How the statistical revolution changes (computational) linguistics

Mark Johnson

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Thanks to Eugene Charniak and the BLLIP group, and Antske Fokkens, John Maxwell, Paola Merlo, Yusuke Miyao and Mark Steedman.

No warranty …

Half the money I spend on advertising is wasted.
The problem is: I don't know which half.

John Wanamaker

What is *computational* linguistics?

- Engineering goals — building useful systems
  - currently relies more heavily on statistics and machine learning than linguistic theory
  - not all scientific knowledge has engineering applications
- Scientific goals — understanding *computational* aspects of linguistic processes
  - language comprehension, production and acquisition (Chomsky's "use of knowledge of language")

Outline

Feature-based grammars and parsing

- Circa 1980 GPSG showed how to decompose long-distance "movement" phenomena into sequences of strictly local dependencies (feature-passing)

⇒ Explosion of mathematical and computational work in "unification-based" grammars that continues today

- Parsing with "unification-based" grammars
  - (computational) linguist devises grammar formalism (e.g., typed feature structure constraints)
  - linguist writes grammar in grammar formalism
  - computational linguist devises parser (inference engine) for grammar formalism

Statistical treebank parsing

- In the late 1980s statistical techniques (e.g., HMMs) became the dominant approach to speech recognition
- Parsing with statistical treebank parsers
  - linguist annotates a corpus with parses
  - computational linguist devises class of statistical models of parses (e.g., features of model)
  - computational linguist devises estimation procedure that maps parsed corpus to statistical model (e.g., feature weights)
  - computational linguist devises parser for statistical model
- *Why has statistical treebank parsing come to dominate computational linguistics?*

Both approaches involve linguistic knowledge

- Linguists write the grammars used in manual grammar-based approaches
- Linguists write the annotation guidelines and direct the annotation effort in statistical treebank parsing
  - how do corpus and annotation choices affect our statistical models?
- Corpus-based approach forces annotators to focus on common constructions (rather than rare constructions that may be scientifically more interesting)
- Large grammars are difficult to construct and maintain (software engineering)
- Treebanks are inherently redundant
  $\Rightarrow$ errors seem less catastrophic

Probabilities and grammars

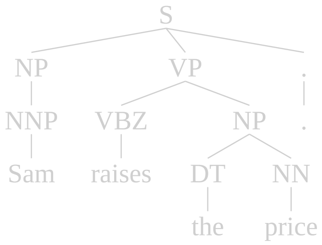
- Abney (1996) showed how to define MaxEnt models over virtually any linguistic representations
  - No requirement that features are independent ("context-free")
  - ⇒ No principled reason why we can't replicate treebank parsing techniques with grammar-based representations
- Are our probabilistic models appropriate?
  - is it reasonable to model P(Sentence)?
  - perhaps we should estimate (and learn from) P(Sentence|Meaning) instead?
  - ⇒ requires *explicit meaning representation*
  - part of attraction of statistical machine translation P(English|French), i.e., French as "language of thought"

Why parse?

- Engineering goal – we hope a general-purpose parser will be useful for other engineering tasks
  - ⇒ broad coverage
  - ⇒ robust
  - ⇒ good *average case* performance
- There are robust, broad-coverage grammar-based parsers
  - HPSG (Miyao and Tsujii, Cholakov et al)
  - LFG (Maxwell and Kaplan, van Genabith and Way)
  - CCG (Hockenmaier, Clark and Curran)
- Complex linguistic representations, but their phrase-structure parsing accuracy is not better than statistical treebank parsers'
- Not that many applications for parsing
  - often used as language model (keep probabilities, throw away parses)

Capturing vs. covering linguistic generalizations

- *Capturing a generalization*: grammar accurately describes phenomenon at appropriate level, e.g., subject-verb agreement via PERSON and NUMBER features
- *Covering a generalization*: model covers common cases of a generalization, perhaps indirectly. E.g., head-to-head POS dependencies



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- But feature design requires *linguistic insight*
  - basic linguistic insights tend to have greatest impact

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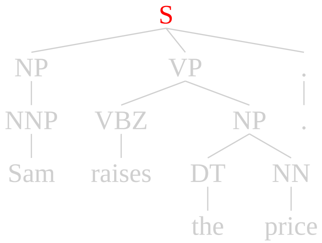

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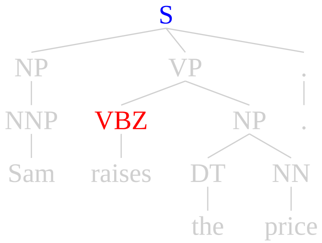

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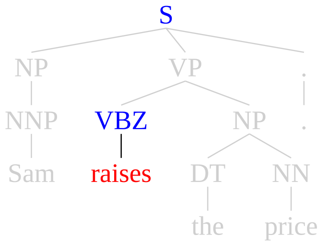

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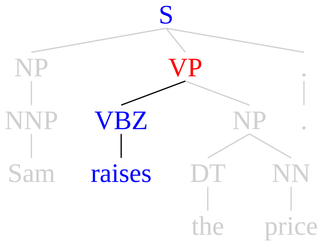

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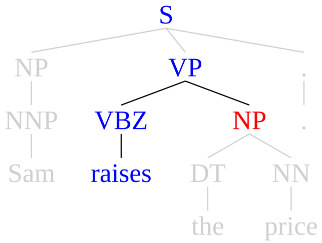

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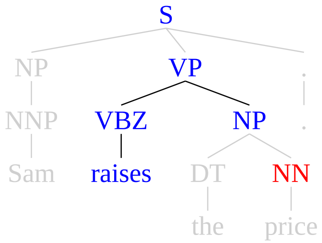

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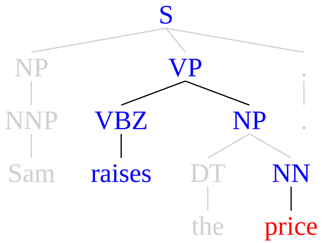

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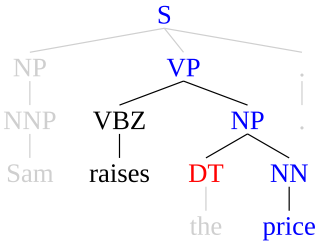

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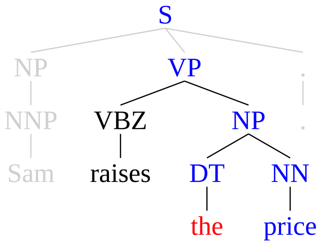

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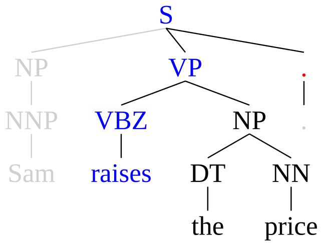

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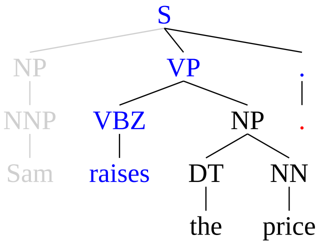

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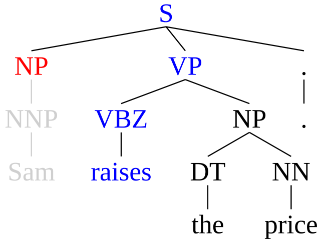

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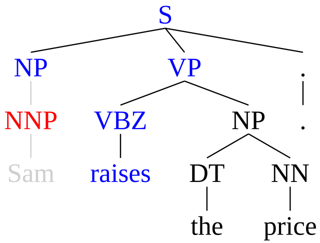

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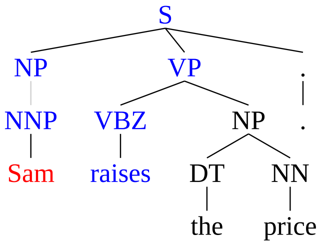

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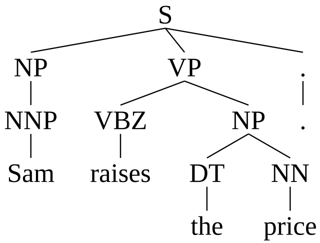

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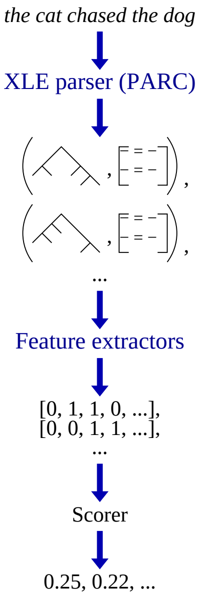
Outline

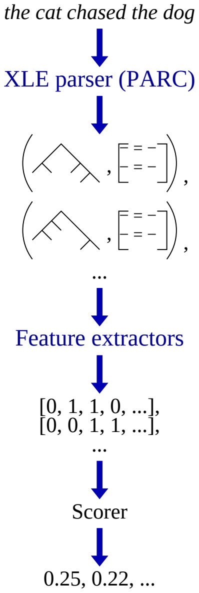
Stochastic Lexical Functional Grammar

- Parc LFG parser produces a set of parses (*c*- and *f*-structure pairs) for input sentence
- A set of "feature extractors" count how often various structures appear in each parse
  - Local trees (i.e., phrase-structure rules)
  - Local *f*-structures (i.e., argument structure frames)
  - Long-distance dependency paths
  - Misc. features: e.g., Coordination features
- Scorer computes "soft max" of weighted linear combination of feature values



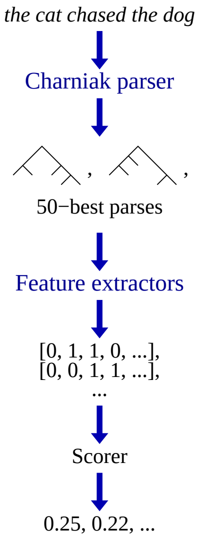
Features in MaxEnt parsing models

- A feature can be *any real-valued function* of the parses
- As far as the statistical model is concerned, *the feature vectors are all that matters*
  - details of linguistic representations are *irrelevant* so long as they are rich enough to compute feature vectors
- The most valuable features were defined on c-structures alone
  - c-structures are finer-grained than f-structures
  - All my f-structure features can be *recoded as* c-*structure features*
- Are there important generalizations that f-structure features cover better?



Discriminative rescoring treebank parser

- Use 50-best parses from Charniak parser
- Log of Charniak's parse probability is one of model's features
  - ⇒ Charniak's features are imported into model
  - ⇒ concentrate on *non-local features* not included in Charniak's model
- Trained from more data than SLFG system was ⇒ more accurate
  - these days it is common to train grammar-based models from PTB translated into grammar-based representations
  - but translated PTB doesn't contain more information than original PTB did



Outline

Conditional estimation for parse rescoring

- Easy to over-fit training data with large number of features

$\Rightarrow$ Regularize by adding a penalty term to log likelihood
  - L1 penalty term $\Rightarrow$ sparse feature weight vector
  - L2 penalty term (Gaussian prior) seems best

- 50-best parses $\mathcal{T}(s)$ may not include true parse $t^\star(s)$

$\Rightarrow$ Train rescorer to prefer parse in $\mathcal{T}_c(s)$ closest to $t^\star(s)$

- Often several parses from 50-best list are equally close to true parse

$\Rightarrow$ EM-inspired (non-convex) loss function

- Direct numerical optimization with L-BFGS (modified for L1 regularizer) produces best results

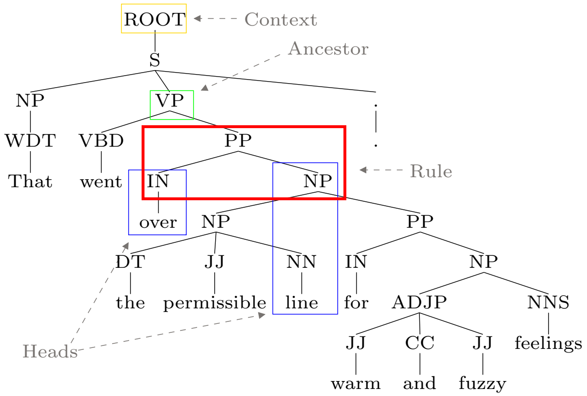
Riezler, King, Kaplan, Crouch, Maxwell and Johnson (2002), Goodman (2004), Andrew and Gao (2007)

Features for rescoring parses

- Parse rescorer's features can be *any computable function* of parse
- Choice of features is the most important and least understood aspect of the parser
  - feature design has a much greater impact on performance than the learning algorithm
- Features can be based on a linguistic theory (or more than one)
- …but need not be
  - "shot-gun" or "hail Mary" features very useful
- Feature selection: a feature's values on $T^{\star}(s)$ and $\mathcal{T}(s) \setminus T^{\star}(s)$ must differ on at least 5 sentences $s \in D$
- The *Charniak parser's log probability* combines all of the generative parser's conditional distributions into a single rescorer feature $\Rightarrow$ rescoring should never hurt

Lexicalized and parent-annotated rules

Lexicalization associates each constituent with its head
Ancestor annotation provides a little "vertical context"
Context annotation indicates constructions that only occur in main clause (c.f., Emonds)



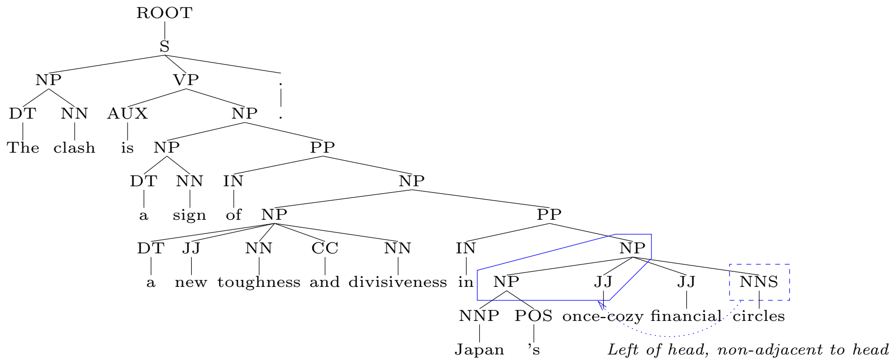
n-gram rule features generalize rules

Collects *adjacent constituents* in a local tree

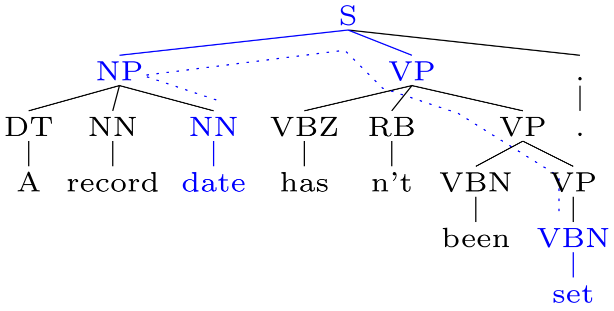
Also includes *relationship to head* (e.g., adjacent? left or right?)

Parameterized by *ancestor-annotation*, *lexicalization* and *head-type*

There are 5,143 unlexicalized rule bigram features and 43,480 lexicalized rule bigram features



Bihead dependency features

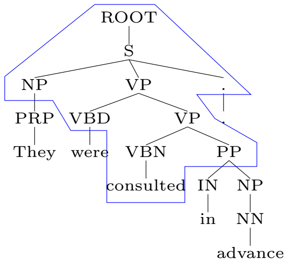


(S (NP (NN date)) (VP (VBN set)))

- Bihead dependency features approximate linguistic function-argument dependencies
- Computed for lexical (≈ semantic) and functional (≈ syntactic) heads
- One feature for each head-to-head dependency found in training corpus (70,000 features in all)

Head trees record all dependencies

- Head trees consist of a (lexical) head, all of its projections and (optionally) all of the siblings of these nodes
- correspond roughly to TAG elementary trees
- parameterized by *head type*, *number of sister nodes* and *lexicalization*

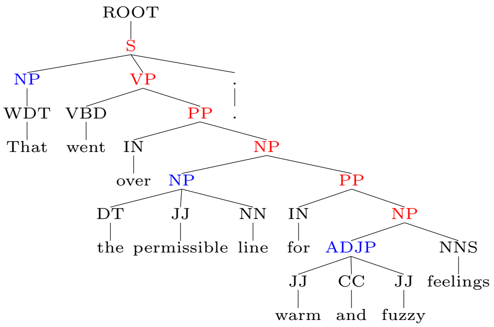


Rightmost branch bias

The RightBranch feature's value is the number of nodes on the right-most branch (ignoring punctuation) (c.f., Charniak 00)

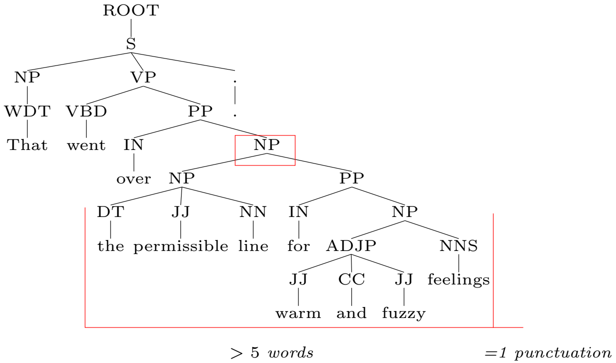
Reflects the tendancy toward right branching in English

Only 2 different features, but very useful in final model!



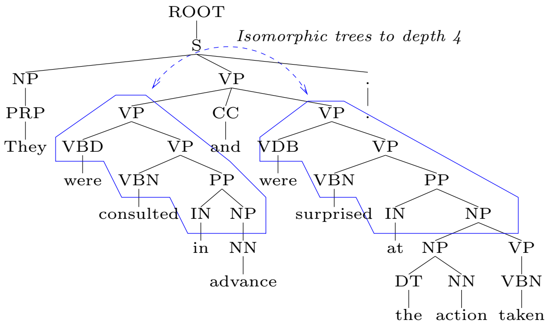
Constituent Heavyness and location

- Heavyness measures the constituent's category, its (binned) size and (binned) closeness to the end of the sentence



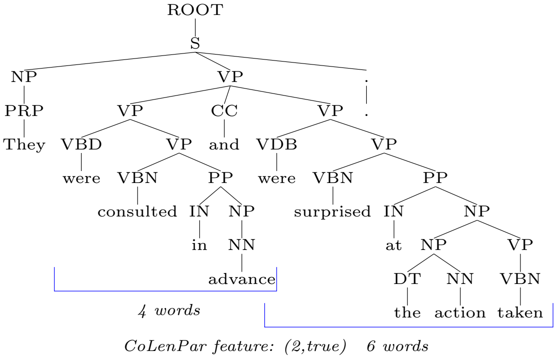
Coordination parallelism (1)

- A CoPar feature indicates the depth to which adjacent conjuncts are parallel



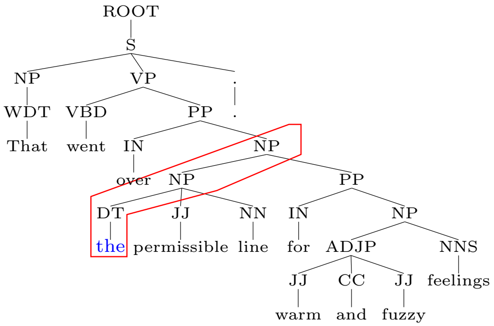
Coordination parallelism (2)

- The CoLenPar feature indicates the difference in length in adjacent conjuncts and whether this pair contains the last conjunct.

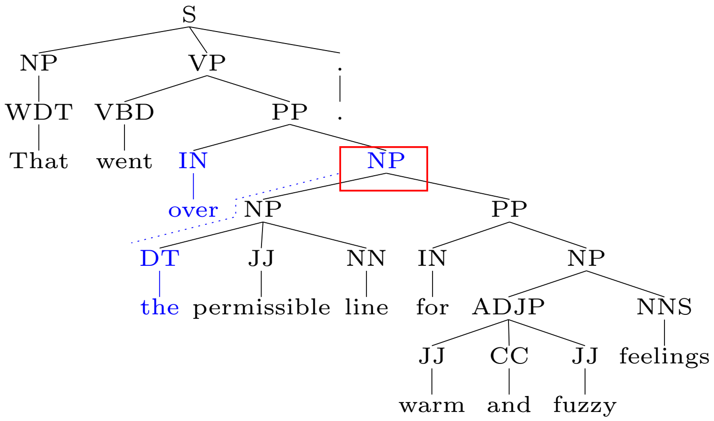


Word

- A Word feature is a word plus n of its parents (c.f., Klein and Manning's non-lexicalized PCFG)
- A WProj feature is a word plus all of its (maximal projection) parents, up to its governor's maximal projection



Constituent "edge neighbour" features

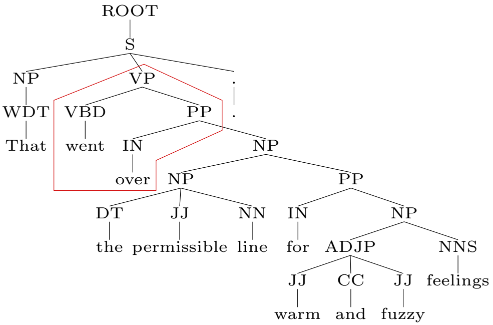


(IN over) (NP (DT the ...))

- Edge features are a kind of bigram context for constituents
- Would be difficult to incorporate into a generative parser

Tree n-gram

- A tree n-gram feature is a tree fragment that connect sequences of adjacent n words, for $n = 2, 3, 4$ (c.f. Bod's DOP models)
- lexicalized and non-lexicalized variants
- There are 62,487 tree n-gram features



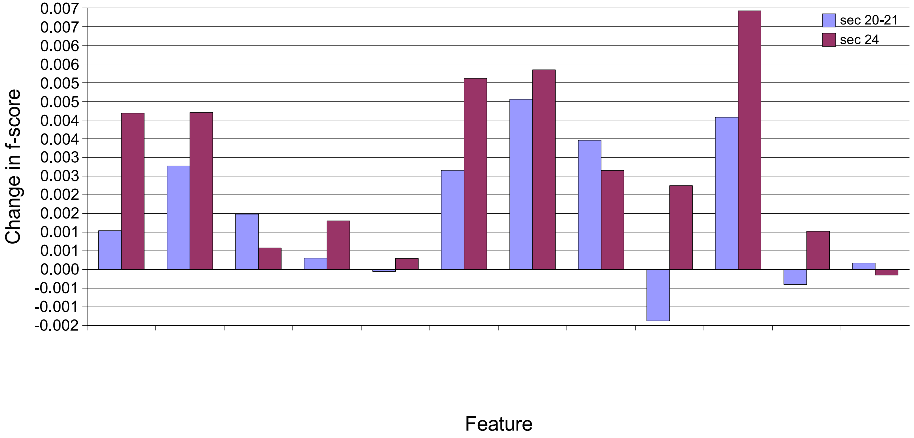
Experimental setup

- Feature tuning experiments done using Collins' split: sections 2-19 as train, 20-21 as dev and 24 as test
- $\mathcal{T}_c(s)$ computed using Charniak 50-best parser
- Features which vary on less than 5 sentences pruned
- Optimization performed using LMVM optimizer from Petsc/TAO optimization package or Averaged Perceptron
- Regularizer constant c adjusted to maximize f-score on dev

Evaluating features

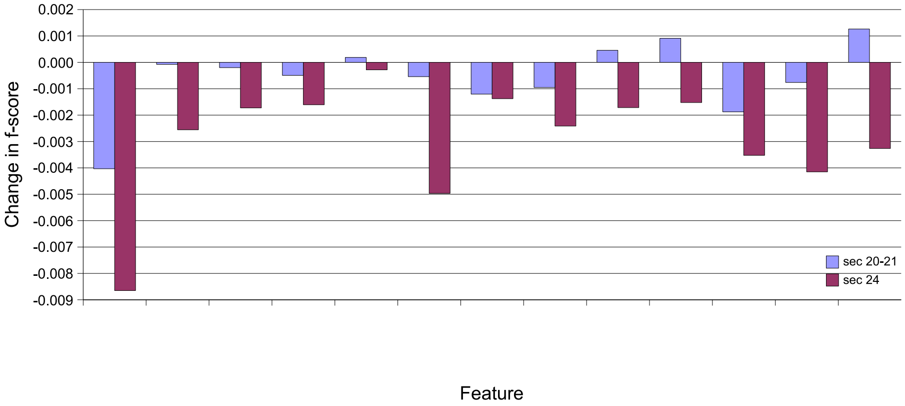
- The feature weights are not that indicative of how important a feature is
- The MaxEnt ranker with regularizer tuning takes approx 1 day to train
- The *averaged perceptron* algorithm takes approximately 2 minutes
  - used in experiments comparing different sets of features
  - Used to compare models with the following features: **NLogP Rule NGram Word WProj RightBranch Heavy NGramTree HeadTree Heads Neighbours CoPar CoLenPar**

Adding one feature class



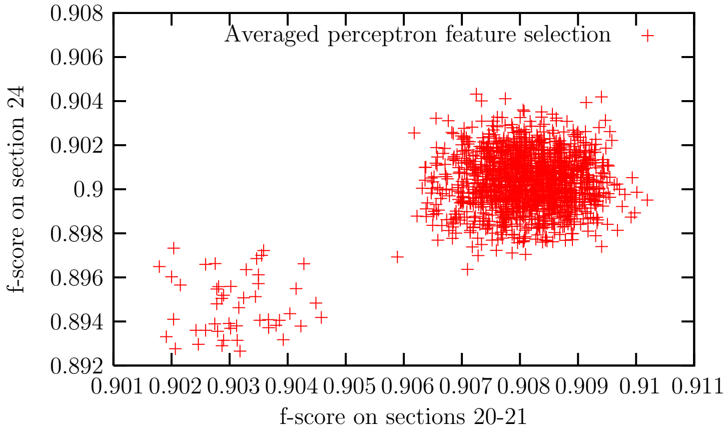
- Averaged perceptron baseline with only base parser log prob feature
  - section 20–21 f-score = 0.894913
  - section 24 f-score = 0.889901

Subtracting one feature class



- Averaged perceptron baseline with all features
  - section 20–21 f-score = 0.906806
  - section 24 f-score = 0.902782

Feature selection is hard!



Greedy feature selection using *averaged perceptron* optimizing f-score on sec 20–21

All models also evaluated on section 24

Comparing estimators

- Training on sections 2–19, regularizer tuned on 20–21, evaluate on 24

Estimator	# features	sec 20-21	sec 24
MaxEnt model, $p = 2$	670,688	0.9085	0.9037
MaxEnt model, $p = 1$	14,549	0.9078	0.9024
averaged perceptron	523,374	0.9068	0.9028
expected f-score	670,688	0.9084	0.9029

- None of the differences are significant
- Because the exponential model with $p = 2$ was the first model I tested new features on, they may be biased to work well with it.

Outline

Conventional grammars are closed-world

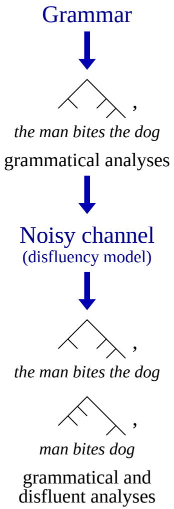
- The *closed world assumption* for grammars
  - Rules and lexical entries define set of grammatical structures
  - Everything not grammatical is ungrammatical
- "Parsing as deduction": parsing is the process of proving the grammaticality of a sentence
- But: goal is *understanding* what the speaker's trying to say; not determining whether the sentence is grammatical
- My ideal parser would be *open-world*
  - even ungrammatical sentences are interpretable
    E.g., *man bites dog* $\neq$ *dog bites man*
  - words and constructions we recognize provide information about sentence's meaning
  - unknown words or phrases do not cause interpretation to fail
    - parsing and acquisition are two aspects of same process
- *Statistical treebank parsers are open-world*
  - every possible tree receives positive probability

Open-world grammar-based parsing via *relaxation*

- Replace "hard" unification equality constraints with "soft" probabilistic features
  - e.g., for subject-verb agreement, introduce feature that fires when subject's agreement disagrees with verb's agreement
- Most techniques for making grammar-based parsers broad-coverage perform grammar or lexicon relaxation
  - Unknown word lexical entry guesser
  - Fragment parsing mechanisms
- Under this approach, grammaticality does not play a central role in parsing
- Statistical treebank parsers relax via *smoothing* and *Markovization*

Open-world grammar-based parsing via *disfluency model*

- Intuition: Ungrammatical sentences are understood by analogy with grammatical ones
- Possible formulation: noisy channel model where channel generates disfluencies
  - source model only generates *grammatical* sentences
- We've used this kind of model to detect and correct disfluencies in speech transcripts



Outline

Statistical models in linguistics

- Scientific side of computational linguistics studies the computational aspects of language
  - computation (the meaning-respecting manipulation of meaning-bearing symbols) is a process
  - ⇒ computational linguistics bears most directly on language comprehension, production and acquisition
- Recent explosion of interest in:
  - computational psycholinguistics (esp. sentence processing) (Bachrach, Hale, Keller, Levy, Roark, etc.)
  - computational models of language acquisition (esp. phonology and morphology)
    (Albright, Boersma, Frank, Goldsmith, Hayes, Pater, etc.)

Optimality theory

- Smolensky's *Optimality Theory* (OT) seems exquisitely designed to permit numerophobes perform optimization
- Detailed OT analyses of many aspects of phonology and morphology
- Optimality Theory is a limiting case of *Harmony Theory* which are equivalent to MaxEnt models
  - OT constraints $\equiv$ MaxEnt features

$\Rightarrow$ Easy for linguists to move from OT analyses to MaxEnt models

Chomsky ought to be a Bayesian!

$$\underbrace{\mathrm{P(Grammar \mid Data)}}_{\text{Posterior}} \propto \underbrace{\mathrm{P(Data \mid Grammar)}}_{\text{Likelihood}} \underbrace{\mathrm{P(Grammar)}}_{\text{Prior}}$$

- Likelihood measures how well grammar describes data
- Prior expresses knowledge of grammar before data is seen
  - can be very specific (e.g., Universal Grammar), or
  - can be generic (e.g., prefer shorter grammars)
  - can express *markedness preferences* that can be overridden by data
- Posterior is *distribution* over grammars
  - expresses uncertainty about which grammar is correct
- In principle we can *empirically evaluate* utility of specific linguistic universals in language acquisition

Bayesian updating integrates parsing and learning

$$\underbrace{\mathrm{P}(\text{Grammar} \mid \text{Sentence}_{1:n})}_{\text{Updated grammar}}$$
$$\propto \underbrace{\mathrm{P}(\text{Sentence}_n \mid \text{Grammar})}_{\approx \text{ parsing}} \underbrace{\mathrm{P}(\text{Grammar} \mid \text{Sentence}_{1:n-1})}_{\text{Previous grammar}}$$

- *Incremental Bayesian belief updating* updates posterior as each data item is encountered
- With e.g. PCFGs the update process requires computing expected rule counts, and adding these to rule count sums.
- *Sampling the sentence's likely parses* is a general way of computing these expectations

⇒ *Learning might be a low-cost by-product of parsing*

Non-parametric Bayesian inference

- Most standard learning methods are based on *optimizing a function of a finite vector of real-valued parameters*
- Learn rules or structures by iterating:
  - generate hopefully useful rules/structures
  - estimate their parameters via a parametric estimator
  - prune low-probabilty rules/structures
- Non-parametric Bayesian methods provide a theoretically sound framework for identifying relevant finite subset from infinite set of entities
  - example: learn finite set of phonemic forms from infinite set of potential phonemic forms
  - Monte Carlo sampling methods

Computational models of word learning

- During their "word spurt", children learn words in "one-shot"
- No obvious limit on number of possible words
  $\Rightarrow$ non-parametric Bayes
- Learn to segment words from *unsegmented broad phonemic transcription* (Brent)
  - Example: *y u w a n t t u s i D 6 b u k*
- Goldwater (2006) learns a bigram model of word sequences *without being told what the words are*
  - Learning inter-word dependencies improves word segmentation
  - Learning intra-word structure (syllable structure) also helps
- There are learning algorithms whose computationally most demanding component is sampling parses of input sequences

Outline

Conclusion

- Be clear about why you're building any computational model
  - usual engineering goals $\Rightarrow$ average case matters
  - open-world parsing (unknown words, fragment parsing)
  - don't have to *capture* a generalization in order to *cover* it
  - what does determining grammaticality have to do with comprehension?
- Statistical models of processing and acquisition are having a major impact
  - probabilistic parsing models are having an increasing impact in psycholinguistics and neurolinguistics
  - (non-parametric) Bayesian models provide new ways of viewing language acquisition