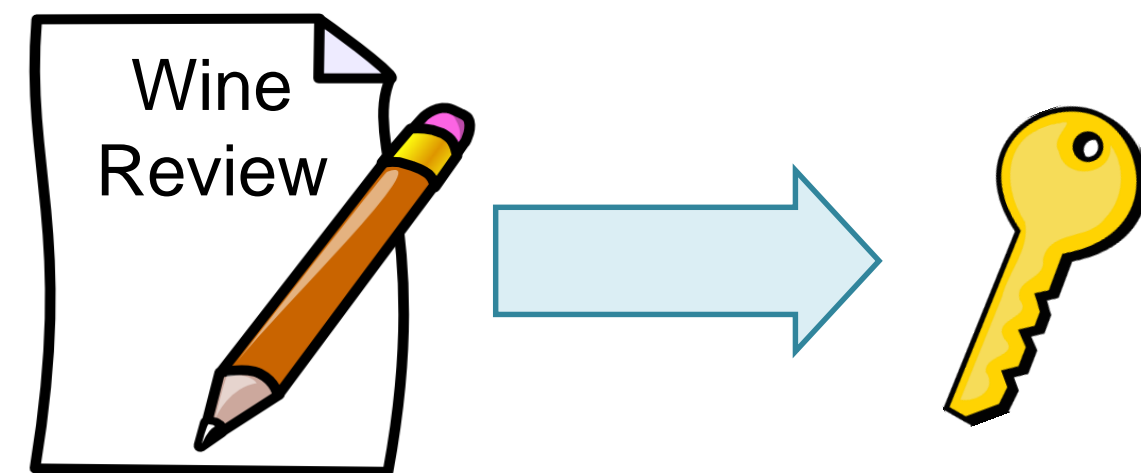


Wine Review Keyword Prediction

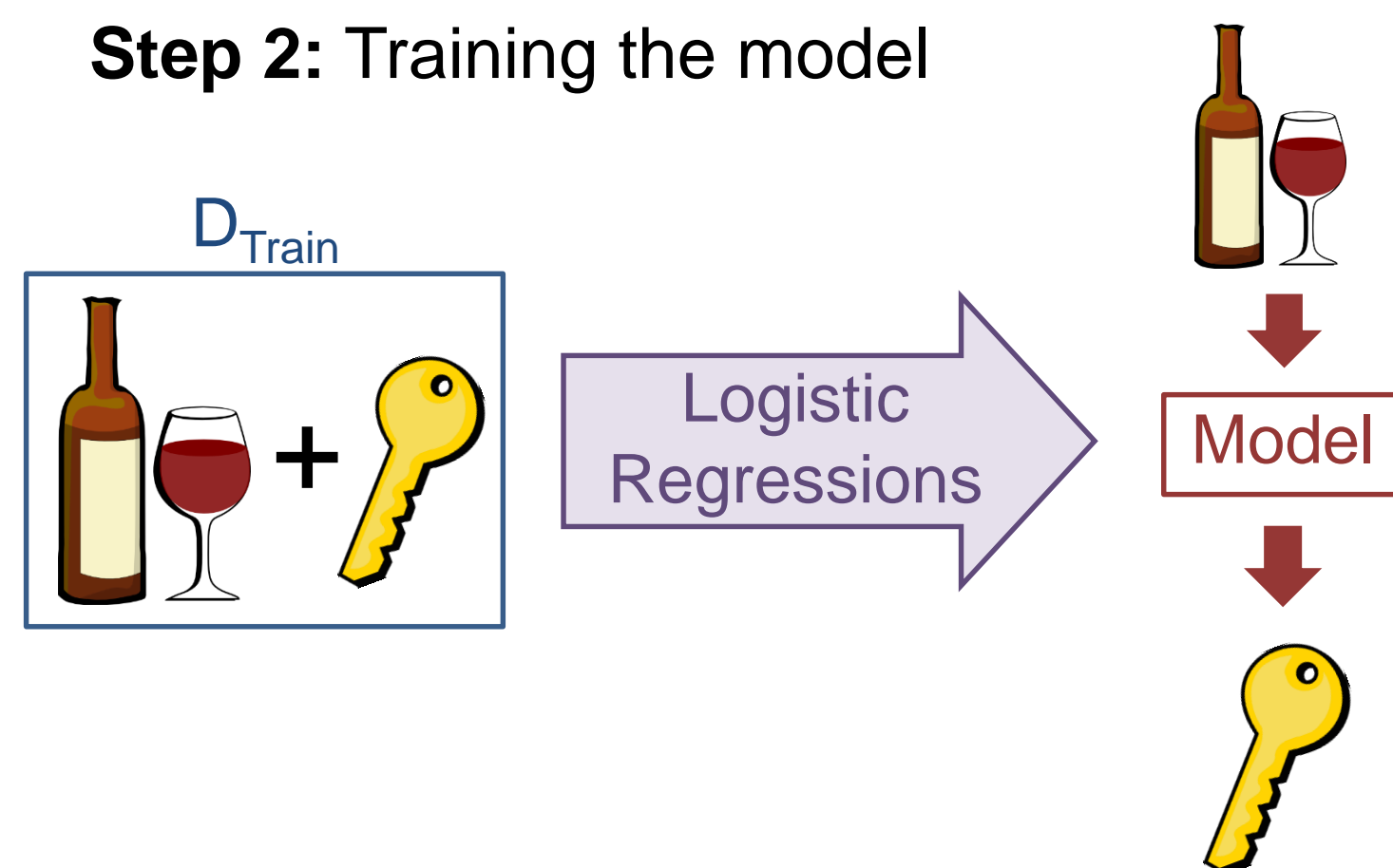
Noam Habet, Mackenzie Pearson, Shalini Ranmuthu
CS221 – Artificial Intelligence, Stanford University

Problem and Motivation

Step 1: Building dictionary of keywords



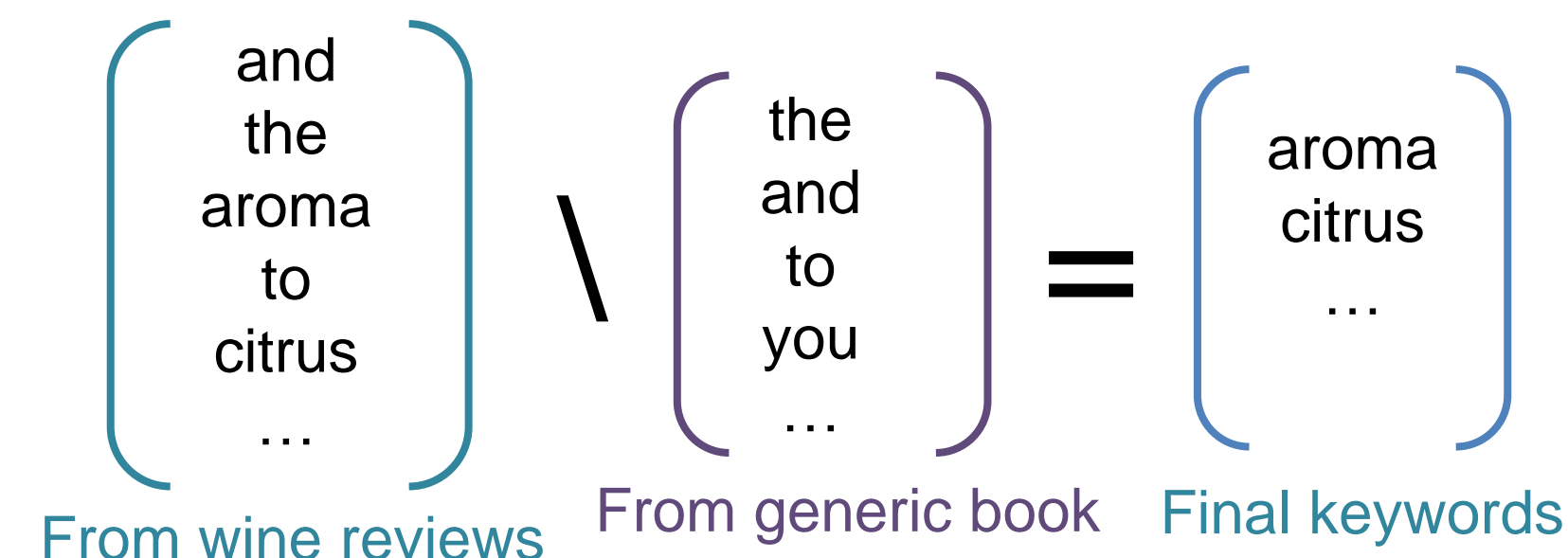
Step 2: Training the model



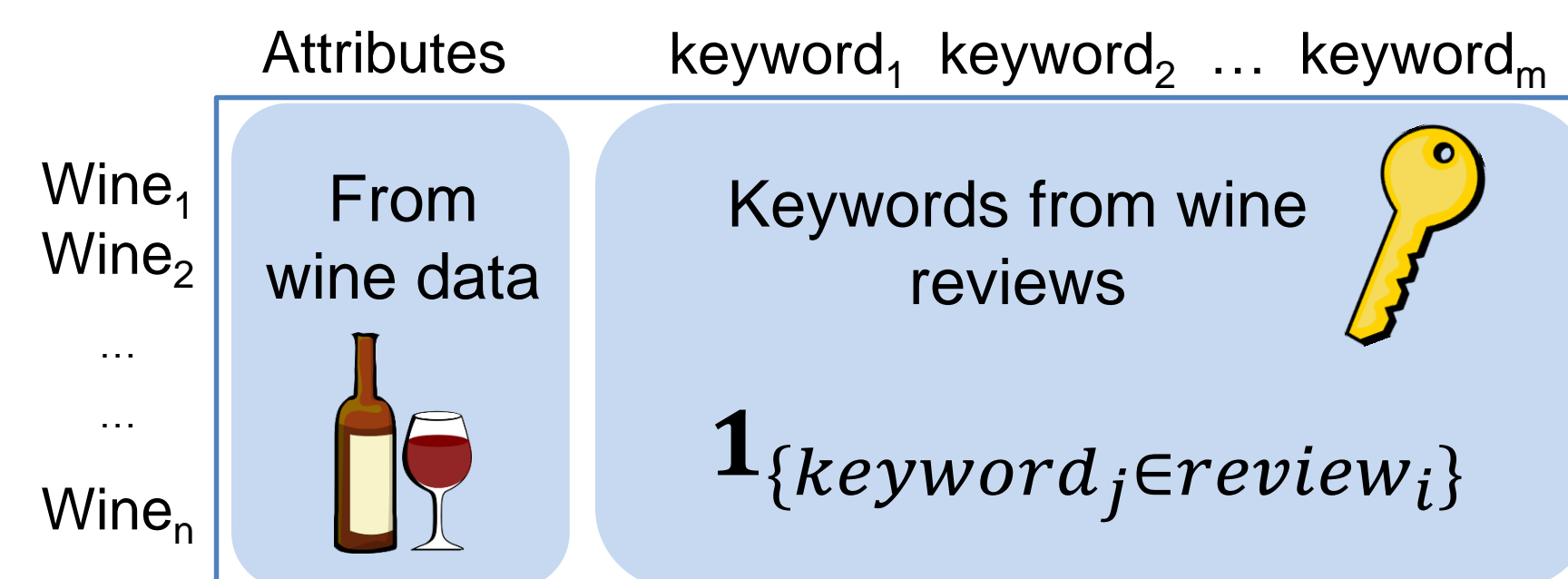
Motivation: To explore correlations between wine attributes and keywords found in reviews

Approach

Step 1: Take most frequent words from each set to get keywords



Step 2: Build D_{train}



- Reduce cardinality of categorical features to increase predictive power of feature labels

- Create m logistic models

$$\log \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$
$$L(\beta_0, \beta) = \prod_{i=1}^n p(x_i)^{y_i} (1 - p(x_i))^{1-y_i}$$

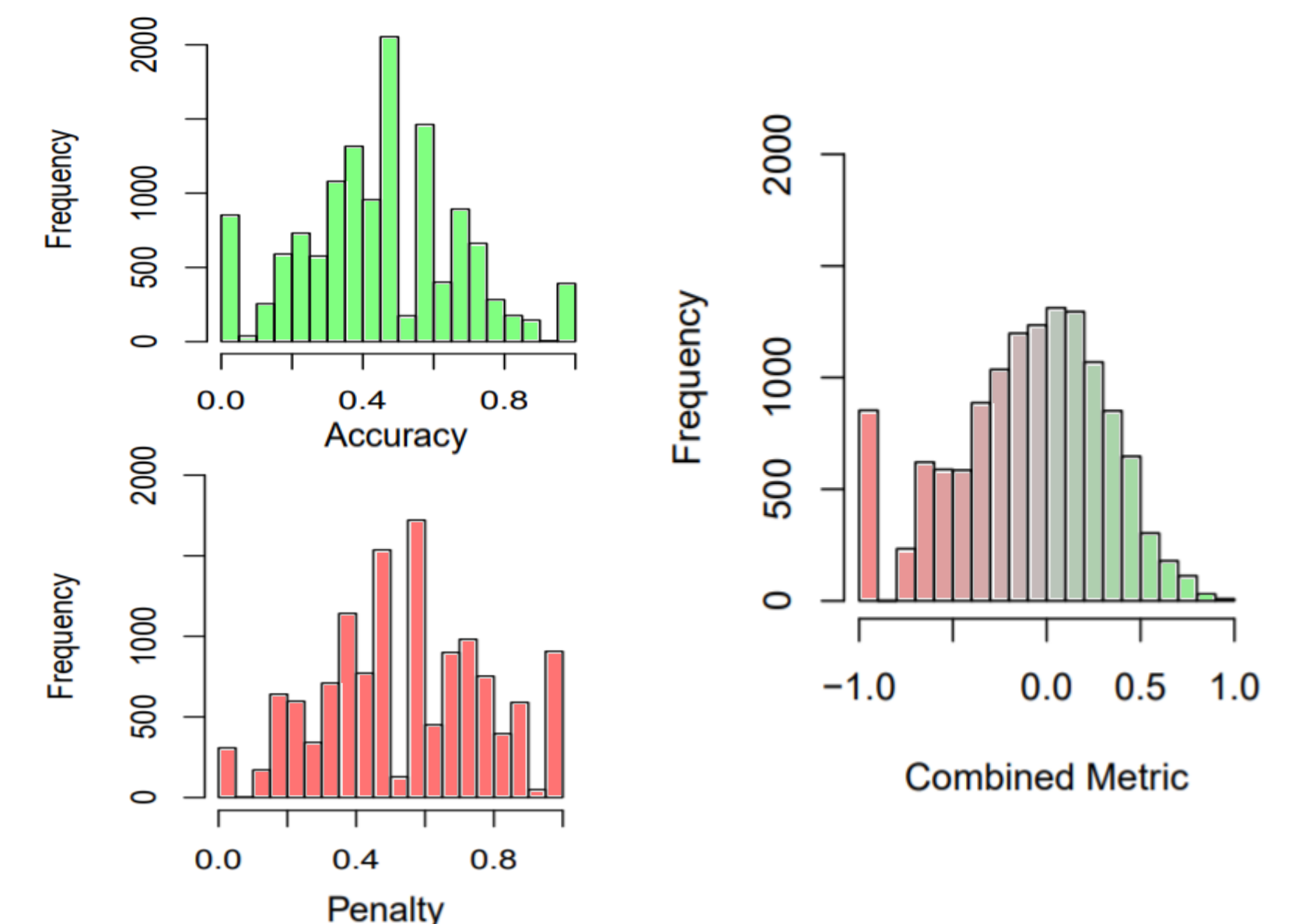
Results

The following evaluation metrics can be calculated for each wine (observation)

1. Accuracy: $\frac{\# \text{ keywords correctly predicted}}{\# \text{ total keywords in review}} \in [0,1]$

2. Penalty: $\frac{\# \text{ keywords incorrectly predicted}}{\# \text{ total keywords predicted}} \in [0,1]$

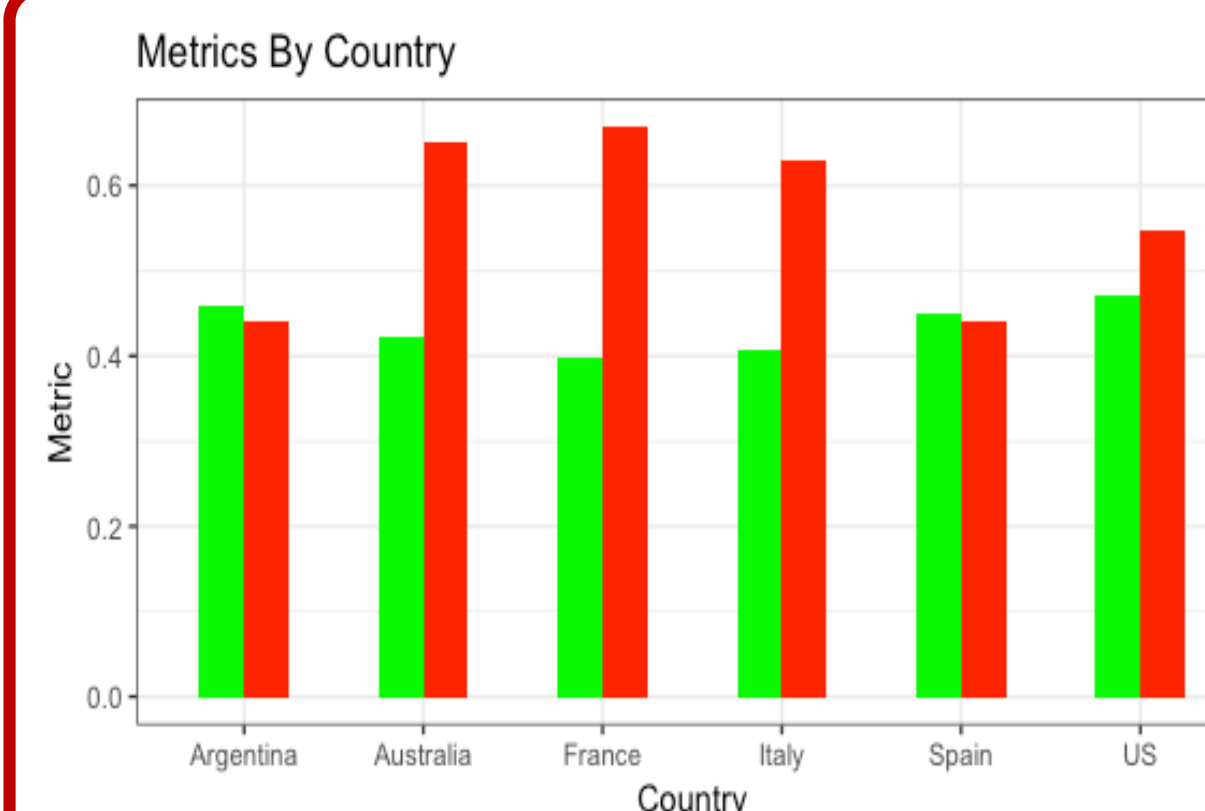
3. Combined: $(\text{Accuracy} - \text{Penalty}) \in [-1,1]$



Challenges and Implementation

- Storing $n \times m$ D_{Train} for quick reload ($n=150,930$ wines, $m=6342$ keywords)
- Computation time (building D_{Train} , creating models, and computing metrics)
- Parallelizing construction & prediction of logistic models for each keyword
- Previously only feasible to predict on top $m=100$ keywords (plan to reach $m=1000$ for final evaluation)
- Testing on the 100 most frequent keywords may mean that the keywords are not strongly correlated with certain wine features

Analysis



- On average, our model predicts half of the correct words, but ~50% of the predicted words are extraneous
- ~7% of the reviews in the test set did not contain keywords used in the model (combined metric = -1)