ФИНАНСОВЫЙ УНИВЕРСИТЕТ
ПРИ ПРАВИТЕЛЬСТВЕ РОССИЙСКОЙ ФЕДЕРАЦИИ

Современные нейросетевые технологии

Лекция 2. Линейная классификация изображений

Учебные вопросы

ФИНАНСОВЫЙ УНИВЕРСИТЕТ

1) Линейный классификатор изображений
2) Преобразование softmax
3) Функция потерь Cross Enthropy Loss

Материалы курса:
github.com/balezz/modern_dl
Срок сдачи A1 – 10.09.2022 г.

Источники:
- dlcourse.ai
- cs231n.stanford.edu
- cs230.stanford.edu

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Image Classification: A core task in Computer Vision

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

→ cat

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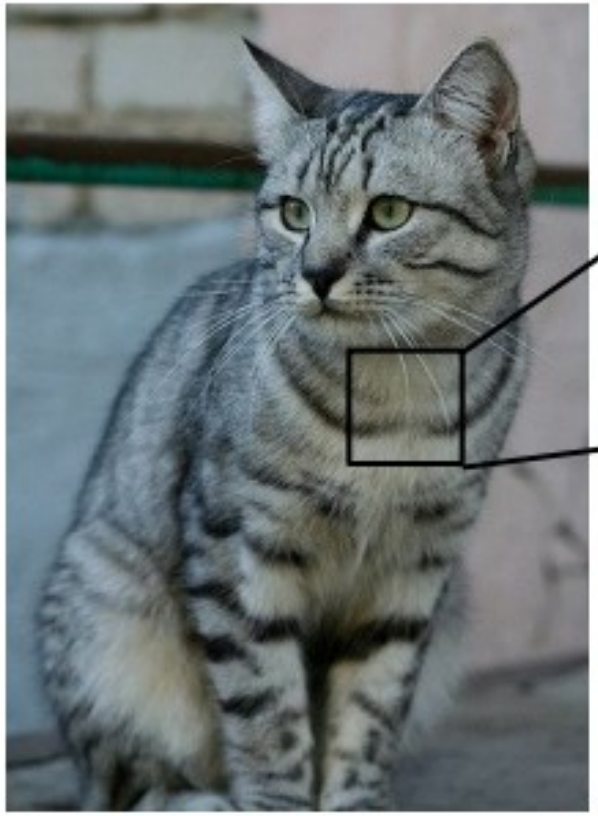
The Problem: Semantic Gap




```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  98 105 128 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  85 101 107 109  98  75  84  96  95]
 [114 108  85  55  55  69  64  54  64  87 112 129  98  74  84  91]
 [133 137 147 103  65  81  80  65  52  54  74  84 102  93  85  82]
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 [127 125 131 147 133 127 126 131 111  96  89  75  61  64  72  84]
 [115 114 109 123 150 148 131 118 113 109 100  92  74  65  72  78]
 [ 89  93  98  97 108 147 131 118 113 114 113 109 106  95  77  80]
 [ 63  77  86  81  77  79 102 123 117 115 117 125 125 130 115  87]
 [ 62  65  82  89  78  71  80 101 124 126 119 101 107 114 131 119]
 [ 63  65  75  88  89  71  62  81 120 138 135 105  81  98 110 118]
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 [123 107  96  86  83 112 153 149 122 109 104  75  88 107 112  99]
 [122 121 102  88  82  86  94 117 145 148 153 102  58  78  92 107]
 [122 164 148 103  71  56  78  83  93 103 119 139 102  61  69  84]]
```

What the computer sees

An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

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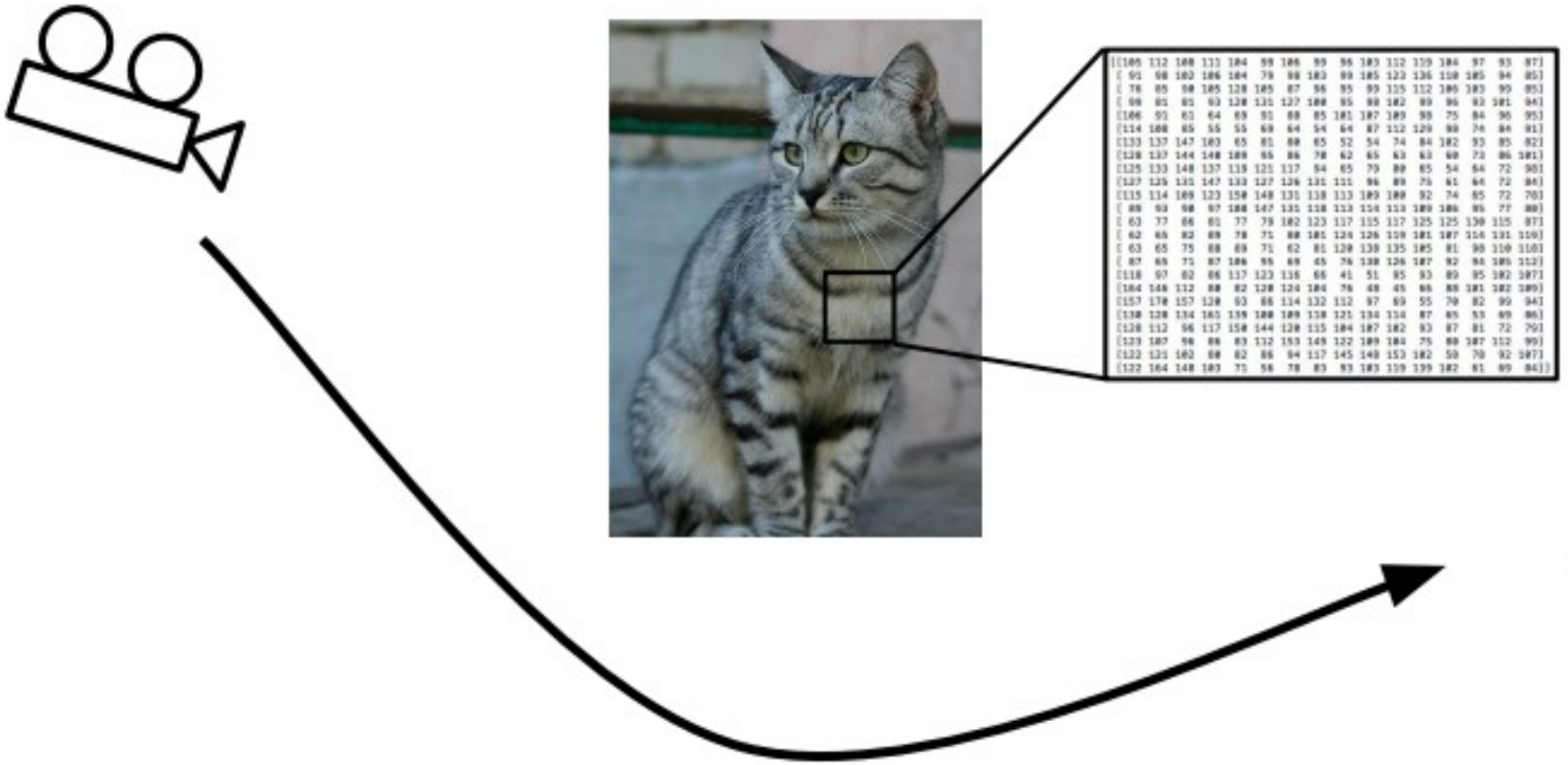
Challenges: Viewpoint variation



All pixels change when the camera moves!

Проблемы классификации

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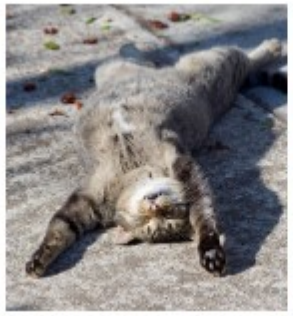







Линейный классификатор

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Naïve image classifier

```
def classify_image(image):
  # Some magic here?
  return class_label
```

Unlike sorting, no obvious way to hard-cod the algorithm for recognizing a cat or other classes

Data driven approach

```
def train(images, labels):
  # Machine learning!
  return model
```

```
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

1. Collect a dataset of images and labels
2. Use Machine Learning to train a classifier
3. Evaluate the classifier on new images

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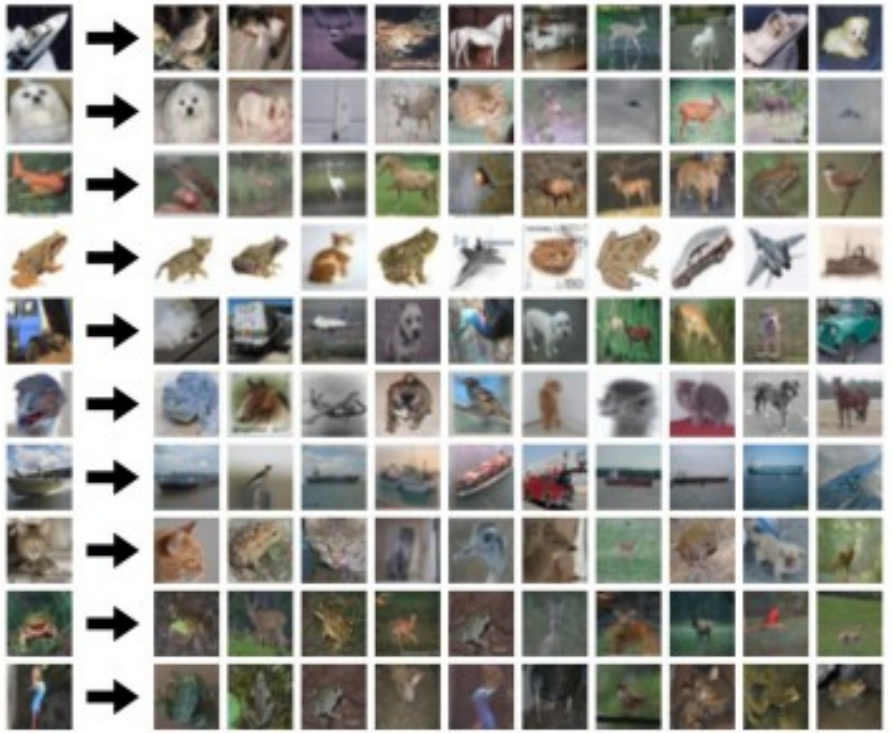
Example Dataset: **CIFAR10**

10 classes
50,000 training images
10,000 testing images

Test images and nearest neighbors



Alex Krizhevsky, "Learning Multiple Layers of Features from Tiny Images", Technical Report, 2009.

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Parametric Approach: Linear Classifier

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

3072x1 — 10x1 — 10x3072 — 10x1

Image

Array of **32x32x3** numbers
(3072 numbers total)

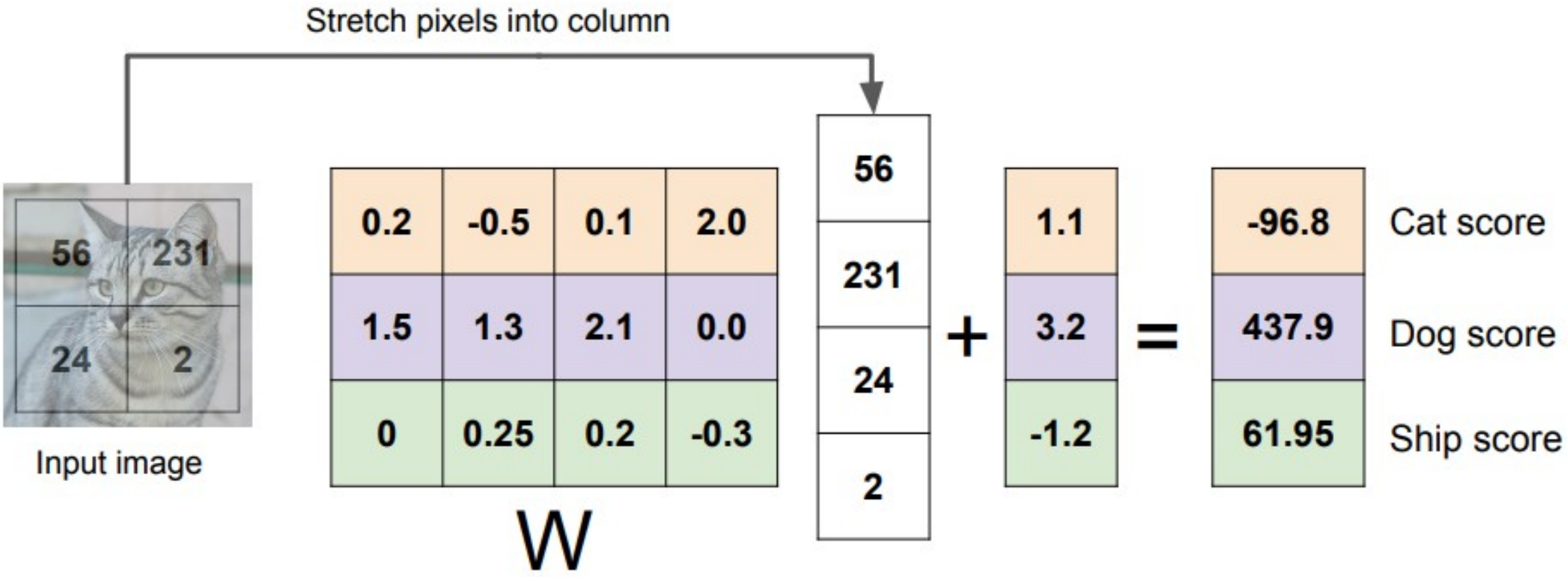
f(**x**,**W**)

10 numbers giving class scores

W

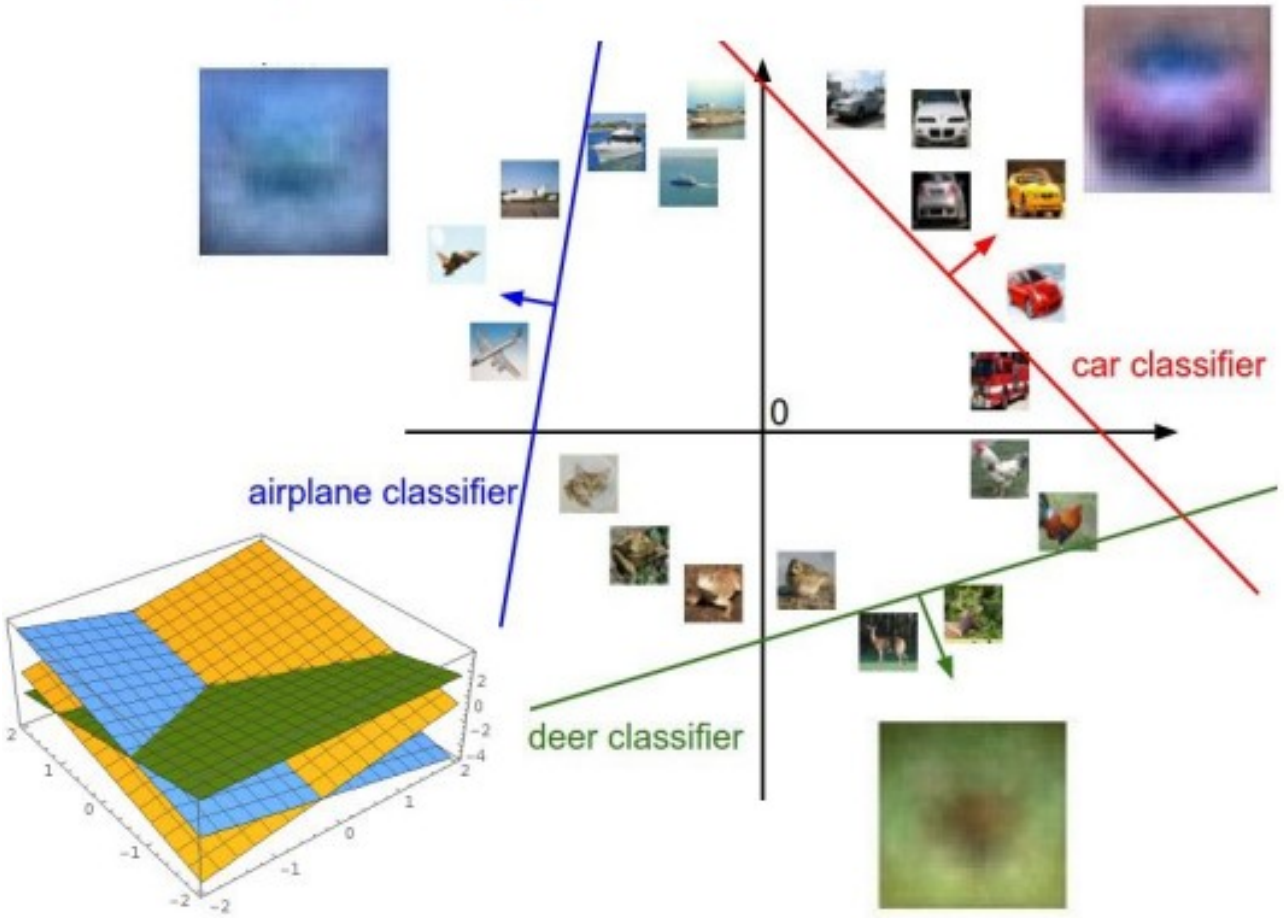
parameters or weights

Линейный классификатор



Линейный классификатор

Interpreting a Linear Classifier



Plot created using Wolfram Cloud

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

Array of **32x32x3** numbers
(3072 numbers total)

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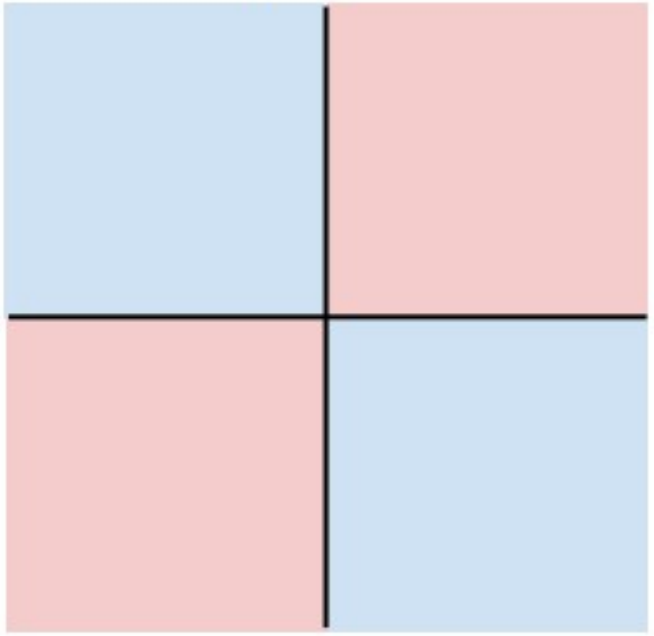
Hard cases for a linear classifier

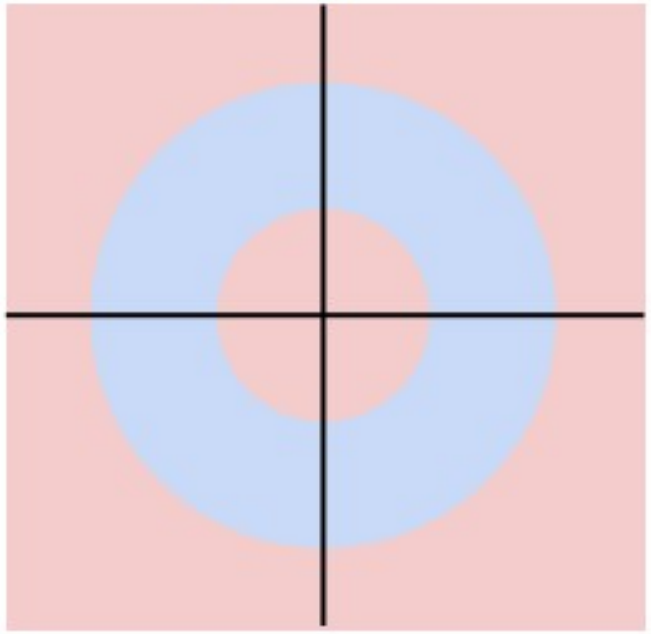
Class 1:
number of pixels > 0 odd

Class 2:
number of pixels > 0 even



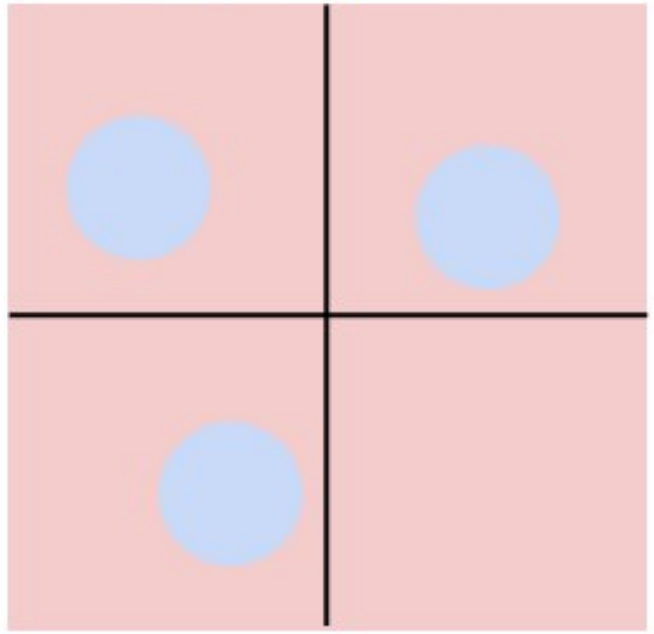
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

Class 2:
Everything else



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So far: Defined a (linear) score function $f(x,W) = Wx + b$

Example class scores for 3 images for some W:

How can we tell whether this W is good or bad?



airplane	-3.45	-0.51	3.42
automobile	-8.87	**6.04**	4.64
bird	0.09	5.31	2.65
cat	**2.9**	-4.22	5.1
deer	4.48	-4.19	2.64
dog	8.02	3.58	5.55
frog	3.78	4.49	**-4.34**
horse	1.06	-4.37	-1.5
ship	-0.36	-2.09	-4.79
truck	-0.72	-2.93	6.14

Функция потерь

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Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

A **loss function** tells how good our current classifier is

Given a dataset of examples

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

Where x_i is image and
y_i is (integer) label

Loss over the dataset is a sum of loss over examples:

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

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Softmax Classifier (Multinomial Logistic Regression)

cat **3.2**

car 5.1

frog -1.7

scores = unnormalized log probabilities of the classes.

$$P(Y = k|X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$ where $$s = f(x_i; W)$$

Want to maximize the log likelihood, or (for a loss function) to minimize the negative log likelihood of the correct class:

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

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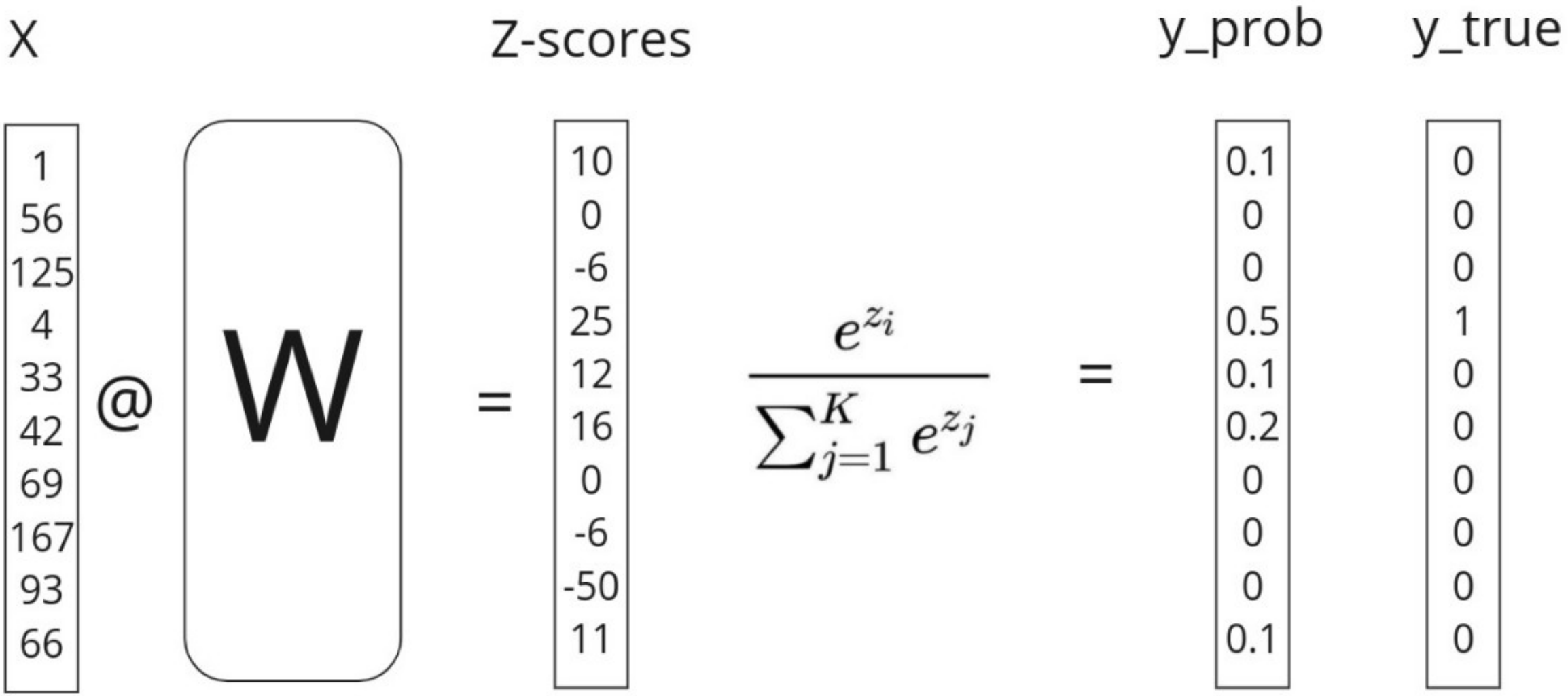
in summary: $$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{s_j}}\right)$$

Функция потерь Cross Enthropy



Функция потерь Cross Enthropy

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y_prob	y_true
0.1	0
0	0
0	0
0.5	1
0.1	0
0.2	0
0	0
0	0
0	0
0.1	0

$$H(p,q) = -\sum_{x \in \mathcal{X}} p(x)\ \log q(x)$$

$$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{s_j}}\right)$$

Функция потерь Cross Enthropy

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Softmax Classifier (Multinomial Logistic Regression)

$$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{s_j}}\right)$$

unnormalized probabilities

cat	**3.2**	**24.5**	**0.13**
car	5.1	164.0	0.87
frog	-1.7	0.18	0.00

exp → normalize →

unnormalized log probabilities

probabilities

L_i = -log(0.13)
= **0.89**