

ECE 884 Deep Learning

Lecture 6: Loss Function

02/04/2021

Logistics

- Google sheet
 - Please form your groups ASAP
- 02/11/2021: Presentations of the Project Ideas
 - Each group has 10mins presentation + 3mins Q&A
 - Please prepare your presentation slides with the following items
 - What topic you aim to work on?
 - What are the existing works?
 - How your idea is different from existing ones?
 - What are the expected results?
 - What is the impact?

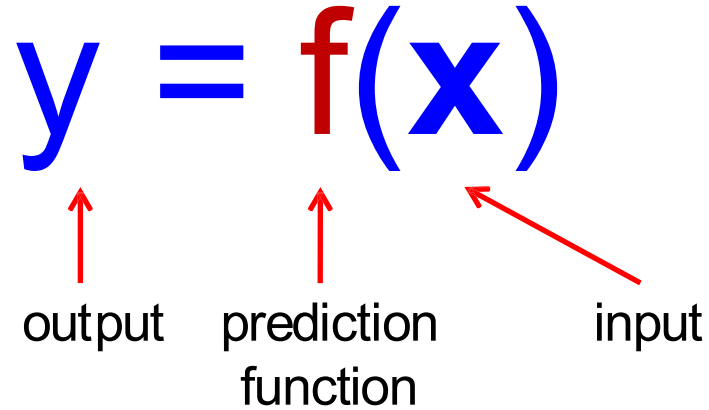
Review of last lecture

- Function form#2: parametric linear models
- Function form#3: parametric nonlinear models (DL models)
 - Understand why deep learning models are powerful and importance of massive computation and large data sets.

Today's lecture

- Loss Function
 - What it is, what is it for?
 - Example: cross-entropy loss function

Recall: Task#1: function form

$$y = f(x)$$


The diagram shows the equation $y = f(x)$ with three red arrows pointing to its components. The first arrow points from the label 'output' to the variable y . The second arrow points from the label 'prediction function' to the function symbol f . The third arrow points from the label 'input' to the variable x inside the parentheses.

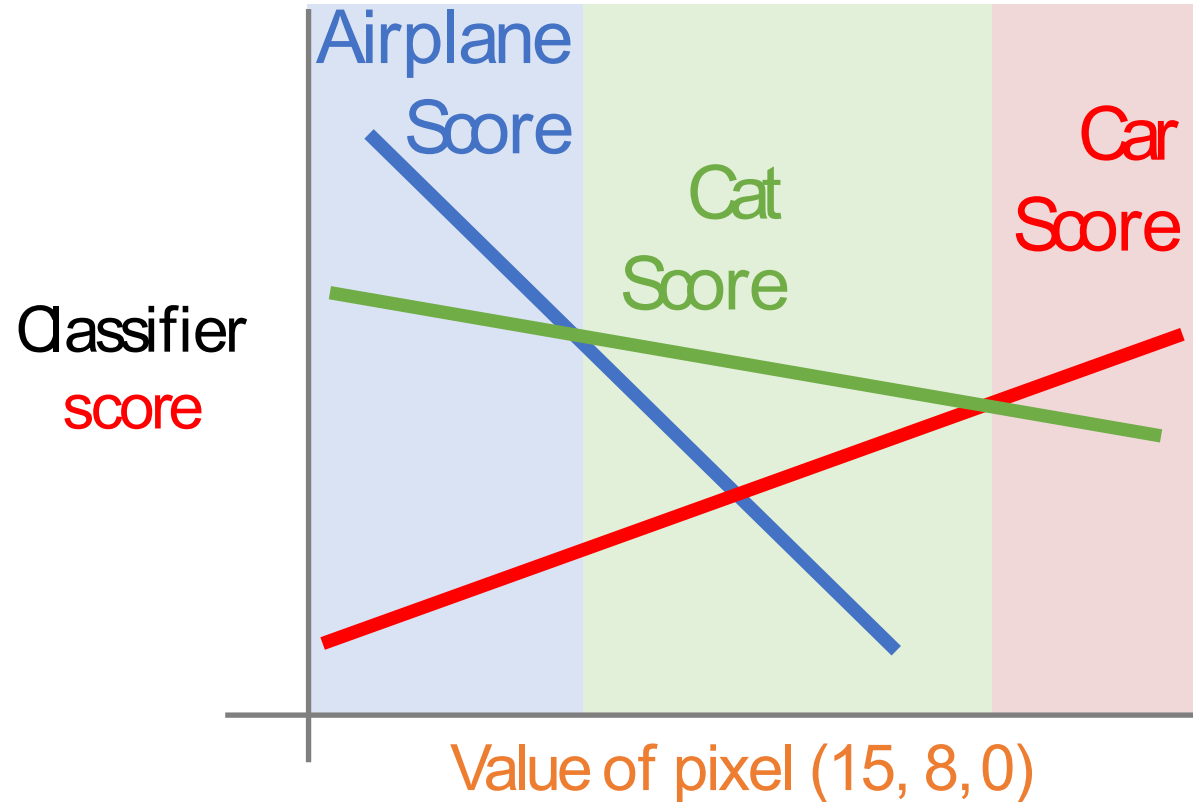
Task#1: function form

Formulation:

- Given training data: $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)\}$,
- Find $y = f(\mathbf{x}) \in \mathcal{Y}$ using training data
- such that f is correct on test data

Score Function

Decision Regions



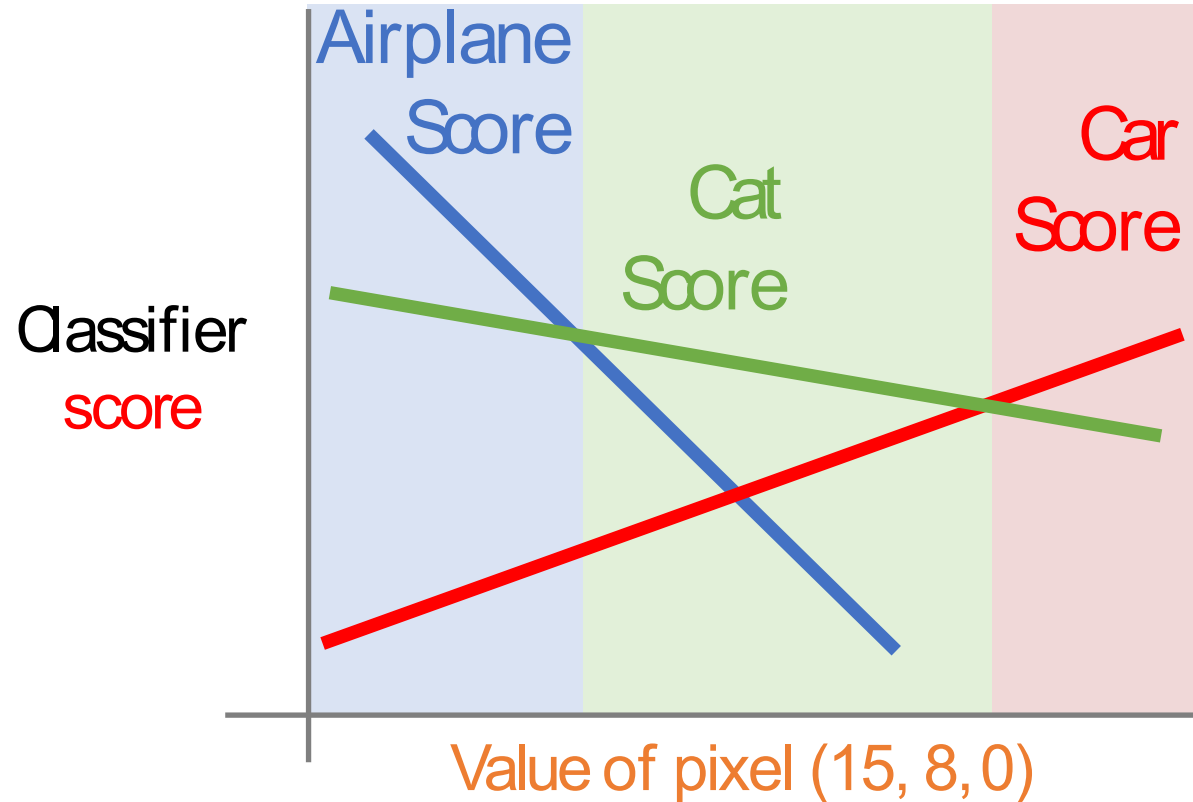
(Linear) Score Function

$$f(x, W) = Wx + b$$

Given a W (and b), we can compute a score for each class given an input x .

Score Function

Decision Regions



(Linear) Score Function

$$f(x, W) = Wx + b$$

Good classifier: output a **high score** for the **correct** class, and a **low score** for the **wrong** class.

Loss Function

What is loss function: a **loss function** is a function that measures how good our classifier is.

Low loss = good classifier

High loss = bad classifier

Loss Function

Input

Output

Function form

Loss Function

Input of the loss function

Given a dataset of examples

$$\{(x_i, y_i)\}_{i=1}^N$$

Where x_i is image and
 y_i is (integer) label

Loss Function

Output: Loss for a single data $\{x_i, y_i\}$

$$L_i(f(x_i, W), y_i)$$

Loss Function

Output: Loss for a single data

$$L_i(f(x_i, W), y_i)$$

Output: Loss for the whole training data set with N data samples

$$L = \frac{1}{N} \sum_i L_i(f(x_i, W), y_i)$$

Loss Function has different forms

Loss Function has different forms

Different problems have different loss functions

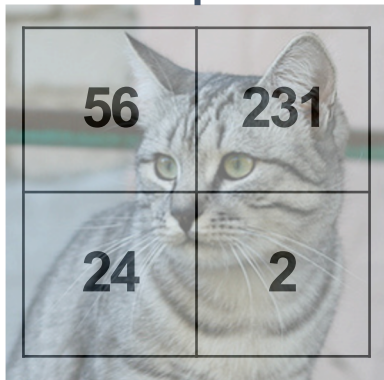
- CV
- NLP
- Speech

Cross-Entropy Loss Function

- One of the most commonly used ones in deep learning
- Nice property: interpret as **probabilities**

Input: X_i

Stretch pixels into column

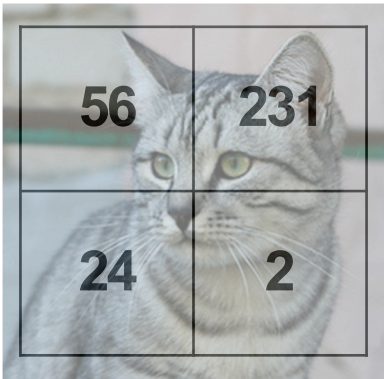


Input image
 X_i



X_i

Output: Y_i

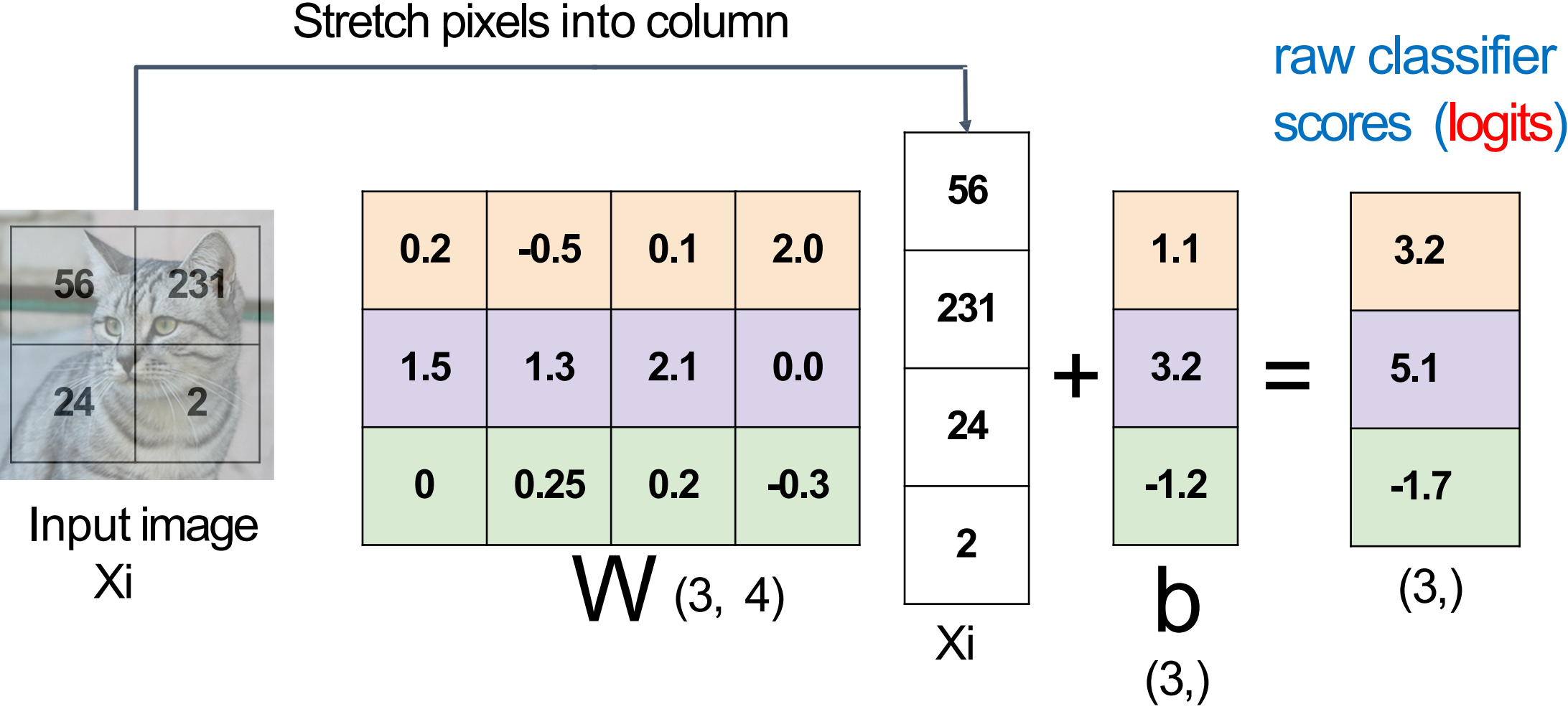


One-hot encoding

1
0
0

Y_i
True Label

Input -> Score Function



Measure how good the classifier by comparing:

raw classifier
scores (logits)

3.2
5.1
-1.7

One-hot encoding

1
0
0

True Label

Measure how good the classifier by comparing:

raw classifier
scores (logits)

This is Not
probability

3.2
5.1
-1.7

One-hot encoding

This is
probability

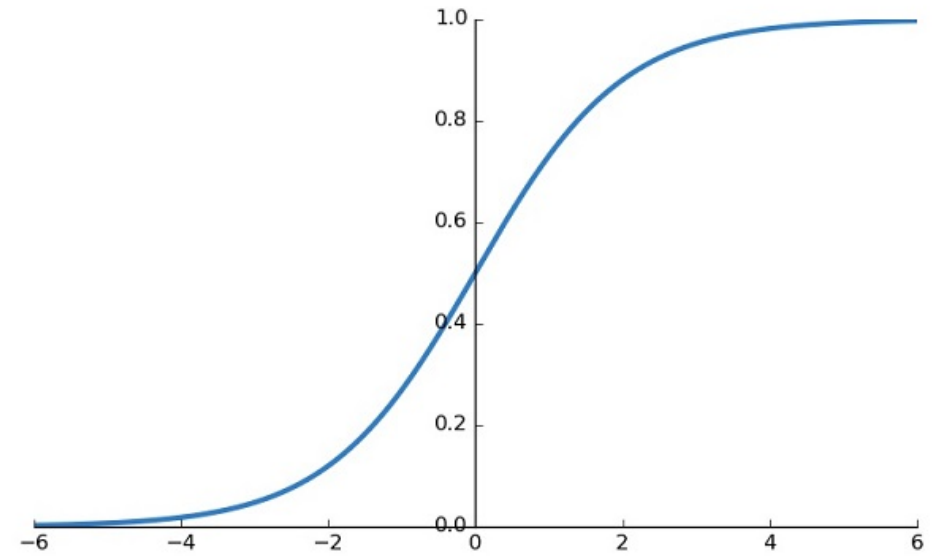
1
0
0

True Label

Softmax Transformation

$$P(Y = k \mid X = x_i) = \frac{\exp(s_k)}{\sum_j \exp(s_j)}$$

logits



Softmax Transformation

raw classifier
scores (logits)

This is Not
probability

3.2
5.1
-1.7

softmax



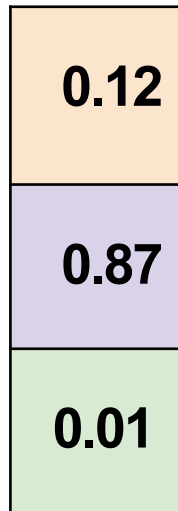
0.12
0.87
0.01

This is
probability

Cross-Entropy:

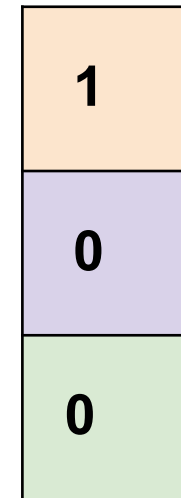
Measure the **distance** between 2 probability vectors

Softmax



Cross Entropy

One-hot encoding



True Label

Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax

q

0.12
0.87
0.01

One-hot encoding

p

1
0
0

Cross Entropy

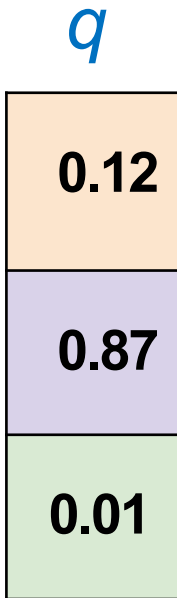
$$H(\mathbf{p}, \mathbf{q}) = -\sum_i p_i \log_2(q_i)$$

True Label

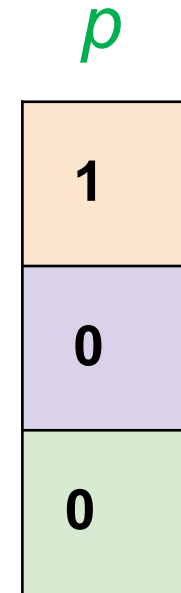
Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax



One-hot encoding



Cross Entropy

$$H(\mathbf{p}, \mathbf{q}) = -\sum_i p_i \log_2(q_i)$$

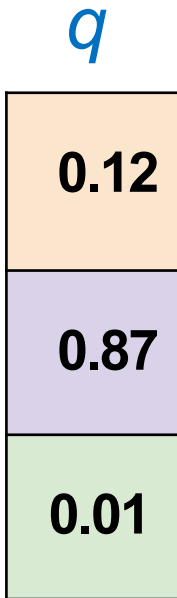
It is not symmetric

True Label

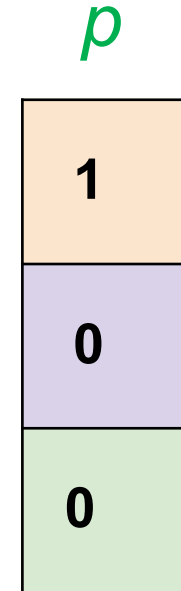
Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax



One-hot encoding



KL Divergence:

$$D_{KL}(p \parallel q) = H(p, q) - H(p)$$

True Label

Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax

q

0.12
0.87
0.01

One-hot encoding

p

1
0
0

Cross Entropy

$$L_i = -\log P(Y = y_i | X = x_i)$$

Only with one-hot

True Label

Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax

q

0.12
0.87
0.01

Cross Entropy

$$L_i = -\log P(Y = y_i | X = x_i)$$

Only with one-hot

One-hot encoding

p

1
0
0

Q: What is the min / max possible loss L_i ?

True Label

Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax

q

0.12
0.87
0.01

Cross Entropy

$$L_i = -\log P(Y = y_i | X = x_i)$$

Only with one-hot

One-hot encoding

p

1
0
0

Q: What is the min / max possible loss L_i ?

A: Min 0, max +infinity

True Label

Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax

q

0.12
0.87
0.01

Cross Entropy

$$L_i = -\log P(Y = y_i | X = x_i)$$

Only with one-hot

One-hot encoding

p

1
0
0

Q: If all scores are small random values, what is the loss?

True Label

Cross-Entropy:

Measure the **distance** between 2 probability vectors

Softmax

q

0.12
0.87
0.01

Cross Entropy

$$L_i = -\log P(Y = y_i | X = x_i)$$

Only with one-hot

One-hot encoding

p

1
0
0

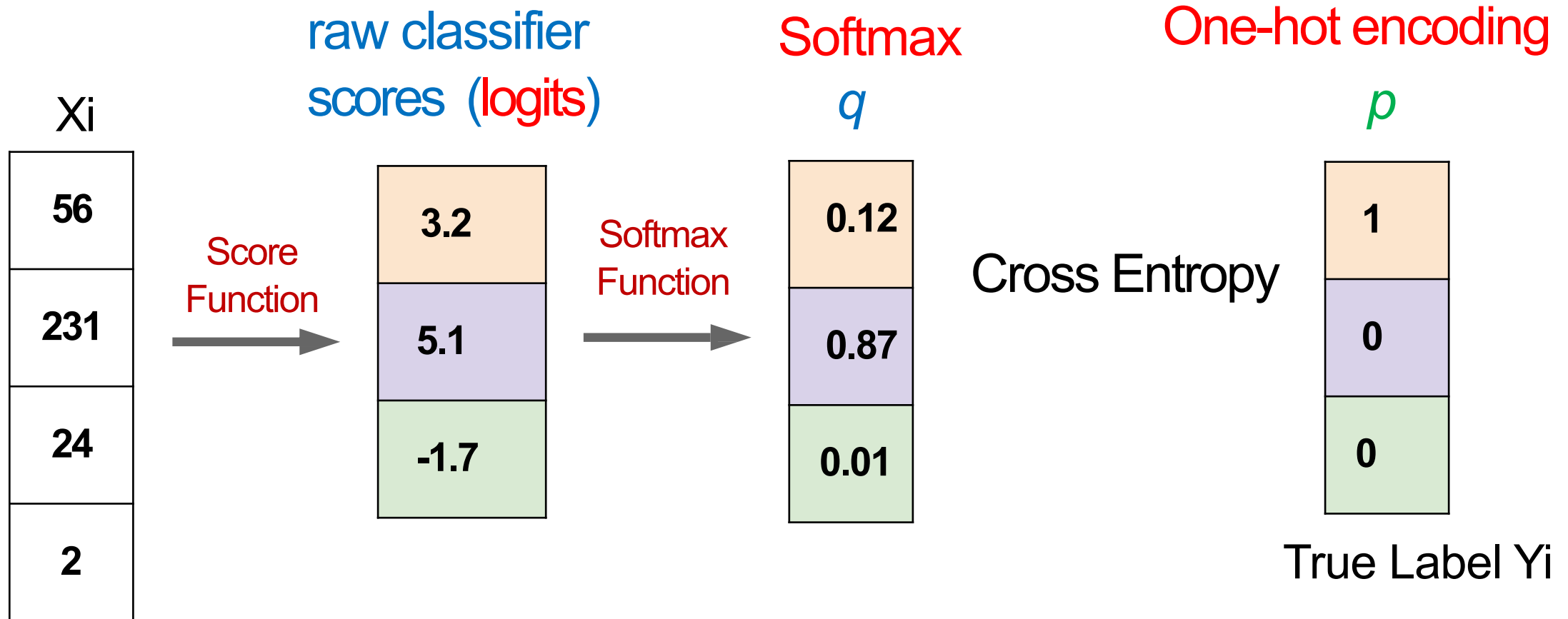
Q: If all scores are small random values, what is the loss?

A: $-\log(1/C)$

$\log(10) \approx 2.3$

True Label

Summary



Any Question ?