BSCS5002: Introduction to Natural Language Processing

Methods of Part-of-Speech Tagging

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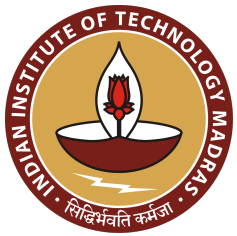

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Methods of POS Tagging

- Rule-based POS tagging
- Transformation-based POS tagging
- Statistical-based POS tagging
  - Stochastic (Probabilistic) POS Tagging
    - Hidden Markov Models (HMM)
    - Maximum Entropy Models
    - Conditional Random Fields (CRF)
- Machine Learning-based POS Tagging
  - Neural Networks
  - Deep Learning Models
  - Large Language Models (like BERT), finetuned
- Hybrid Methods
  - Combination of rule-based, statistical, and machine learning approaches.
  - Example: Integration of CRFs with neural network features.

1. Rule-based Tagging

- Typically start with a dictionary of words and possible tags
- Assign all possible tags to words using the dictionary
- Write rules by hand to selectively remove tags
- Stop when each word has exactly one (presumably correct) tag

Example

She promised to back the bill

- 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)

Example

She promised to back the bill

- she: PRP
- promised: ~~VBN~~,VBD
- to: ~~PRP~~, TO
- back: VB, ~~JJ, RB, NN~~
- the: DT
- bill: NN, ~~VB~~

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

EngCG ENGTWOL Tagger

- A rule-based POS tagger designed for English and other languages.
- Richer Dictionary includes morphological and syntactic features (e.g., subcategorization frames) as well as possible POS.
- Uses two-level morphological analysis on input and returns all possible POS.
- Apply negative constraints (>3744) to rule out incorrect POS.

Rule-based POS Tagging: Pros and Cons

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:

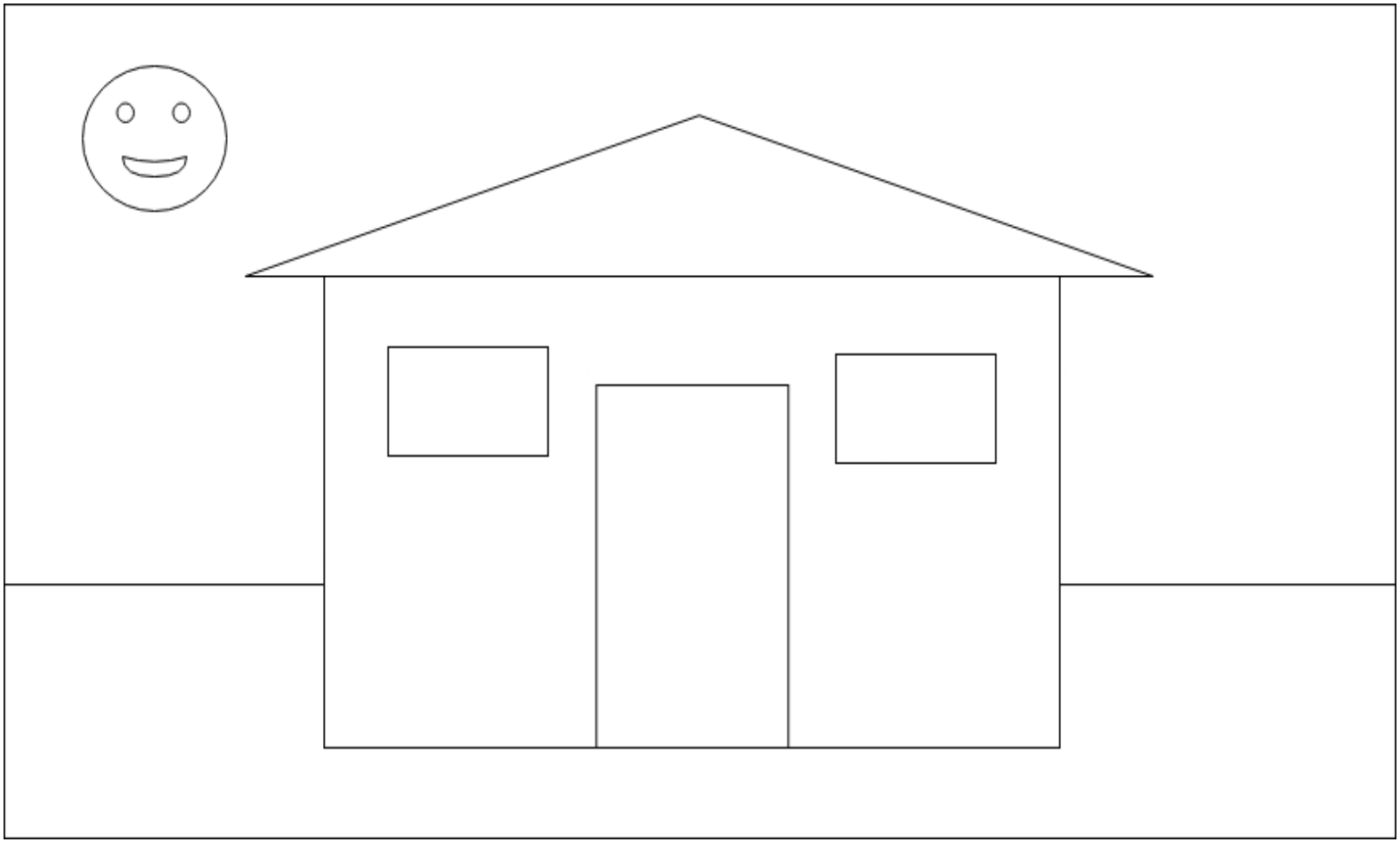
- **Limited Coverage:** May miss out on complex linguistic phenomena.
- **Scalability:** Difficult to maintain as the number of rules increases.
- **Performance:** Generally less accurate than statistical or machine learning methods.

Transformation-based Tagging

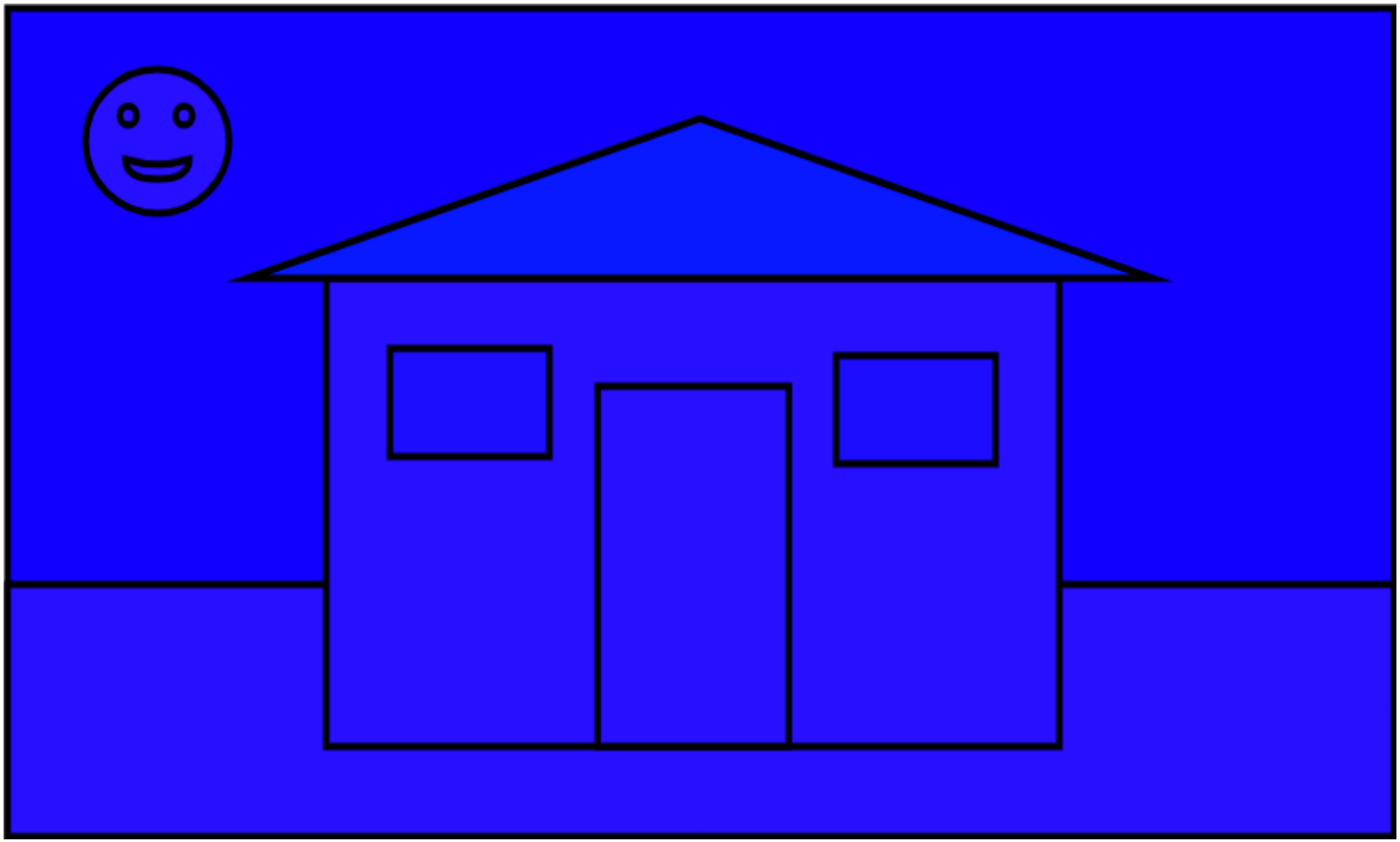
Transformation-based Tagging (TBL)

- **Introduced by:** Eric Brill in 1992.
- **Objective:** Develops a rule-based model that iteratively refines an initial state through transformations.
- **Key Components:**
  - **Initial State:** Assigns a naive label, often using a simple method like the most frequent tag.
  - **Transformations:** Rules that correct errors in the current tagging based on context.
  - **Learning Process:**
    - Identify errors in current tagging.
    - Create a transformation rule to correct these errors.
    - Apply the rule and iterate.
  - **Final Output:** A sequence of rules applied to improve tagging accuracy.

TBL as Painting Analogy



TBL as Painting Analogy



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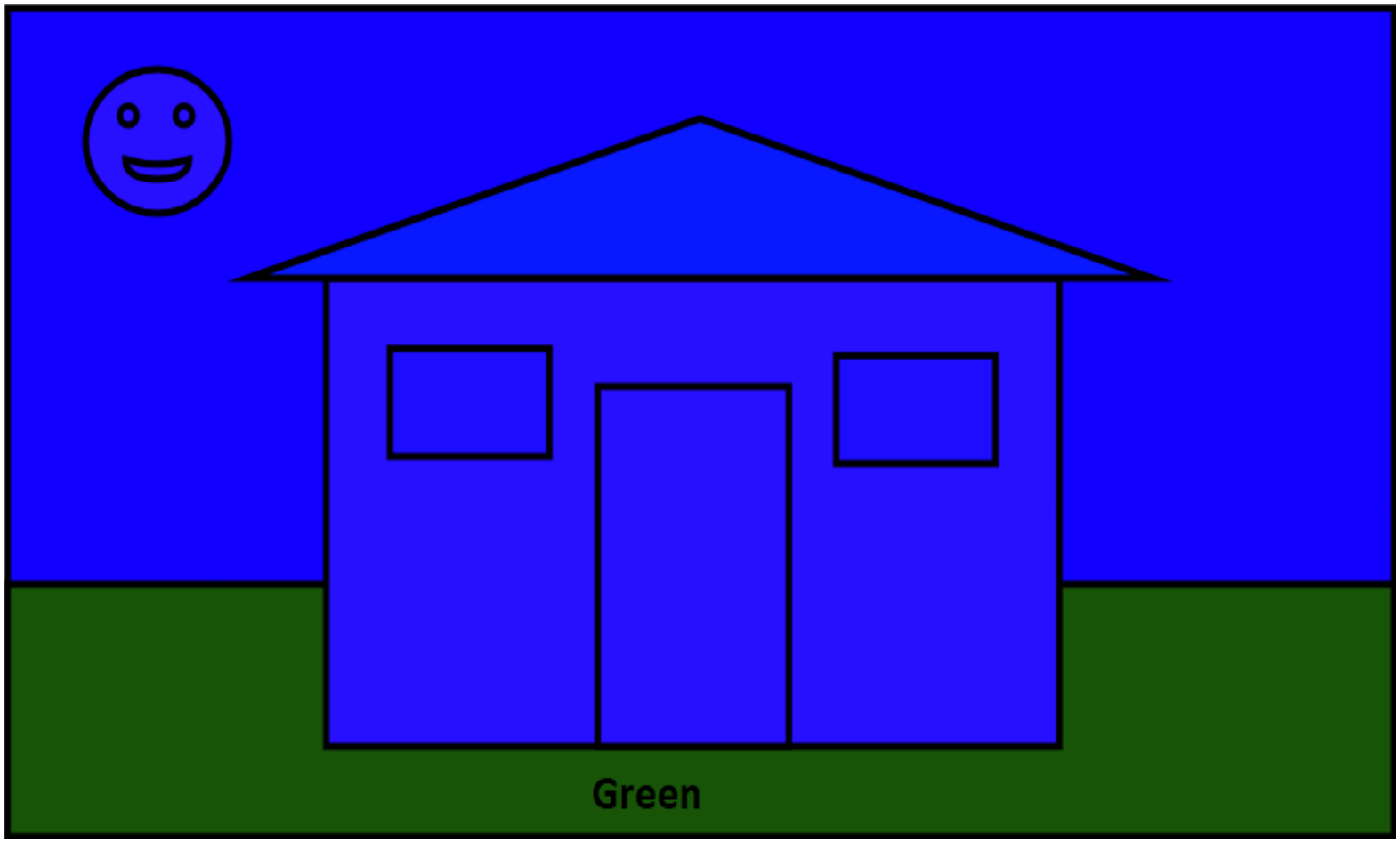

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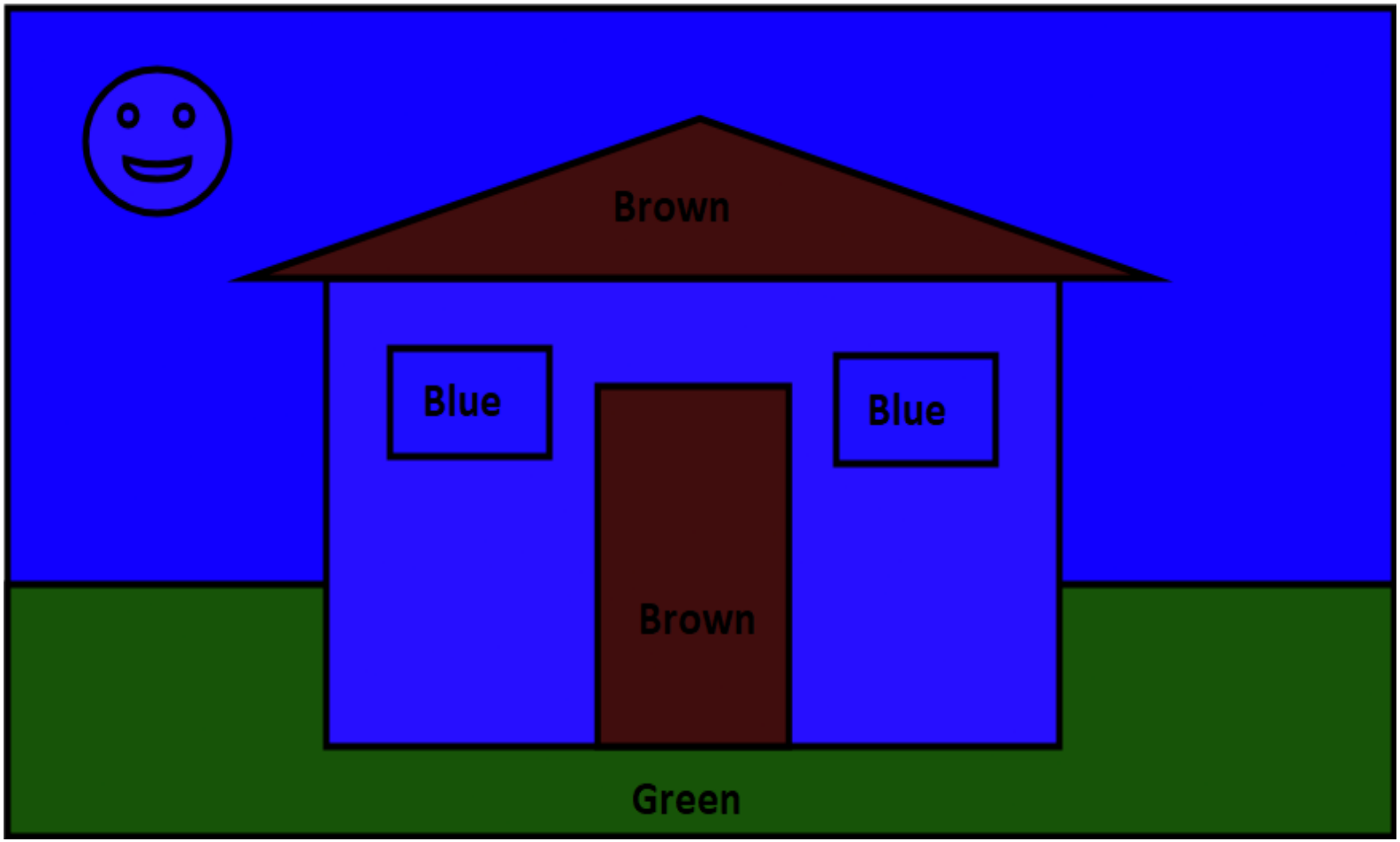

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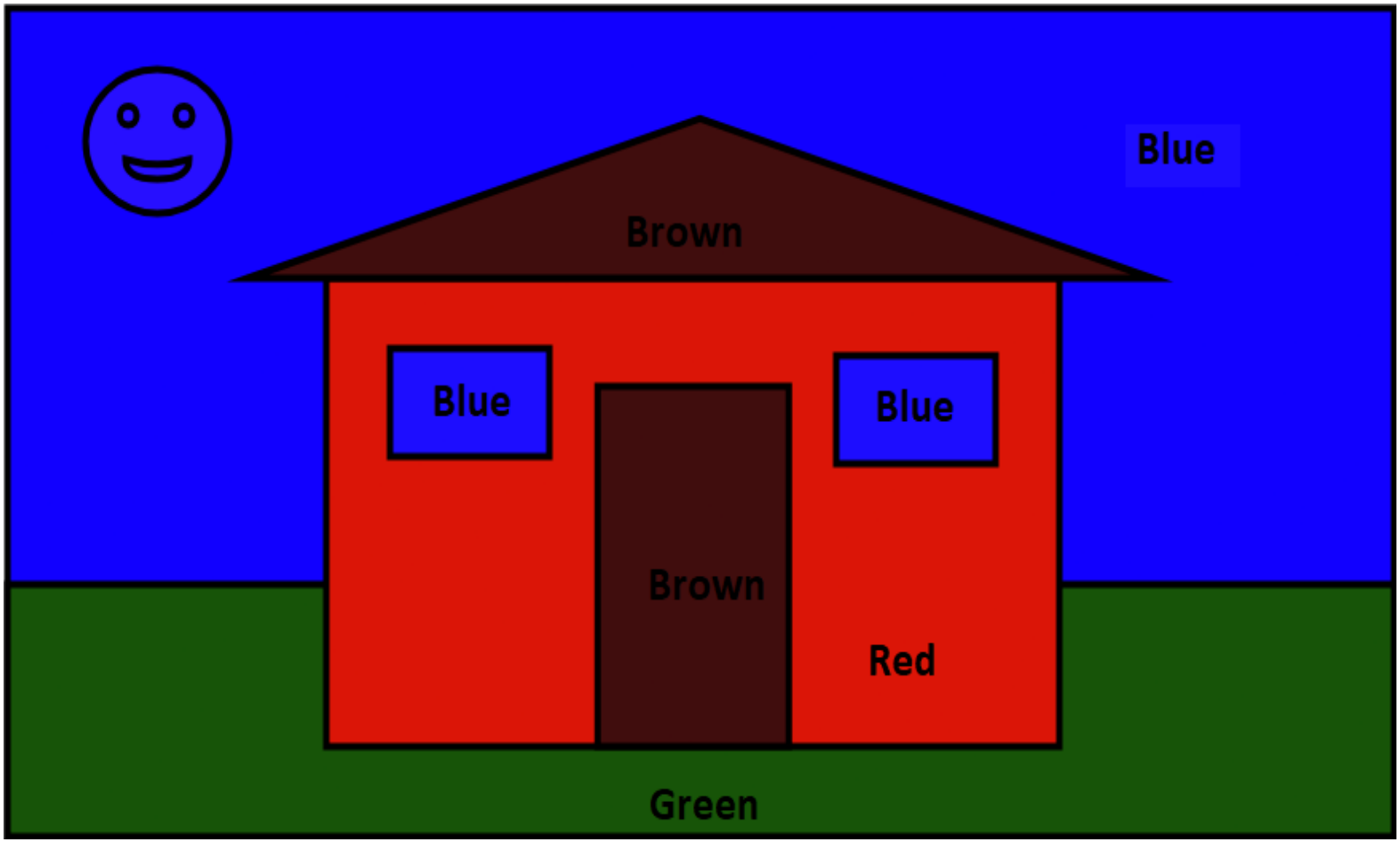

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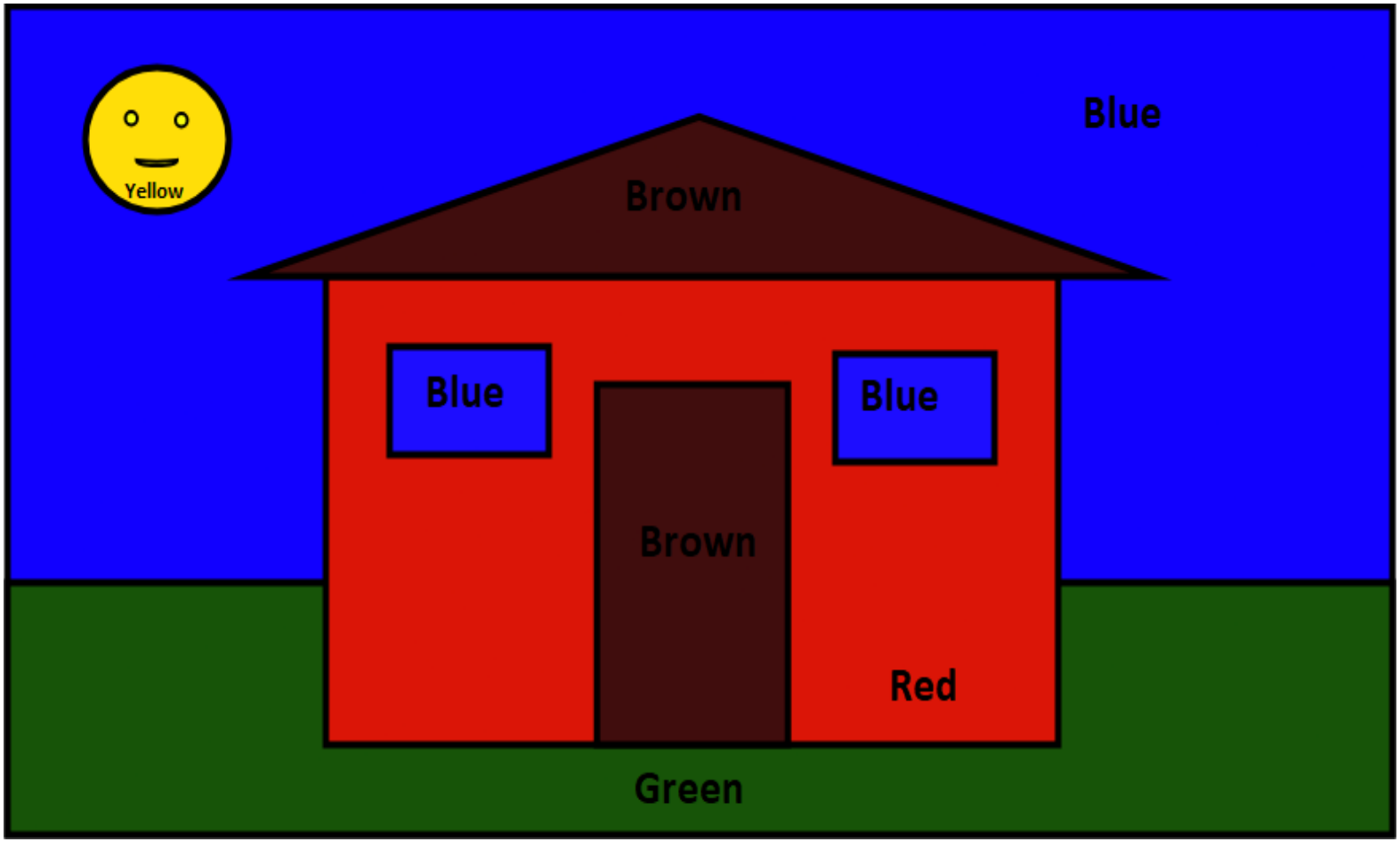


Transformation Rules

Change tag `a` to `b` when:

- **Internal evidence:** Based on morphology.
- **Contextual evidence:**
  - One or more of the preceding/following words has a specific tag.
  - One or more of the preceding/following words is a specific word.
  - One or more of the preceding/following words has a certain form.
- **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:

- **Rule 1:**
  If a word is currently tagged `NN`, and has a suffix of length 1 which consists of the letter `'s'`, change its tag to `NNS`.
- **Rule 2:**
  If a word has a suffix of length 2 consisting of the letter sequence `'ly'`, change its tag to `RB` (regardless of the initial tag).
- **Rule 3:**
  Change `VBN` to `VBD` if the previous word is tagged as `NN`.
- **Rule 4:**
  Change `VBD` to `VBN` if the previous word is `'by'`.

Transformation-based Tagging: Example Sequence

Example after Lexical Lookup:

- Booth/NP killed/VBN Abraham/NP Lincoln/NP
- Abraham/NP Lincoln/NP was/AUX shot/VBD by/BY Booth/NP
- He/PPS witnessed/VBD Lincoln/NP killed/VBN by/BY Booth/NP

After Applying Contextual Rule: `vbn` $\rightarrow$ `vbd PREVTAG np`

- Booth/NP killed/**VBD** Abraham/NP Lincoln/NP
- Abraham/NP Lincoln/NP was/AUX shot/**VBD** by/BY Booth/NP
- He/PPS witnessed/**VBD** Lincoln/NP killed/VBD by/BY Booth/NP

After Applying Contextual Rule: `vbd` $\rightarrow$ `vbn NEXTWORD by`

- Booth/NP killed/**VBD** Abraham/NP Lincoln/NP
- Abraham/NP Lincoln/NP was/AUX shot/**VBN** by/BY Booth/NP
- He/PPS witnessed/**VBD** Lincoln/NP killed/VBN by/BY Booth/NP

Transformation-Based (Brill) Tagging

Combines Rule-based and Stochastic Tagging:

- **Rule-based:** Uses rules to specify tags in a certain environment.
- **Stochastic approach:** Utilizes a tagged corpus to find the best-performing rules.

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.

Brill Tagger: Process Overview

Initial Tagging:

- **Step 1:** The Brill Tagger starts with a base tagging method that assigns a preliminary tag to each word.
- **Method:** Often uses a simple statistical model, such as the most frequent tag for each word.

Rule Learning:

- **Step 2:** Iteratively applies a set of transformation rules to refine the initial tags.
- **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.

Brill Tagger: Process Overview

Evaluation and Application:

- **Step 3:** After each rule is applied, the tagging accuracy is evaluated.
- **Selection:** The rule that most improves accuracy is retained.
- **Iteration:** Process is repeated until a stopping criterion is met (e.g., no further improvements).

Final Output:

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

TBL Tagging Algorithm

Step 1:
Label every word with the most likely tag (from dictionary).

Step 2:
Check every possible transformation and select the one which most improves tag accuracy (compared to the gold standard).

Step 3:
Re-tag the corpus by applying this rule, and add the rule to the end of the rule set.

Repeat Steps 2-3
Continue until some stopping criterion is reached, e.g., X% correct with respect to the training corpus.

Result:
An ordered set of transformation rules to use on new data that is tagged only with the most likely POS tags.

Transformation-Based Tagging: Example

Step 1: Label every word with its most-likely tag

- **Example:**
  The word "race" occurs in the Brown corpus with the following probabilities:
  `P(NN|race) = 0.98`
  `P(VB|race) = 0.02`
- Initial tagging:
  `... is/VBZ expected/VBN to/TO race/NN tomorrow/NN`

Step 2: Apply Transformation Rule

- **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.

3. Stochastic (Probabilistic) Tagging

Overview:

- Uses statistical methods to predict POS tags based on probabilities.
- Models the likelihood of tag sequences and word-tag pairs.

Key Concepts:

- **Probability Model:** Estimates the probability of a sequence of tags given a sequence of words.
- **Training Data:** A tagged corpus is used to estimate probabilities.
- **Tag Sequences:** Determines the most likely sequence of tags for a given sequence of words.

How do they work?

Training a POS Tagger: Key Points

- **Training Process:**
  - The tagger must be "trained" on a corpus of tagged data.
  - Training involves learning tagging rules automatically from this data.
- **Training Corpus:**
  - 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.
- This probability helps in determining the likelihood of each possible tag for a word.

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:

- Consider the word "run" which occurs 4800 times in the training corpus.
  - 3600 times as a verb
  - 1200 times as a noun
- The probability of "run" being a verb is calculated as:

$$P(\text{verb} \mid \text{run}) = \frac{\text{Number of occurrences of "run" as a verb}}{\text{Total number of occurrences of "run"}} = \frac{3600}{4800} = 0.75$$

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.

Tag Sequence Probability

Tag Sequence Probability:

- The probability that a given tag sequence $t_1, t_2, \ldots, t_n$ is appropriate for a given word sequence $w_1, w_2, \ldots, w_n$ is denoted as:

$$P(t_1, t_2, \ldots, t_n \mid w_1, w_2, \ldots, w_n)$$

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.

Subsequence Models for Tag Probability

Using Subsequences:

- Direct computation of full sequence probabilities is complex.
- Simplified models using smaller subsequences (2 or 3 tags) are more tractable.
- **Bigram Model:**
  - Uses a sequence of 2 tags.
  - Probability of a tag sequence t_1, t_2 is:

$$P(t_1, t_2) = P(t_2 \mid t_1)$$

- **Trigram Model:**
  - Uses a sequence of 3 tags.
  - Probability of a tag sequence t_1, t_2, t_3 is:

$$P(t_1, t_2, t_3) = P(t_2 \mid t_1) \times P(t_3 \mid t_2)$$

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

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

Common Models:

- **Hidden Markov Model (HMM):**
  - Models sequences of tags (states) and words (observations).
  - Uses transition probabilities (tag-to-tag) and emission probabilities (word-to-tag).
- **Maximum Entropy Models:**
  - Uses a probabilistic model to handle multiple features and constraints.
- **Conditional Random Fields (CRF):**
  - Models the conditional probability of a tag sequence given the observed data.
  - Handles dependencies between tags more flexibly.

POS Evaluation

Evaluating POS (Part-of-Speech) tagging systems involves measuring how well the system's output matches the gold standard (human-defined) labels.
We will explore:

- Confusion Matrix
- Accuracy
- Precision and Recall
- F-Measure

Confusion Matrix

A confusion matrix visualizes how a tagging system performs relative to gold labels. It includes:

- **True Positives (TP)**: Correctly identified positive cases
- **False Positives (FP)**: Incorrectly identified as positive
- **True Negatives (TN)**: Correctly identified negative cases
- **False Negatives (FN)**: Incorrectly identified as negative

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

Accuracy

Accuracy measures the overall correctness of the tagging system. It is defined as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

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

Precision and Recall

Precision measures the accuracy of positive predictions:

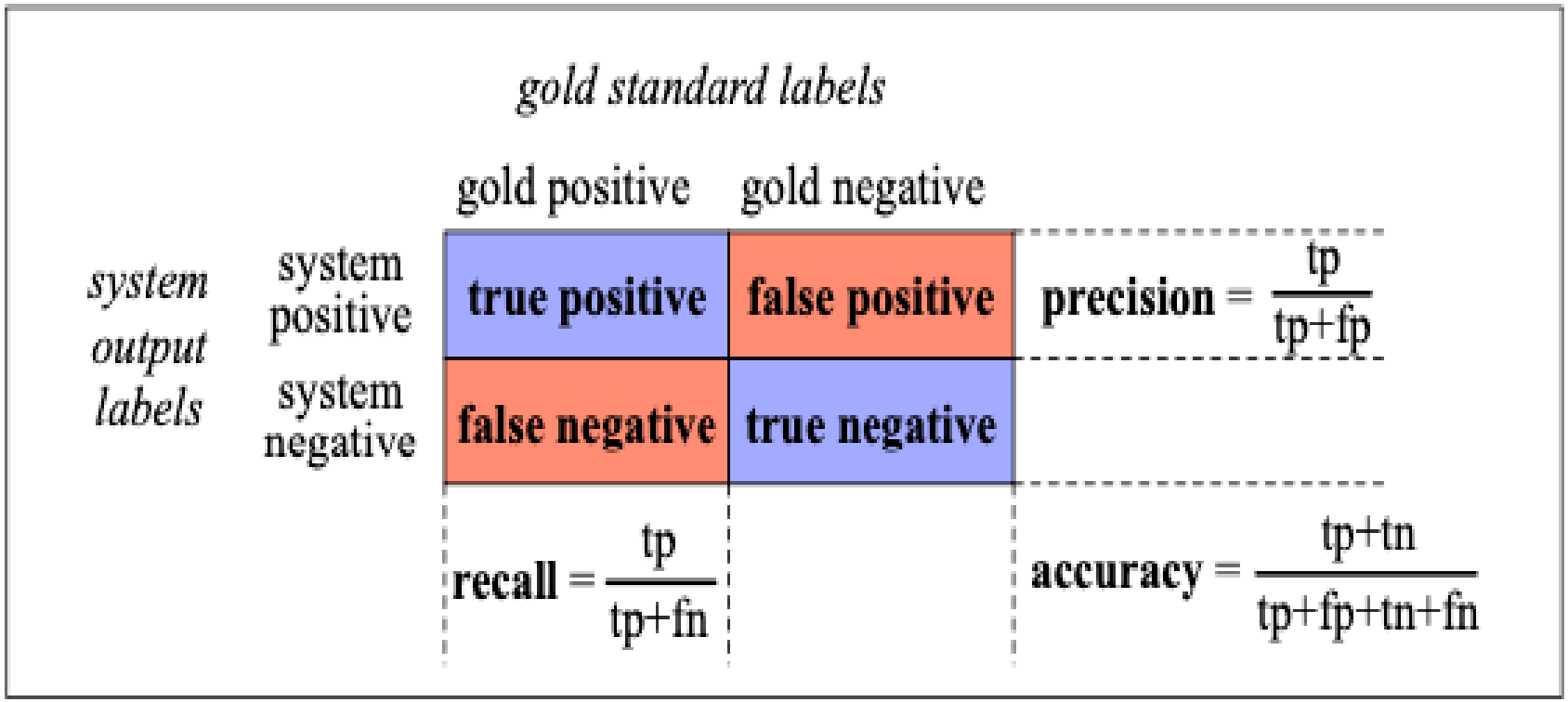
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

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



F-Measure

The F-measure combines precision and recall into a single metric. It is defined as:

$$F_\beta = \frac{(1+\beta^2) \cdot \text{Precision} \cdot \text{Recall}}{\beta^2 \cdot \text{Precision} + \text{Recall}}$$

For $\beta = 1$, it simplifies to the F1 score:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

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