Parse rescoring

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Outline

Linear models for parse rescoring

- Charniak ℓ-best parser supplies *parses* $C = (x_1, \ldots, x_\ell)$ for each sentence
  - We typically use around $\ell = 50$ parses per sentence
- A *feature* f is a function that maps a parse x to real number $f(x)$
  - $\mathbf{f} = (f_1, \ldots, f_m)$ is vector of features
  - $\mathbf{f}(x) = (f_1(x), \ldots, f_m(x))$ is a vector of *feature values*
- A *feature weight vector* is a real-valued vector $\mathbf{w} = (w_1, \ldots, w_m)$ that associates each feature f_j with a weight w_j
- The *score* $s_{\mathbf{w}}(x)$ of a parse x is:

$$s_{\mathbf{w}}(x) \quad = \quad \mathbf{w} \cdot \mathbf{f}(x) \quad = \quad \sum_{j=1}^{m} w_j f_j(x)$$

- The *optimal parse* $\hat{x} \in C$ is the one with the highest score:

$$\hat{x} \quad = \quad \operatorname*{argmax}_{x \in C} s_{\mathbf{w}}(x)$$

- Our goal: choose $\mathbf{f}$ and $\mathbf{w}$ to *make $\hat{x}$ as accurate a parse as possible*

What can features be?

- A feature can be *any real-valued function of the parse*
- By convention, $f_0(x)$ is the log probability of parse from Charniak's parser
- Examples of useful features:
  - The number of times the tree fragment `(S (NP (DT) (NN)) (VP (VB)))` occurs in the parse tree
  - The number of `NP`s in the parse tree beginning with a `DT` and ending with an `NNS` and followed by a punctuation symbol `,`
  - The number of nodes on the *right-most branch* of the parse tree
  - The number of `VP`s with less than 5 non-punctuation words between their right edge and the end of the sentence
- We typically have $m \approx 1,000,000$ features
- I don't know how to identify the most useful features (if you can think of a good way, let me know!)

Supervised learning of feature weights

- All we know about the parses x are:
  - their feature vectors $\mathbf{f}(x)$, and
  - how accurate each parse $x \in C$ is, so we can identify the *best parse* $x^\star \in C$
- Choose feature weights $\mathbf{w}$ so that best parse $x^\star$ is optimal parse $\hat{x}$

Best: $x^\star$	**Rest:** $C \setminus \{x^\star\}$		
$(0, 0, 0, 1, 2)$	$(0, 1, 0, 0, 2)$	$(1, 0, 0, 0, 2)$	$(0, 0, 1, 0, 2)$
$(0, 0, 0, 0, 2)$	$(0, 0, 0, 2, 0)$	$(1, 0, 0, 0, 1)$	
$\ldots$	$\ldots$		

- The weight vector $\mathbf{w} = (-2, -2, -2, -1, 0)$ correctly classifies this data
- Supervised learning problem: given features and the ℓ-best parses for n sentences, find $\mathbf{w}$ such that $\hat{x} = x^\star$ as often as possible
- A variety of methods can be used to do this, including:
  - *MaxEnt*, which maximizes likelihood of $\mathrm{P}(x^\star | C)$ under a log-linear model
  - *Boosting*, which maximizes an approximate margin between $x^\star$ and $\hat{x}$
  - *Perceptron*, which is a fast on-line learning algorithm

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Why are they *Maximum Entropy* models?

- Goal: learn a probability distribution $\widehat{\mathrm{P}}$ as close as possible to distribution P that generated training data D.
- But what does "as close as possible" mean?
  - Require $\widehat{\mathrm{P}}$ to have *same distribution of features* as D
  - As size of data $|D| \rightarrow \infty$, feature distribution in D will approach feature distribution in P
  - so distribution of features in $\widehat{\mathrm{P}}$ will approach distribution of features in P
- But there are many $\widehat{\mathrm{P}}$ that have same feature distributions as D. Which one should we choose?
  - The *entropy* measures the *amount of information* in a distribution
  - Higher entropy $\Rightarrow$ less information
  - Choose the $\widehat{\mathrm{P}}$ with *maximum entropy* that whose feature distributions agree with D
    $\Rightarrow \widehat{\mathrm{P}}$ has the least extraneous information possible

Maximum Entropy models

- A *conditional Maximum Entropy model* $\mathrm{P}_{\mathbf{w}}$ consists of a vector of features $\mathbf{f}$ and a vector of feature weights $\mathbf{w}$.
- The probability $\mathrm{P}_{\mathbf{w}}(x|C)$ of an outcome $x \in C$ is:

$$\begin{aligned}
\mathrm{P}_{\mathbf{w}}(x|C) &= \frac{1}{Z_{\mathbf{w}}(C)} \exp\left(s_{\mathbf{w}}(x)\right) \\
&= \frac{1}{Z_{\mathbf{w}}(C)} \exp\left(\sum_{j=1}^{m} w_j f_j(x)\right), \text{ where:} \\
Z_{\mathbf{w}}(C) &= \sum_{x' \in C} \exp\left(s_{\mathbf{w}}(x')\right)
\end{aligned}$$

- $Z_{\mathbf{w}}(C)$ is a normalization constant called the *partition function*

Feature dependence ⇒ MaxEnt models

- Many probabilistic models *assume that features are independently distributed* (e.g., Hidden Markov Models, Probabilistic Context-Free Grammars)

⇒ Estimating feature weights is simple (relative frequency)

- But features in most linguistic theories interact in complex ways
  - Long-distance and local dependencies in syntax
  - Many markedness and faithfulness constraints interact to determine a single syllable's shape

⇒ *These features are not independently distributed*

- MaxEnt models can handle these feature interactions
- Estimating feature weights of MaxEnt models is more complicated
  - generally requires numerical optimization

A rose by any other name . . .

- Like most other good ideas, Maximum Entropy models have been invented many times . . .
  - In statistical mechanics (physics) as the *Gibbs* and *Boltzmann distributions*
  - In probability theory, as *Maximum Entropy models*, *log-linear models*, *Markov Random Fields* and *exponential families*
  - In statistics, as *logistic regression*
  - In neural networks, as *Boltzmann machines*

A brief history of MaxEnt models in Computational Linguistics

- Logistic regression used in socio-linguistics to model "variable rules" (Sedergren and Sankoff 1974)
- Hinton and Sejnowski (1986) and Smolensky (1986) introduce the Boltzmann machine for neural networks
- Berger, Dell Pietra and Della Pietra (1996) propose Maximum Entropy Models for *language models with non-independent features*
- Abney (1997) proposes MaxEnt models for *probabilistic syntactic grammars with non-independent features*
- (Johnson, Geman, Canon, Chi and Riezler (1999) propose conditional estimation of regularized MaxEnt models)

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Finding the MaxEnt model by maximizing likelihood

- Can prove that the MaxEnt model $\mathrm{P}_{\widehat{\mathbf{w}}}$ for features $\mathbf{f}$ and data $D = ((C_1, x_1), \ldots, (C_n, x_n))$ is:

$$\mathrm{P}_{\widehat{\mathbf{w}}}(x \mid C) \;=\; \frac{1}{Z_{\widehat{\mathbf{w}}}(C)} \exp(\, s_{\widehat{\mathbf{w}}}(x)\,) \;=\; \frac{1}{Z_{\widehat{\mathbf{w}}}(C)} \exp \sum_{j=1}^{m} \widehat{w}_j \, f_j(x)$$

where $\widehat{\mathbf{w}}$ *maximizes the likelihood* $\mathrm{L}_D(\mathbf{w})$ *of the data* D

$$\widehat{\mathbf{w}} \;=\; \operatorname*{argmax}_{\mathbf{w}} \mathrm{L}_D(\mathbf{w}) \;=\; \operatorname*{argmax}_{\mathbf{w}} \prod_{i=1}^{n} \mathrm{P}_{\mathbf{w}}(x_i \mid C_i)$$

I.e., choose $\widehat{\mathbf{w}}$ to make the winners x_i *as likely as possible* compared to losers $C_i \setminus \{x_i\}$

Finding the feature weights $\widehat{\mathbf{w}}$

- Standard method: use a *gradient-based* numerical optimizer to *minimize the negative log likelihood* $-\log \mathrm{L}_D(\mathbf{w})$
  (Limited memory variable metric optimizers seem to be best)

$$
\begin{aligned}
-\log \mathrm{L}_D(\mathbf{w}) &= \sum_{i=1}^{n} -\log \mathrm{P}_{\mathbf{w}}(x_i \mid C_i) \\
&= \sum_{i=1}^{n} \left(\log Z_{\mathbf{w}}(C_i) - \sum_{j=1}^{m} w_j \, f_j(x_i) \right) \\
\frac{\partial \ -\log \mathrm{L}_D(\mathbf{w})}{\partial w_j} &= \sum_{j=1}^{n} \left(\mathrm{E}_{\mathbf{w}}[f_j | C_i] - f_j(x_i) \right), \text{ where:} \\
\mathrm{E}_{\mathbf{w}}[f_j | C_i] &= \sum_{x' \in C_i} f_j(x') \, \mathrm{P}_{\mathbf{w}}(x')
\end{aligned}
$$

- I.e., find feature weights $\widehat{\mathbf{w}}$ that make the *model's distribution of features over C_i equal distribution of features in winners x_i*

Finding the optimal feature weights $\widehat{\mathbf{w}}$

- Numerically optimizing likelihood involves calculating $-\log \mathrm{L}_D(\mathbf{w})$ and its derivatives
- Need to calculate $Z_{\mathbf{w}}(C_i)$ and $\mathrm{E}_{\mathbf{w}}[f_j|C_i]$, which are sums over C_i, the set of candidates for example i
- If C_i can be infinite:
  - depending on $\mathbf{f}$ and C, might be possible to *explicitly calculate* $Z_{\mathbf{w}}(C_i)$ and $\mathrm{E}_{\mathbf{w}}[f_j|C_i]$, or
  - may be able to *approximate* $Z_{\mathbf{w}}(C_i)$ and $\mathrm{E}_{\mathbf{w}}[f_j|C_i]$, especially if $\mathrm{P}_{\mathbf{w}}(x|C)$ is concentrated on few x.
- Aside: using MaxEnt for *unsupervised learning* requires $Z_{\mathbf{w}}$ and $\mathrm{E}_{\mathbf{w}}[f_j]$, but these are typically *hard to compute*
- If feature weights w_j should be negative (e.g., OT constraint violations can only "hurt" a candidate), then replace optimizer with a *numerical optimizer/constraint solver*
  (e.g., TAO package from Argonne labs)

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Why regularize?

- MaxEnt selects $\widehat{\mathbf{w}}$ so that winners are as likely as possible
- Might not want to do this with *noisy training data*
- *Pseudo-maximal or minimal* features cause numerical problems
  - A feature f_j is *pseudo-minimal* iff for all $i = 1, \ldots, n$ and $x' \in C_i$, $f_j(x_i) \leq f(x')$ (i.e., $f_j(x_i)$ is the minimum value f_j has in C_i)
  - If f_j is *pseudo-minimal*, then $\widehat{\mathbf{w}}_j = -\infty$
- Example: Features 1, 2 and 3 are pseudo-minimal below:

Winner x_i	**Losers** $C_i \setminus \{x_i\}$		
$(0,0,0,1,2)$	$(0,1,0,0,2)$	$(1,0,0,0,2)$	$(0,0,1,0,2)$
$(0,0,0,0,2)$	$(0,0,0,2,0)$	$(1,0,0,0,1)$	
$\ldots$	$\ldots$		

so we can make (some of) the losers have arbitrarily low probability by setting the corresponding feature weights as negative as possible

Regularization, or "keep it simple"

- Slavishly optimizing likelihood leads to over-fitting or numerical problems

$\Rightarrow$ Regularize or smooth, i.e., try to find a "good" $\widehat{\mathbf{w}}$ that is "not too complex"

- Minimize the *penalized negative log likelihood*

$$\widehat{\mathbf{w}} \quad = \quad \underset{\mathbf{w}}{\operatorname{argmin}} \quad -\log \mathrm{L}_D(\mathbf{w}) + \alpha \sum_{j=1}^{m} |w_j|^k$$

where $\alpha \geq 0$ is a parameter (often set by *cross-validation on held-out training data*) controlling amount of regularization

Aside: Regularizers as Bayesian priors

- Bayes inversion formula

$$\underbrace{\mathrm{P}(\mathbf{w} \mid D)}_{\text{posterior}} \quad \propto \quad \underbrace{\mathrm{P}(D \mid \mathbf{w})}_{\text{likelihood}} \; \underbrace{\mathrm{P}(\mathbf{w})}_{\text{prior}}$$

  or in terms of log probabilities:

$$-\log \mathrm{P}(\mathbf{w} \mid D) \quad = \quad \underbrace{-\log \mathrm{P}(D \mid \mathbf{w})}_{-\text{ log likelihood}} \quad \underbrace{-\log \mathrm{P}(\mathbf{w})}_{-\text{ log prior}} + c$$

$\Rightarrow$ The regularized estimate $\widehat{\mathbf{w}}$ is also the Bayesian *maximum a posteriori* (MAP) estimate with prior

$$\mathrm{P}(\mathbf{w}) \quad \propto \quad \exp\left(-\alpha \sum_{j=1}^{m} |w_j|^k\right)$$

- When $k = 2$ this is a *Gaussian prior*

Understanding the effects of the priors

- The log penalty term for a *Gaussian prior* ($k = 2$) is $\alpha \sum_j w_j^2$ so its derivative $2\alpha w_j \to 0$ as $w_j \to 0$
- Effect of Gaussian prior decreases as w_j is small

$\Rightarrow$ Gaussian prior prefers all w_j to be small but not necessarily zero

- The log penalty term for a *1-norm prior* ($k = 1$) is $\alpha \sum_j |w_j|$ so its derivative $\alpha \text{sign}(w_j)$ is α or $-\alpha$ unless $w_j = 0$
- Effect of 1-norm prior is constant no matter how small w_j is

$\Rightarrow$ 1-norm prior prefers most w_j to be zero (*sparse solutions*)

- My personal view: If most features in your problem are irrelevant, prefer a sparse feature vector.
  But if most features are noisy and weakly correlated with the solution, prefer a dense feature vector (averaging is the solution to noise).

MaxEnt in syntactic parsing

- MaxEnt model used to *pick correct parse from 50 parses* produced by Charniak parser
  - C_i is set of 50 parses from Charniak parser, x_i is best parse in C_i
  - Charniak parser's accuracy ≈ 0.898 (picking tree it likes best)
  - Oracle accuracy is ≈ 0.968
  - EM-like method for dealing with ties (training data C_i contains several equally good "best parses" for a sentence i)
- MaxEnt model uses 1,219,273 features, encoding a wide variety of syntactic information
  - including the Charniak model's *log probability* of the tree
  - trained on parse trees for 36,000 sentences
  - prior weight α set by *cross-validation* (don't need to be accurate)
- Gaussian prior results in all feature weights non-zero
- L1 prior results in $\approx 25,000$ non-zero feature weights
- Accuracy with both Gaussian and L1 priors ≈ 0.916 (Andrew and Gao, *ICML 2007*)

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Stochastic gradient ascent

- MaxEnt: choose $\widehat{\mathbf{w}}$ to maximize log likelihood
- If $\mathbf{w} \neq \widehat{\mathbf{w}}$ and δ is sufficiently small, then

$$\log \mathrm{L}_D \left(\mathbf{w} + \delta \frac{\partial \log \mathrm{L}_D(\mathbf{w})}{\partial \mathbf{w}} \right) \quad > \quad \log \mathrm{L}_D(\mathbf{w})$$

  i.e., small steps in direction of derivative increase likelihood

$$\frac{\partial \log \mathrm{L}_D(\mathbf{w})}{\partial w_j} = \sum_{j=1}^{n} \left(f_j(x_i) - \mathrm{E}_{\mathbf{w}}[f_j \mid C_i] \right), \text{ where:}$$

$$\mathrm{E}_{\mathbf{w}}[f_j | C_i] = \sum_{x' \in C_i} f_j(x') \, \mathrm{P}_{\mathbf{w}}(x')$$

- *Gradient ascent* optimizes the log likelihood in this manner.
  - It is usually *not* an efficient optimization method
- *Stochastic gradient ascent* updates immediately in direction of contribution of training example i to derivative
  - It is a simple and sometimes very efficient method

Perceptron updates as a MaxEnt approx

- Perceptron learning rule: Let $x_i^\star$ be the model's current prediction of the optimal candidate in C_i

$$x_i^\star \quad = \quad \underset{x' \in C_i}{\text{argmax}}\ s_{\mathbf{w}}(x')$$

If $x_i^\star \neq x_i$, where x_i is the correct candidate in C_i, then increment the current weights $\mathbf{w}$ with:

$$\delta \left(\mathbf{f}(x_i) - \mathbf{f}(x_i^\star) \right)$$

- MaxEnt stochastic gradient ascent update:

$$\delta \, \frac{\partial \, \log \mathrm{L}_D(\mathbf{w})}{\partial \, \mathbf{w}} \quad = \quad \delta \left(\mathbf{f}(x_i) - \mathrm{E}_{\mathbf{w}}[\mathbf{f} \mid C_i] \right)$$

If $\mathrm{P}_{\mathbf{w}}(x \mid C_i)$ is peaked around $x_i^\star$, then $\mathrm{E}_{\mathbf{w}}[\mathbf{f} \mid C_i] \approx \mathbf{f}(x_i^\star)$

$\Rightarrow$ The Perceptron rule approximates the MaxEnt stochastic gradient ascent update

Regularization as weight decay

- When we approximate regularized MaxEnt as either Stochastic Gradient Ascent or the Perceptron update, *regularization corresponds to weight decay* (a popular smoothing method for neural networks)

- Contribution of *Gaussian prior* to log likelihood is $-\alpha \sum_j w_j^2$
  so derivative of regularizer is $-2\alpha w_j$

$\Rightarrow$ weights *decay proportionally to their current value* each iteration

- Contribution of *1-norm prior* to log likelihood is $-\alpha \sum_j |w_j|$
  so derivative of regularizer is $-\alpha \operatorname{sign}(w_j)$

$\Rightarrow$ non-zero weights *decay by a constant amount* each iteration

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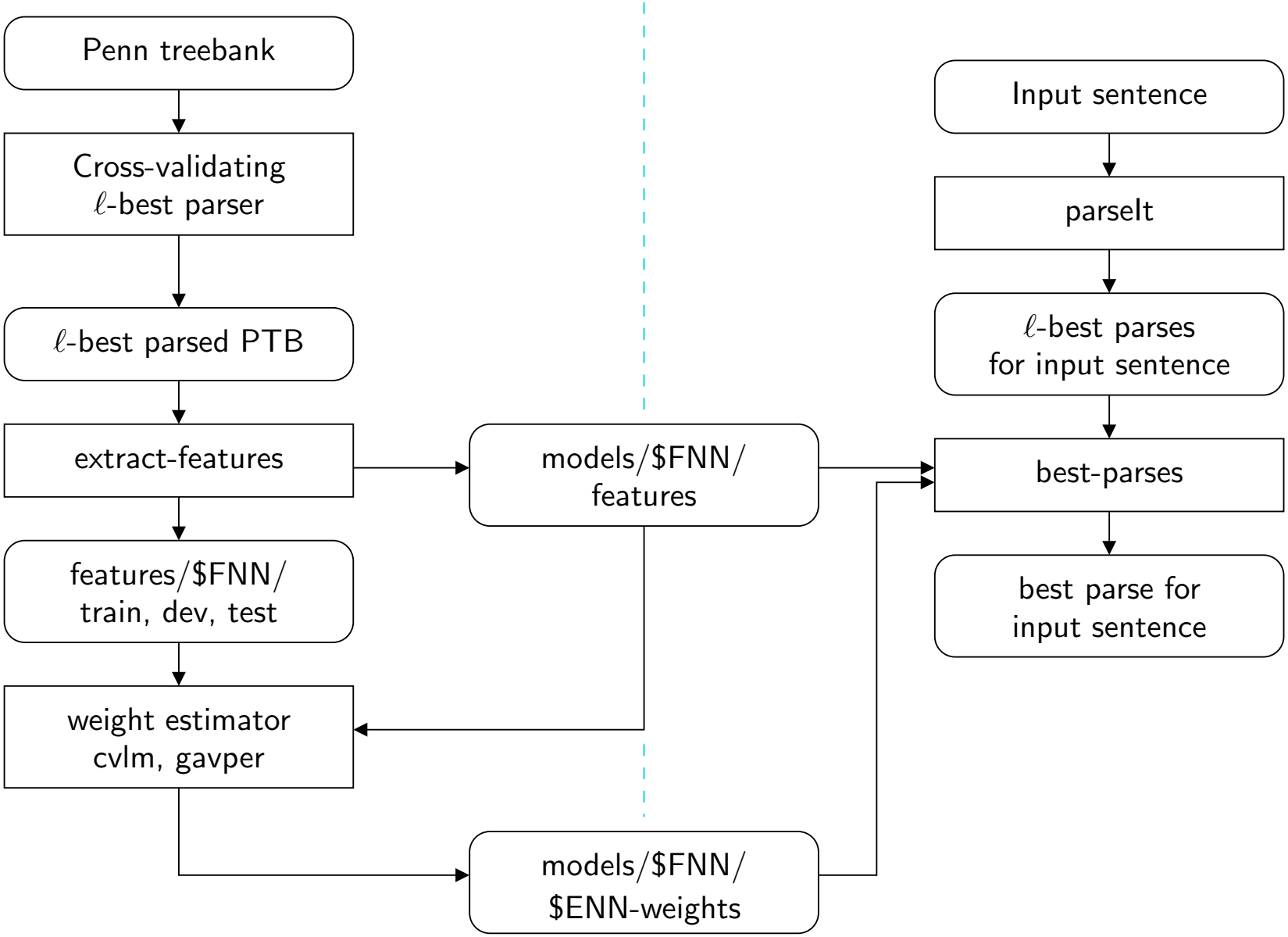
Overview of the parse rescorer



Pruning useless features with two-pass feature extraction

- There are too many features to store every feature for every parse
- The job of a feature is to *distinguish the best parse from the rest of the parses*

$\Rightarrow$ Only keep features whose value on the best parse differs from their value on at least one other parse *in at least 5 sentences*

  - A feature is *pseudo-constant* iff its value is the same for all parses of each sentence

$\Rightarrow$ Two passes over training data in feature extraction:

  - first pass counts how often each feature distinguishes the best from the rest, and only keeps useful features
  - second pass prints out how often each useful feature appears in each parse

Features are implemented by feature classes

- Groups of related features (e.g., all tree fragments up to a certain size) are implemented by the same *feature class*
- A feature class is a C++ class that implements a group of features. It must:
  - define the virtual function `identifier`, which returns a unique identifying string for this feature class, e.g., `TreeFrag`
  - define the type `Feature`, which are the features belonging to this feature class
  - define the function `parse_featurecount`, which maps each parse to the feature values for each feature in the feature class.
- Features can be any kind of object that:
  - can be written to a single line with <<, and read back in with >>
  - can be hashed with `hash<Feature>()`
  - if you use (vectors of) the predefined symbols or trees, this is automatically done for you by templates

How feature classes communicate with the program

- The `FeatureClassPtrs` object is a vector of pointers to the feature classes used by the feature extractor. Its constructor usually calls function that pushes the feature classes to be used

```
inline void FeatureClassPtrs::features_connll() {
  push_back(new NLogP());
  push_back(new Rule());
  push_back(new Rule(0, 1));
  push_back(new Rule(0, 0, true));
  push_back(new Rule(0, 0, false, true));
  ...
```

- The feature class is called with a parse and *feature count map* `feat_count`
  - A feature count map is a "smart" map object that (appears to) map features to non-negative integers
- If a feature f has value v in the parse, then the feature class should set

$$\texttt{feat\_count}[f] \quad = \quad v$$

Since the value of many features is the number of times the feature appears in the parse tree, it can be easier to increment the feature `++feat_count`$[f]$

Types of feature classes

- A *parse* consists of a *parse tree* together with other information, e.g., Charniak parser probability, etc.
- Features are functions from parses to real numbers, but most features count how often specific configurations occur in the parse tree. The tree-walking code needed to do this is already encapsulated in a `NodeFeatureClass`.
- Feature classes inheriting directly from `FeatureClass` (e.g., `BinnedLogCondP`) define

```
template <typename FeatClass, typename Feat_Count> void
parse_featurecount(FeatClass& fc, const sp_parse_type& parse,
                   Feat_Count& feat_count)
```

- Feature classes inheriting from `NodeFeatureClass` (e.g., `SubjVerbAgr`) define

```
template <typename FeatClass, typename Feat_Count>
void node_featurecount(FeatClass& fc, const sptree* node,
                       Feat_Count& feat_count)
```

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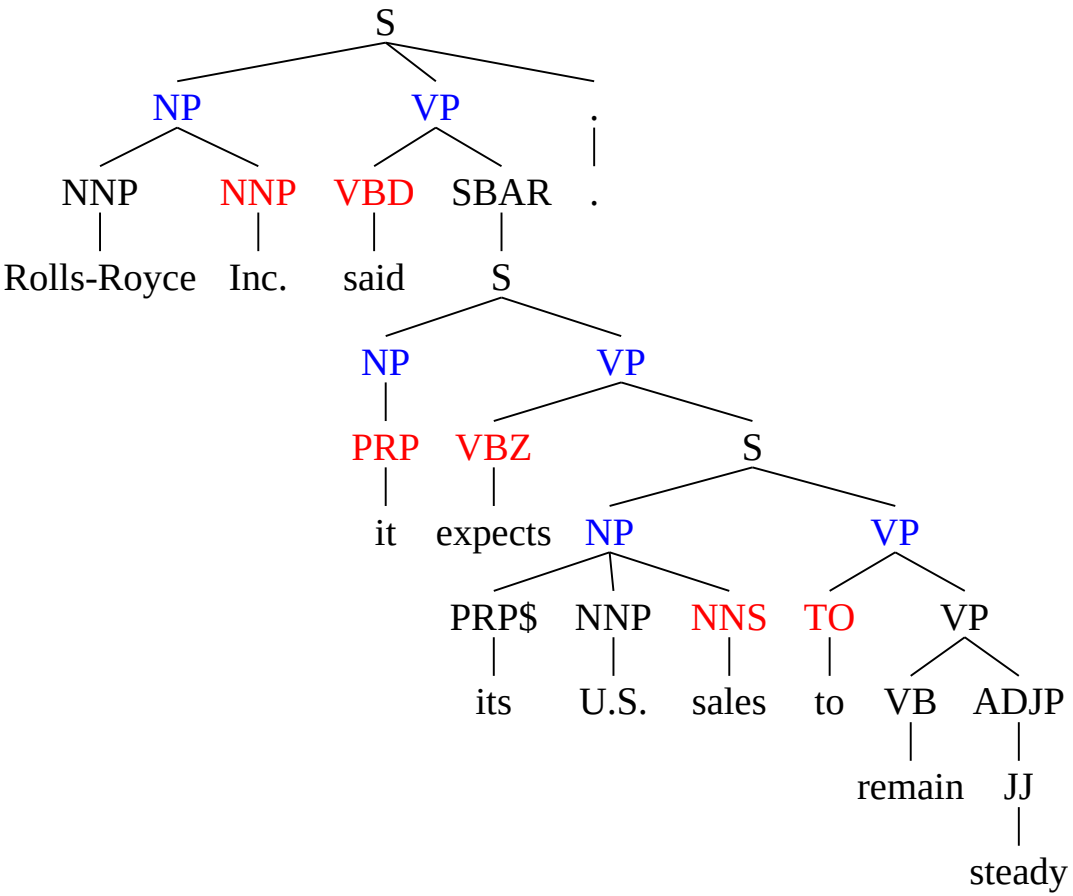
Example feature class: SubjVerbAgr

- Goal: add a feature that will (roughly) capture subject-verb agreement
- Penn POS tags distinguish singular and plural nouns and verbs
- Idea: create a feature consisting of the subject NP's head's POS and the VP's head's POS.
- Good (NP head POS, VP head POS) combinations will have positive weights, bad combinations will have negative weights (we hope)



SubjVerbAgr feature class

```
class SubjVerbAgr : public NodeFeatureClass {
public:

  // Feature is vector of symbols
  typedef std::vector<symbol> Feature;

  template <typename FeatClass, typename Feat_Count>
  void node_featurecount(FeatClass& fc, const sptree* node,
                         Feat_Count& feat_count);

  virtual const char * identifier() const {
    return "SubjVerbAgr";
  }

  // Macro defines functions that every feature class needs
  SPFEATURES_COMMON_DEFINITIONS;
};
```

SubjVerbAgr feature class feature counting

```
template <typename FeatClass, typename Feat_Count>
void SubjVerbAgr::node_featurecount(FeatClass& fc, const sptree* node,
                                    Feat_Count& feat_count) {
  if ((node->label.cat != S() && node->label.cat != SINV())
      || node->label.syntactic_lexhead == NULL)
    return;
  const sptree* subject = NULL;          // subject is last NP before VP
  for (const sptree* child = node->child; child != NULL;
       child = child->next)
    if (child->label.cat == NP())
      subject = child;
    else if (child->label.cat == VP())
      break;
  if (subject == NULL || subject->label.semantic_lexhead == NULL)
    return;
  Feature f;
  f.push_back(subject->label.semantic_lexhead->label.cat);
  f.push_back(node->label.syntactic_lexhead->label.cat);
  ++feat_count[f];
}
```

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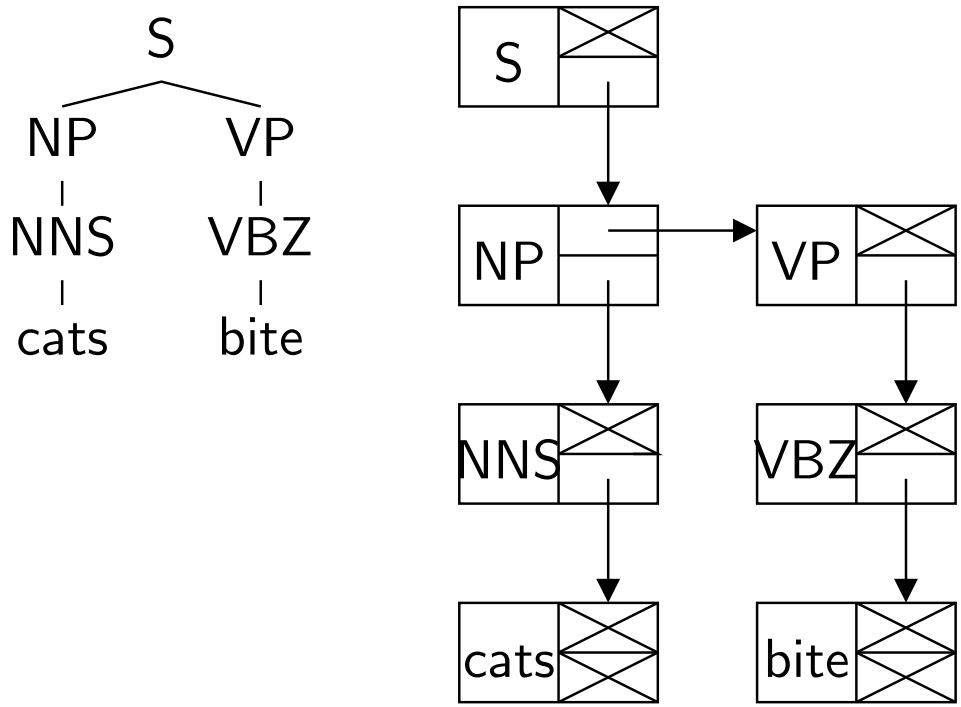
The representation of trees

- A tree includes a `label` and a pointer to `next` and `child` trees



- The `label` is a template class argument to the `tree_node` class
- A node's `label` must include a category `cat` field, but it may include other fields as well
- The labels of `sptrees` include pointers to syntactic and semantic lexical head nodes, string positions of left and right edges of this node, etc.