Computational Linguistics

Methods of Part-of-Speech Tagging

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  - Neural Networks
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  - Language Models (like BERT), finetuned
- Hybrid Methods
  - Combination of rule-based, statistical, and machine learning approaches.
  - Example: Integration of CRFs with neural network features.

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Example

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- She: PRP (Pronoun)
- promised: VBD (Verb, past tense) / VBN (Verb, past participle)
- to: PRP (Preposition) / TO (Infinitive marker)
- back: VB (Verb) / JJ (Adjective) / RB (Adverb) / NN (Noun)
- the: DT (Determiner)
- bill: NN (Noun) / VB (Verb)

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- **Second Stage:**
  - Applies large lists of hand-written disambiguation rules to narrow down the list to a single part-of-speech for each word.

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Rule-based POS Tagging: Pros and Cons

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Pros:

- **Transparency:** Easy to understand and interpret.
- **Customization:** Can be tailored to specific languages or domains.
- **No Training Data Required:** Doesn't require a large annotated corpus.

Cons:

- **Limited Coverage:** May miss out on complex linguistic phenomena.
- **Scalability:** Difficult to maintain as the number of rules increases.
- **Performance:** Generally less accurate than statistical or machine learning methods.

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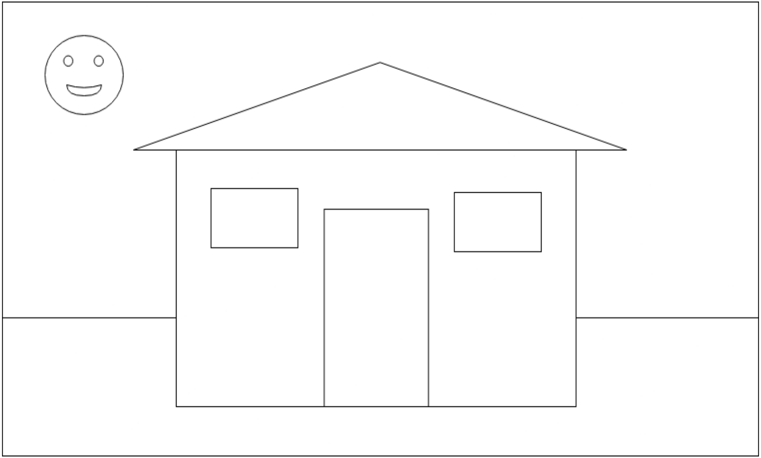
  - **Final Output:** A sequence of rules applied to improve tagging accuracy.

TBL as Painting Analogy



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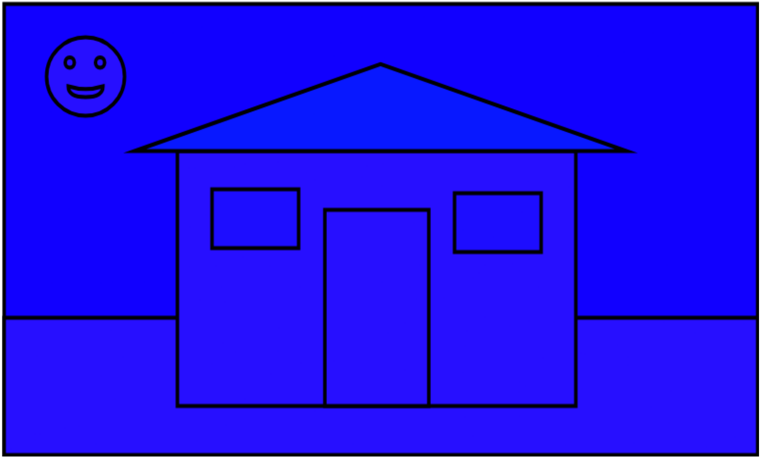

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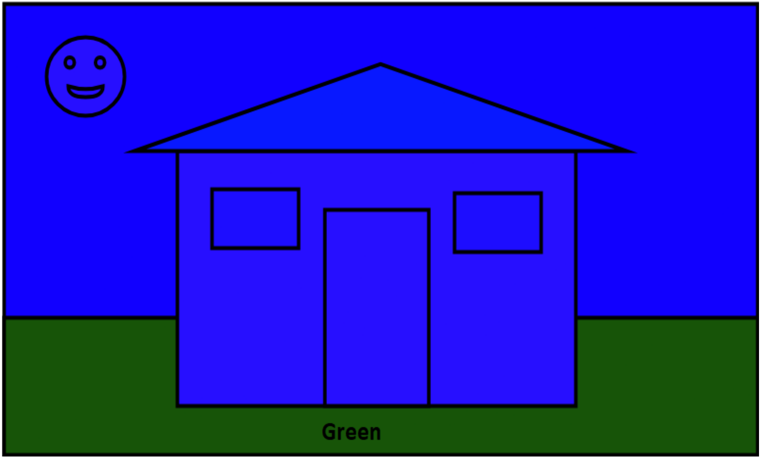

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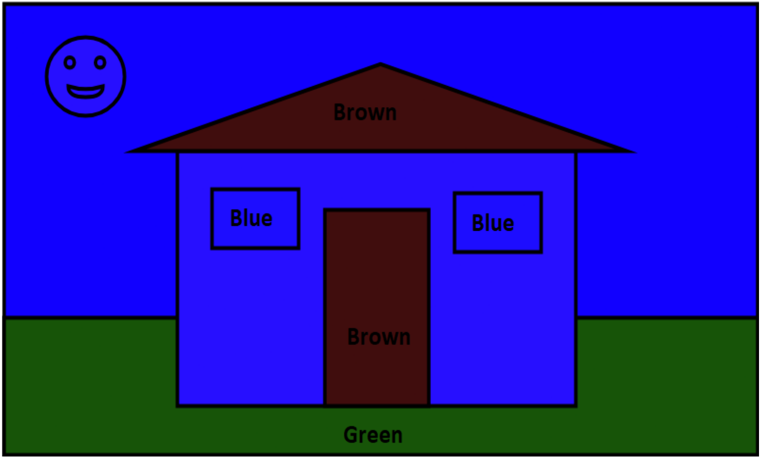

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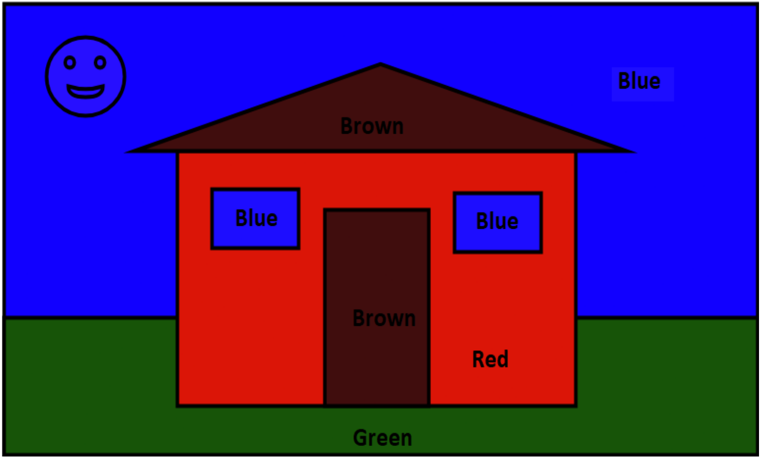

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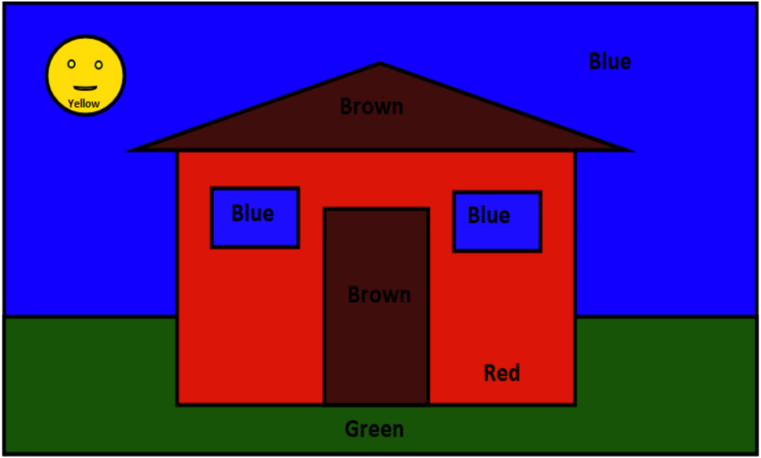

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- **Order of rules is important.**
- **Cascading effects:**
  - Rules can change a correct tag into an incorrect tag.
  - Another rule might be required to correct that "mistake."

Transformation-based Tagging: Examples

Examples of Transformation Rules:

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- **Rule 4:**
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Key Features:

- Rules are learned from data.

Input:

- **Tagged Corpus:** Provides the training data for learning rules.
- **Dictionary:** Contains the most frequent tags associated with words.

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- **Transformation Rules:** Each rule consists of a condition and an action. For example:
  - *Condition:* If a word is tagged as a noun and follows a preposition.
  - *Action:* Change the tag to a verb.

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Final Output:

- **Result:** A sequence of ordered transformation rules applied to new data to produce accurate POS tags.

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  `P(NN|race) = 0.98`
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- Initial tagging:
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- **Rule:**
  "Change `NN` to `VB` when the previous tag is `TO`."
- Tagging after applying rule:
  `... is/VBZ expected/VBN to/TO race/VB tomorrow/NN`

Explanation:

- The word "race" was initially tagged as a noun (`NN`) because it is more commonly used as a noun (with a probability of 0.98). However, based on the context provided by the preceding word "to" (tagged as `TO`), the rule changes the tag to `VB` (verb), which makes more sense in this context.

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- Two types of Probabilities
  - Individual word Probabilities

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  - Typically, a small "training corpus" is used.
  - The corpus is hand-tagged with POS tags to provide a reference.
- **Learning Tagging Rules:**
  - Rules are defined to identify the most likely sequence of tags.
  - Rules are based on:
    - **Internal Evidence:** Morphological features of words (e.g., suffixes).
    - **External Evidence:** Context provided by surrounding words.
    - **Probabilities:** Statistical models estimating the likelihood of tag sequences.
- Two types of Probabilities
  - Individual word Probabilities
  - Tag Sequence Probabilities

Learning Individual Word Probabilities

Individual Word Probabilities:

- The probability that a given tag t is appropriate for a given word w is estimated from the training corpus.
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Formula for Learning Individual Word Probabilities:

- The probability $P(t \mid w)$ is the probability that a given tag t is appropriate for a given word w.
- It is calculated using:

$$P(t \mid w) = \frac{f(t, w)}{f(w)}$$

Where:

- $f(t, w)$ is the frequency of the word w occurring with the tag t.
- $f(w)$ is the total frequency of the word w in the corpus.

Example:

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Interpretation:

- $P(\text{verb} \mid \text{run}) = 0.75$ indicates that there is a 75% probability that the word "run" is used as a verb.

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Challenge:

- Calculating this probability directly for the entire sequence is complex.
- Instead, it's often simplified using the chain rule:

$$P(t_1, t_2, t_3, \ldots \mid w_1, w_2, w_3, \ldots) = P(t_1) \times P(t_2 \mid t_1) \times P(t_3 \mid t_1, t_2) \times \cdots$$

Explanation:

- The joint probability is decomposed into a product of conditional probabilities.
- This approach reduces complexity by breaking down the problem into manageable parts.

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- **N-gram Model:**
  - Generalizes to sequences of N tags.
  - Probability of a tag sequence $t_1, t_2, \ldots, t_N$ is:

$$P(t_1, t_2, \ldots, t_N) = \prod_{i=2}^{N} P(t_i \mid t_{i-1}, \ldots, t_{i-N+1})$$

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	Gold Positive	Gold Negative
System Positive	TP	FP
System Negative	FN	TN

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Accuracy can be misleading in cases of class imbalance, where one class is much more frequent than the other.

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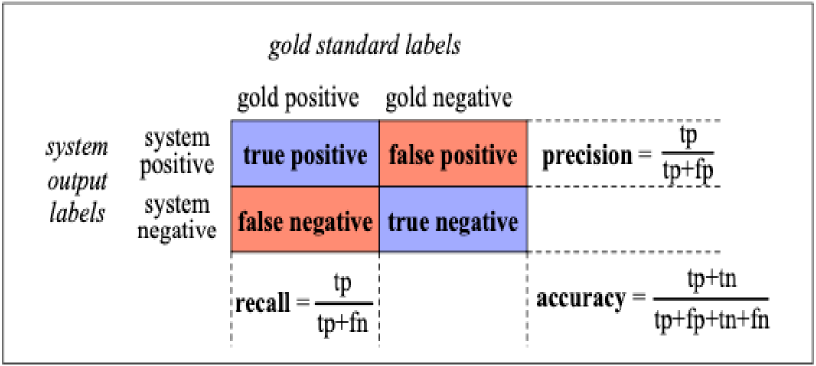
Recall measures the ability to find all relevant positive instances:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Both precision and recall are important metrics, especially in cases of unbalanced datasets.

Precision, Recall and Accuracy



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The F-measure balances precision and recall, with β adjusting the importance of recall versus precision.