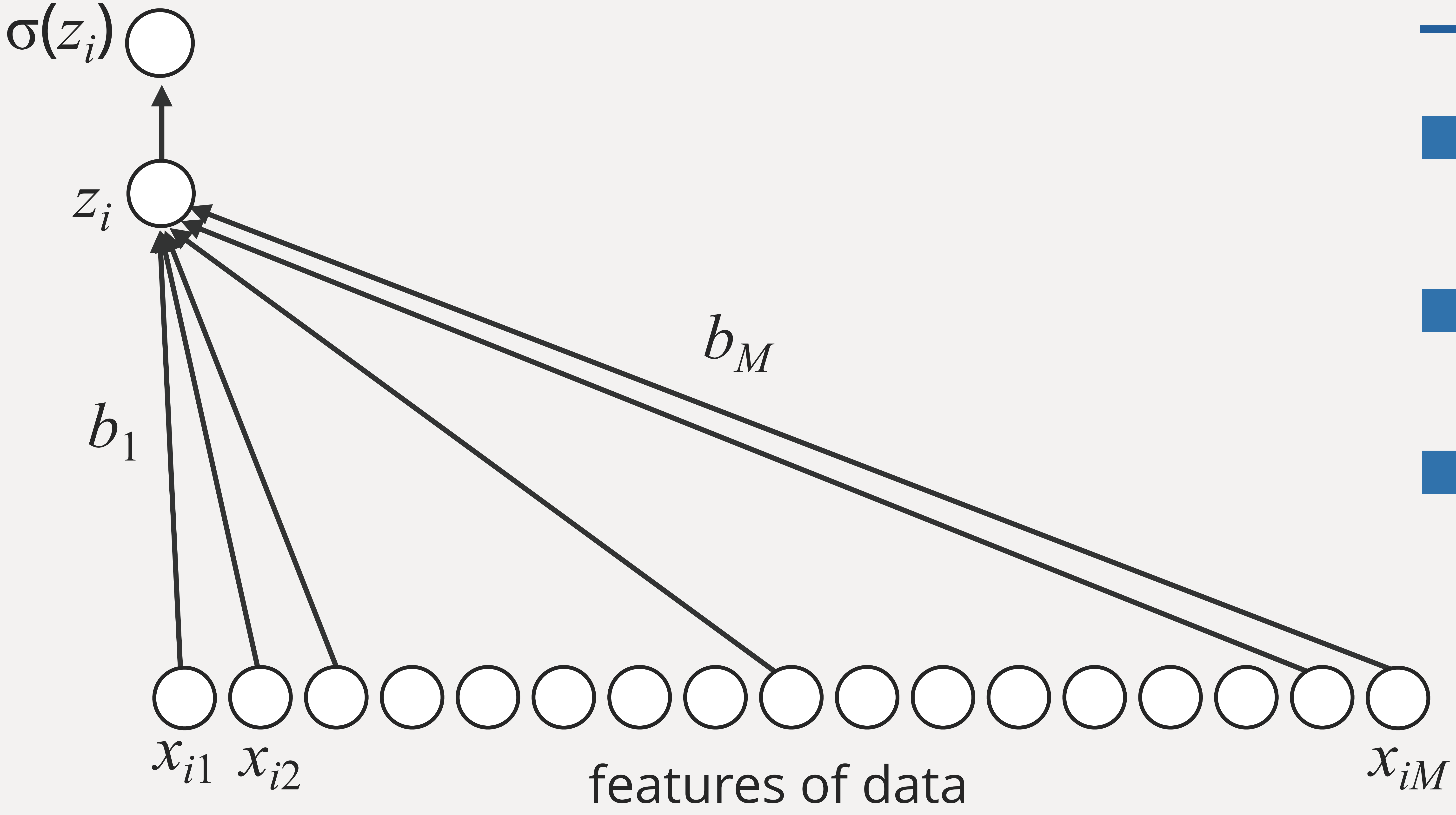


What We Are Trying to Do

- Learn parameters to give us the best performance
- Given data, find the best b for that data
- Define what is performance

Empirical Risk Minimization

- A loss function defines a penalty for poor predictions
- Want to minimize average loss

loss function

guess

$$b^* = \arg\min_b \frac{1}{N} \sum_i^N \ell(y_i, \sigma(z_i))$$

optimal parameters

true label

loss function

guess

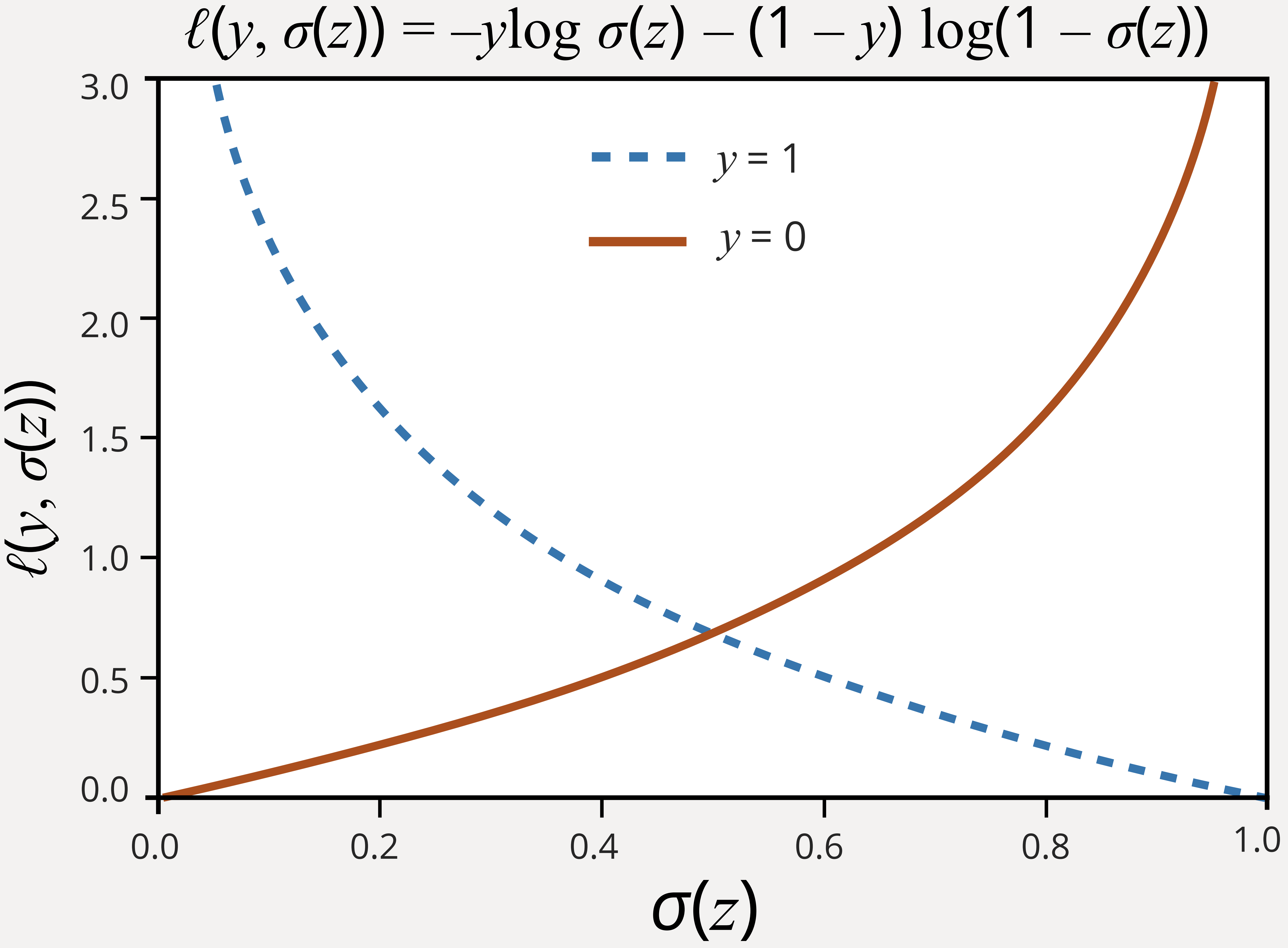
$$b^* = \arg\min_b \frac{1}{N}\sum_i^N \ell(y_i, \sigma(z_i))$$

optimal parameters

true label

Loss Function

- Define $\sigma(z_i)$ as the predicted probability
- y_i is our true label
- Viewed as the negative log-likelihood:
  $\ell(y_i, \sigma(z_i)) = -\log p(y_i | \sigma(z_i))$
- Specific mathematical form:
  $\ell(y, \sigma(z)) = -y \log \sigma(z) - (1 - y) \log(1 - \sigma(z))$



Predicting Probability of One

- When we give 100% of a 1, we pay no penalty
- If we are overconfident or wrong, we pay an increasing penalty

Binary Classification Optimization

- Goal is to minimize the average loss

$$b^* = \arg\min_b \frac{1}{N} \sum_i^N \ell(y_i, \sigma(z_i))$$

$$\ell(y, \sigma(z)) = -y \log \sigma(z) - (1 - y) \log(1 - \sigma(z))$$

Binary Classification Optimization

- Goal is to minimize the average loss
- Binary (0/1) problems can use the logistic or cross-entropy loss

Learned Model Parameters