: (adj) **small** (slight or limited; especially in degree or intensity or scope) *"a series of death struggles with small time in between"*
- S: (adj) humble, low, lowly, modest, **small** (low or inferior in station or quality) *"a humble cottage"; "a lowly parish priest"; "a modest man of the people"; "small beginnings"*
- S: (adj) little, minuscule, **small** (lowercase) *"little a"; "small a"; "e.e.cummings's poetry is written all in minuscule letters"*
- S: (adj) little, **small** ((of a voice) faint) *"a little voice"; "a still small voice"*
- S: (adj) **small** (have fine or very small constituent particles) *"a small misty rain"*
- S: (adj) modest, **small** (not large but sufficient in size or amount) *"a modest salary"; "modest inflation"; "helped in my own small way"*
- S: (adj) belittled, diminished, **small** (made to seem smaller or less (especially in worth)) *"her comments made me feel small"*

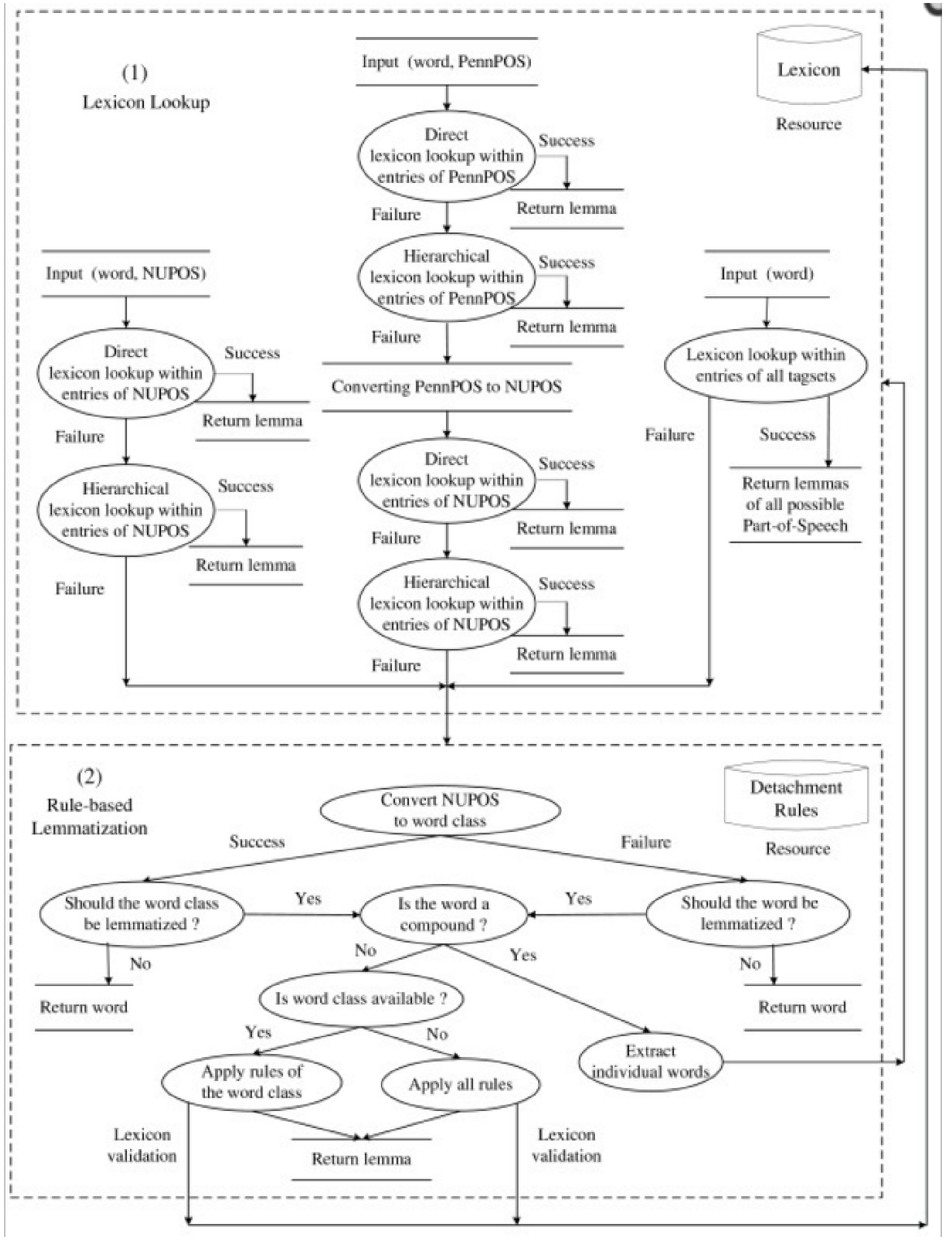
Adverb

- S: (adv) **small** (on a small scale) *"think small"*

(https://wordnet.princeton.edu/
http://search.cpan.org/~tpederse/WordNet-Similarity-2.05/lib/WordNet/stem.pm)

Use case: BioLemmatizer

- Based on MorphAdorner
- Enriched with biomedical-specific resources (lexicon)



Machine learning-based morphological parsing

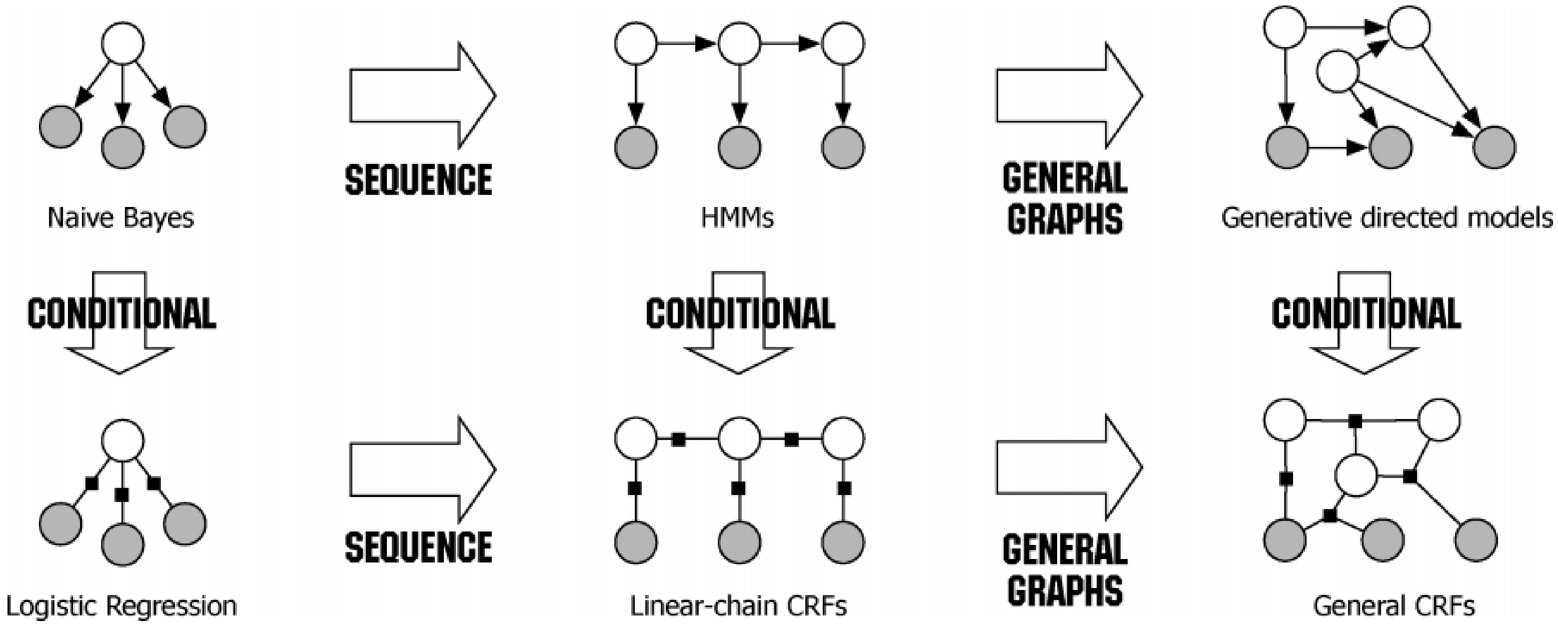
- Based on available training data, e.g., from the Morpho Challenge

Language	Examples	
English	baby-sitters indoctrinated	baby_N sit_V er_s +PL in_p doctrine_N ate_s +PAST
Finnish	linuxiin makaronia	linux_N +ILL makaroni_N +PTV
German	choreographische zurueckzubehalten	choreographie_N isch +ADJ-e zurueck_B zu be halt_V +INF
Turkish	kontrole popUlerliGini	kontrol +DAT popUler +DER_lHg +POS2S +ACC, popUler +DER_lHg +POS3 +ACC3

(http://morpho.aalto.fi/events/morphochallenge2010/datasets.shtml)

Conditional random fields (CRF)

- A discriminative undirected probabilistic graphical model for structured prediction



(http://homepages.inf.ed.ac.uk/csutton/publications/crftut-fnt.pdf)

Conditional random fields (CRF)

- Morphology parsing as a classification task
- Linear-chain CRF is to exploit the dependencies between the output variables using a chain structured undirected graph

$$drivers \longrightarrow driv + er + s$$

START	B	M	M	E	B	E	S	STOP
<w>	d	r	i	v	e	r	s	</w>

(http://www.aclweb.org/anthology/W13-3504)

Conditional random fields (CRF)

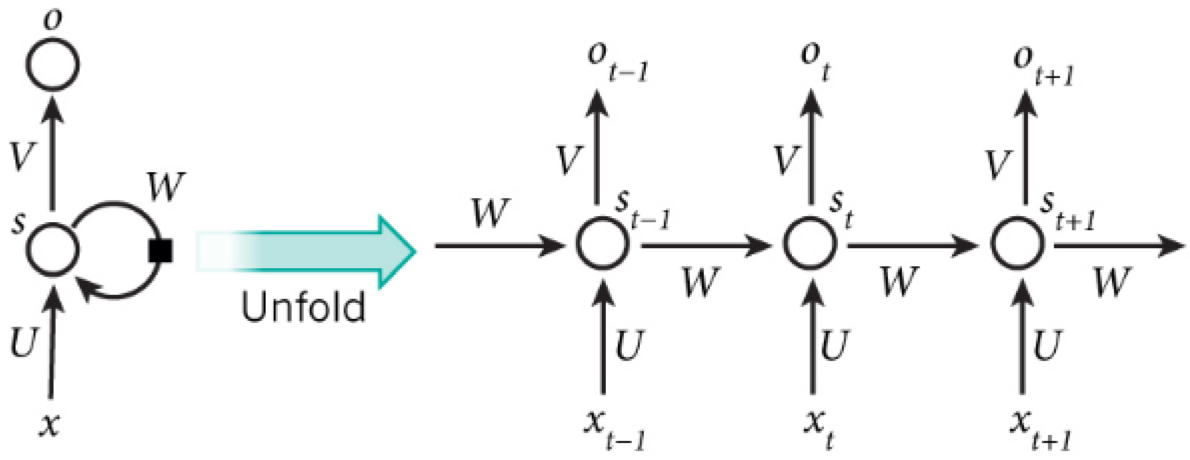
- Features:
  - Left and right substrings, e.g., {v, iv, riv, driv, <w>driv} and {e, er, ers, ers</w>} for „driver“
  - Rules, such as the following for -ed words („talked“, „played“ and „speed“):
    - position *t* is a segment boundary if its right context is *ed* and the left context is not *spe*.

(http://www.aclweb.org/anthology/W13-3504)

(http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/)

Recurrent neural networks language model (RNNLM)

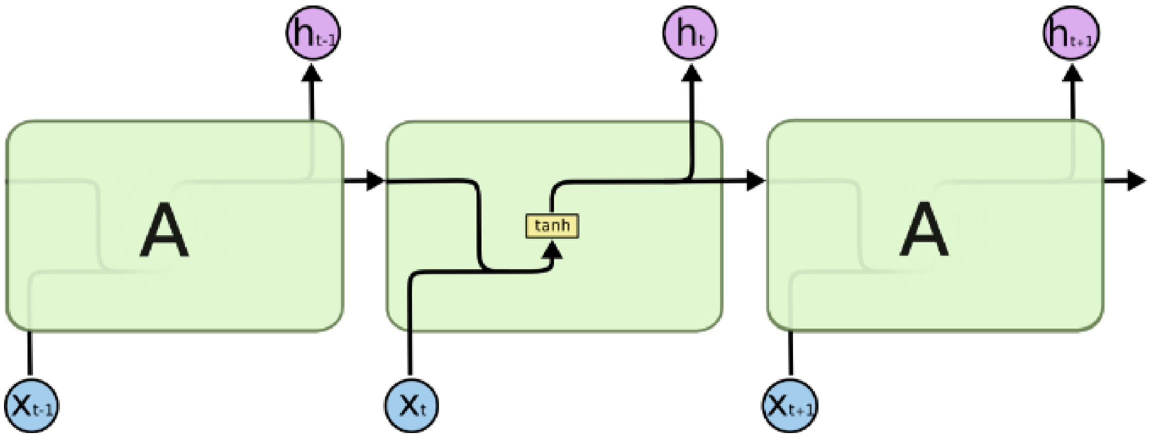
- Recurrent neural networks (RNN) is a class of NN in which connections between the units form a directed cycle.
- It makes use of sequential information.
- It does not assume independence between input and output.



A recurrent neural network and the unfolding in time of the computation involved in its forward computation. Source: Nature

Long short-term memory (LSTM)

- It is a special kind of RNN that connects previous information to the present task.
- It is capable to learn long-term dependencies and is suitable for sequence learning tasks.

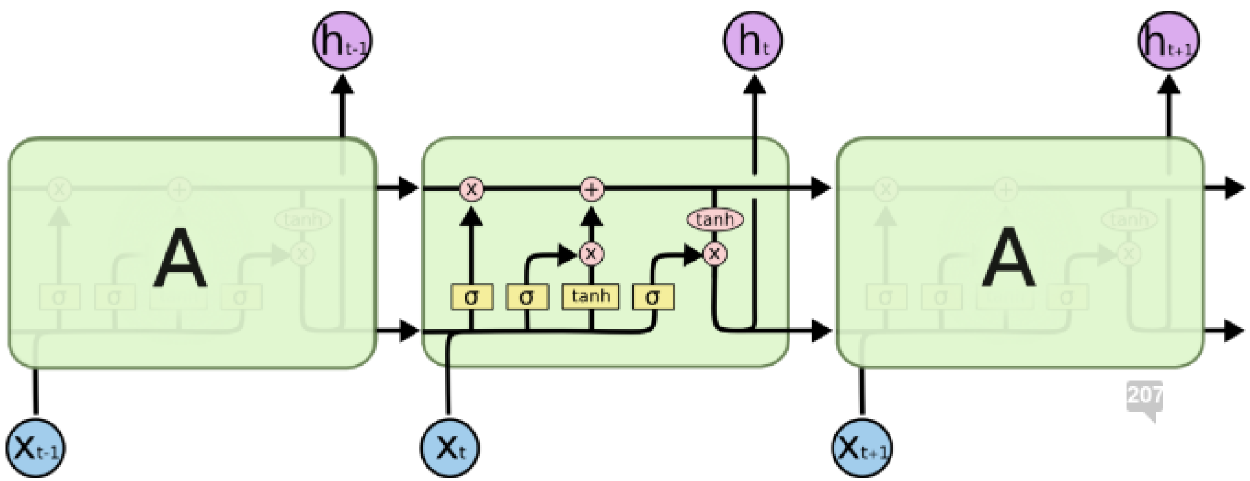


The repeating module in a standard RNN contains a single layer.

(http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

Long short-term memory (LSTM)

- LSTMs usually have four interating layers (but there are many variations of the architecture).



The repeating module in an LSTM contains four interacting layers.

(http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

(http://iiis.tsinghua.edu.cn/~weblt/papers/window-lstm-morph-segmentation.pdf)

LSTM for morphological segmentation

- Instead of relying heavily on linguistic knowledge (e.g., CRFs), the NN automatically learns the structure of input sequences and predict morphological boundaries for words.
- Series of window-based LSTM architectures for morphological segmentation.
- Predictions based on both past and future inputs, i.e., left and right neighbors.
- Classification task based on {B,M,E,S} classes:

<w>	a	c	t	o	r	s	</w>
START	B	M	E	B	E	S	STOP

(http://iiis.tsinghua.edu.cn/~weblt/papers/window-lstm-morph-segmentation.pdf)

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LSTM for morphological segmentation

- Simple Window LSTM model considers a new character window and label independently at each step.

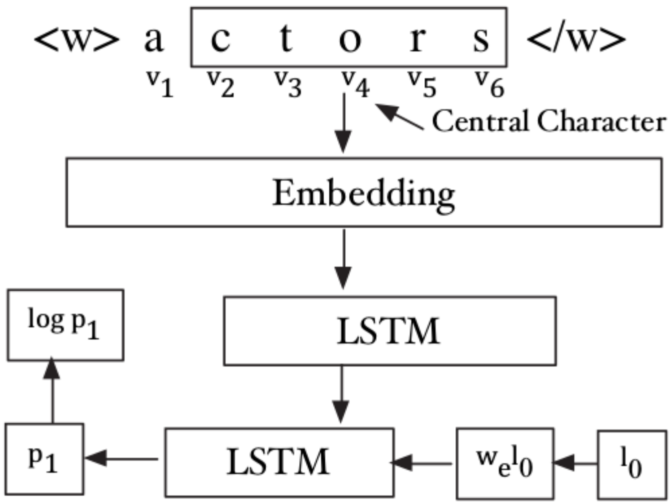

Figure 2: Window LSTM Model

(http://iiis.tsinghua.edu.cn/~weblt/papers/window-lstm-morph-segmentation.pdf)

LSTM for morphological segmentation

- Multi-Window LSTM model processes an entire word jointly.

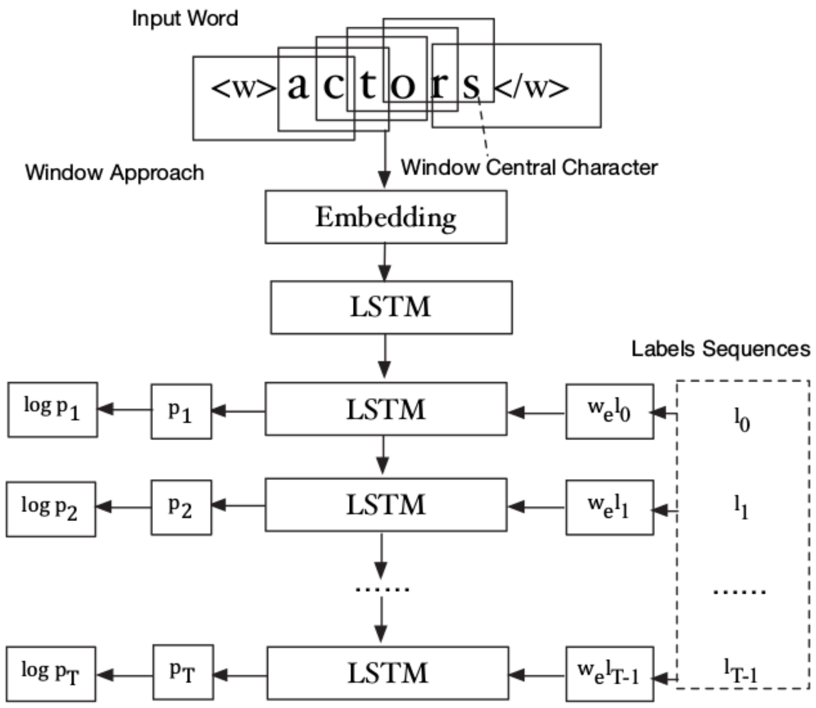

Figure 3: Multi-Window LSTM model

(http://iiis.tsinghua.edu.cn/~weblt/papers/window-lstm-morph-segmentation.pdf)

LSTM for morphological segmentation

- The model first makes a forward pass to process the sequence in the normal order.
- Then adopts an additional backward pass to process it in reverse order.
- With these bidirectional passes, the network is able to learn even more fine-grained features from the input words and corresponding label sequences.

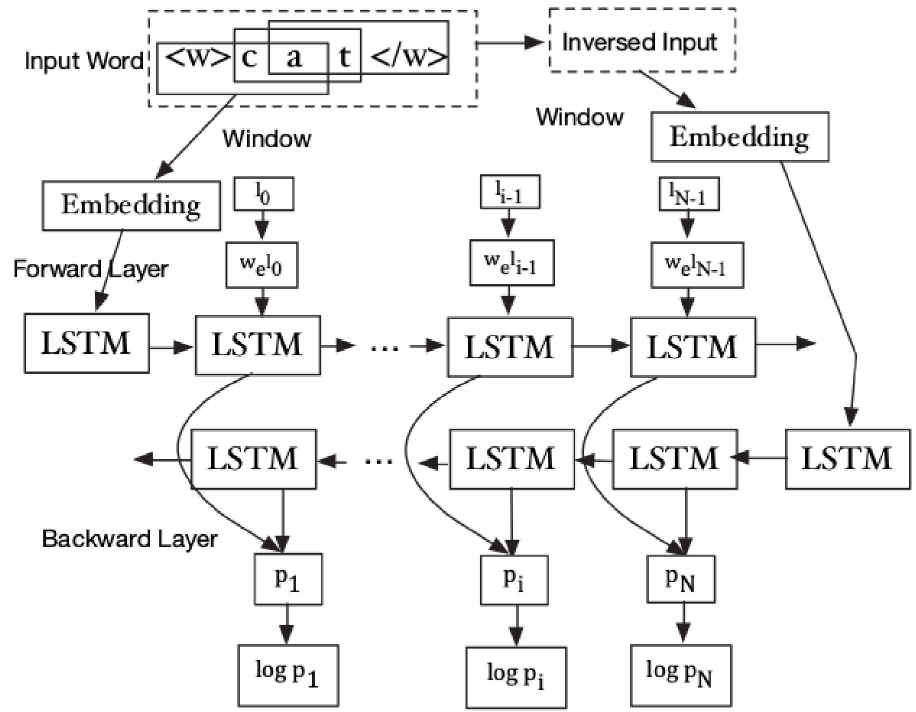

Figure 4: Bidirectional Multi-Window LSTM model

Summary

- Morphological parsing
- Methods:
  - Finite-state autonoma & lexicon
  - Finte-state transistors
  - Machine learning
    - Training data & features
    - Sequential algorithms, e.g., CRFs and RNN-LSTM

Exercise

- Project:
  - Could morphological parsing support your project?
  - Choose a morphological parser and try it in your document collection. Manually check a sample of the results.

Tools

- FS-based morpha: https://github.com/knowitall/morpha
- WordNet lemmatizer: http://search.cpan.org/~tpederse/WordNet-Similarity-2.05/lib/WordNet/stem.pm
- MorphAdoner: http://morphadorner.northwestern.edu/morphadorner/
- CLEAR parser: https://code.google.com/archive/p/clearparser/
- BioLemmatizer: http://biolemmatizer.sourceforge.net/
- NLP DotNet (on-line): http://nlpdotnet.com/services/Morphparser.aspx
- Morphisto (German): https://code.google.com/archive/p/morphisto/

Further reading

- NLP book: Chapter 3
- DL book: Chapter 10
  - http://www.deeplearningbook.org/contents/rnn.html
- Other references:
  - BioLemmatizer (good overview of various lemmatizers): https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3359276/
  - morpha: http://dl.acm.org/citation.cfm?id=973922