Illustration: Frank Rosenblatt's Perceptron

BBM406

Fundamentals of Machine Learning

FIG. 1 — Organization of a biological brain. (Red areas indicate active cells, responding to the letter X.)

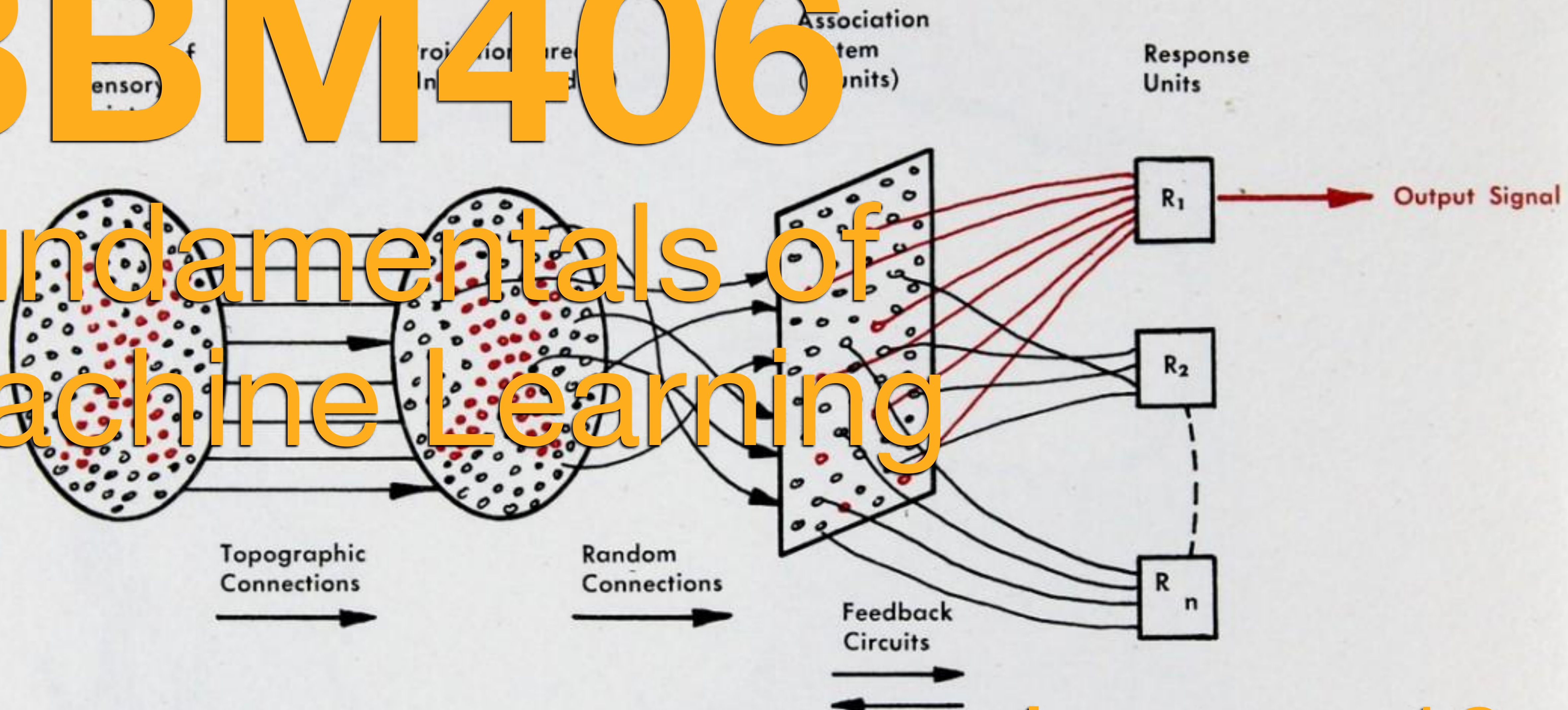


FIG. 2 — Organization of a perceptron.

Lecture 10:
Linear Discriminant Functions
Perceptron

HACETTEPE UNIVERSITY COMPUTER VISION LAB

Aykut Erdem // Hacettepe University // Fall 2019

- **Assignment 2** is out!
  - It is due **November 22** (i.e. in 2 weeks)
  - Implement Naive Bayes classifier for fake news detection

image credit: Frederick Burr Opper

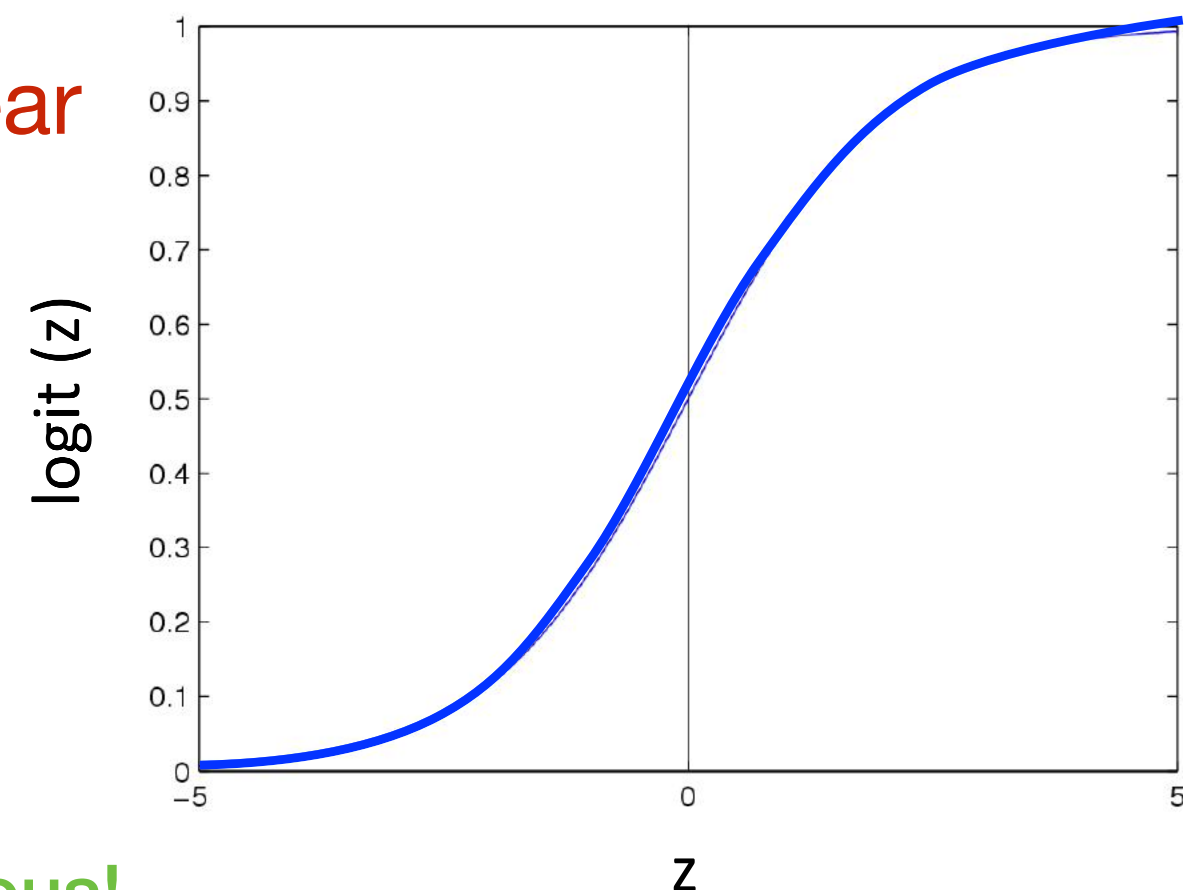
Last time... **Logistic Regression**

Assumes the following functional form for P(Y|X):

$$P(Y=1|X) = \frac{1}{1+\exp(w_0 + \sum_i w_i X_i)}$$

Logistic function applied to linear function of the data

Logistic function (or Sigmoid): $\frac{1}{1+exp(-z)}$



Features can be discrete or continuous!

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Last time.. **Logistic Regression vs. Gaussian Naïve Bayes**

- LR is a linear classifier
  - decision rule is a hyperplane
- LR optimized by maximizing conditional likelihood
  - no closed-form solution
  - concave ! global optimum with gradient ascent
- Gaussian Naïve Bayes with class-independent variances representationally equivalent to LR
  - Solution differs because of objective (loss) function
- In general, NB and LR make different assumptions
  - NB: Features independent given class! assumption on P(**X**|Y)
  - LR: Functional form of P(Y|**X**), no assumption on P(**X**|Y)
- Convergence rates
  - GNB (usually) needs less data
  - LR (usually) gets to better solutions in the limit

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Linear Discriminant Functions

Linear Discriminant Function

- Linear discriminant function for a vector $\mathbf{x}$

$$y(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + w_0$$

where $\mathbf{w}$ is called weight vector, and w_0 is a bias.

- The classification function is

$$C(\mathbf{x}) = \text{sign}(\mathbf{w}^T \mathbf{x} + w_0)$$

where step function sign(·) is defined as

$$\text{sign}(a) = \begin{cases} +1, & a \geqslant 0 \\ -1, & a < 0 \end{cases}$$

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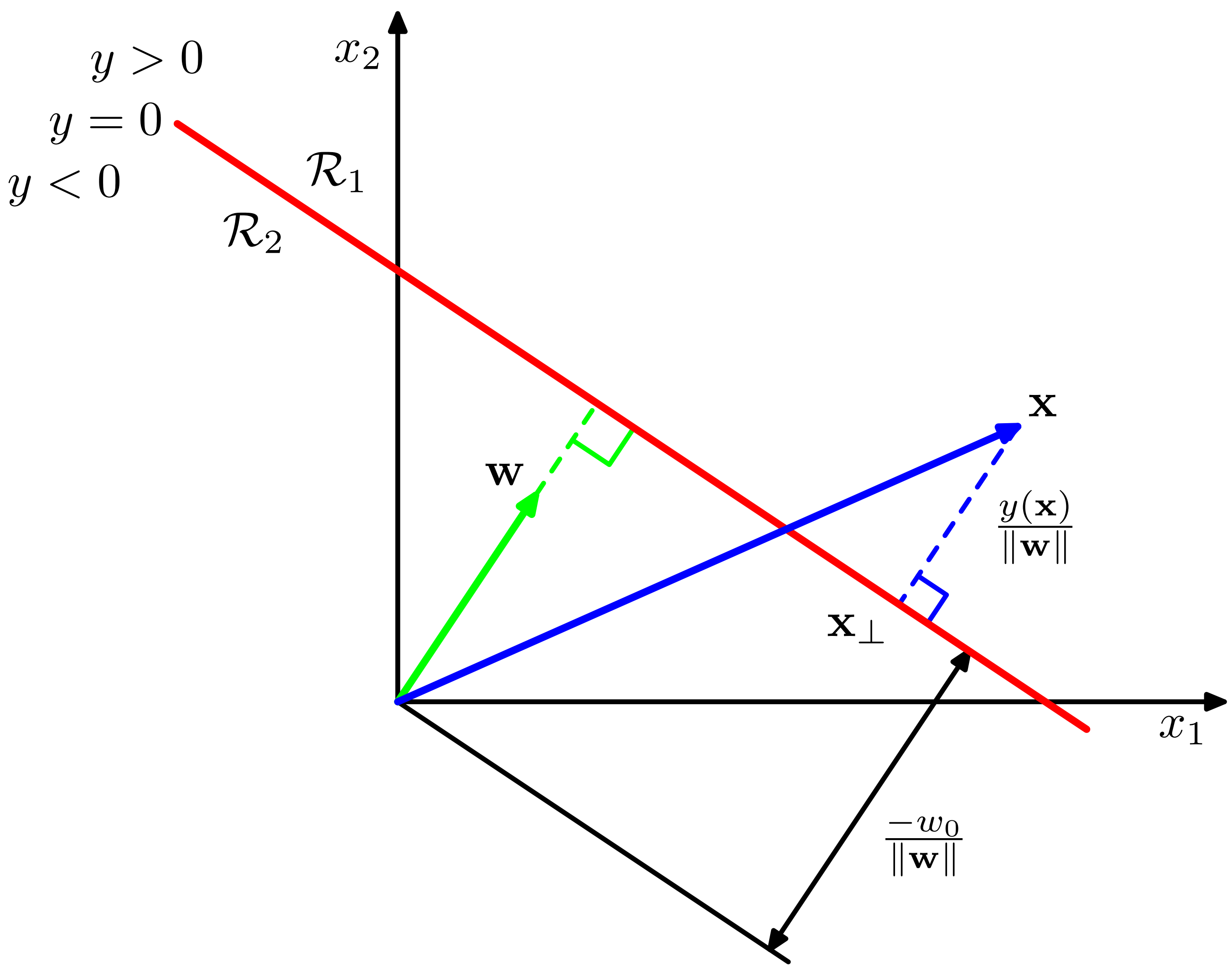
Properties of Linear Discriminant Functions



- The decision surface, shown in red, is perpendicular to $\mathbf{w}$, and its displacement from the origin is controlled by the bias parameter w_0.
- The signed orthogonal distance of a general point $\mathbf{x}$ from the decision surface is given by $y(\mathbf{x})/\|\mathbf{w}\|$
- $y(\mathbf{x})$ gives a signed measure of the perpendicular distance r of the point $\mathbf{x}$ from the decision surface

- $y(\mathbf{x}) = 0$ for $\mathbf{x}$ on the decision surface. The normal distance from the origin to the decision surface is

$$\frac{\mathbf{w}^T\mathbf{x}}{\|\mathbf{w}\|} = -\frac{w_0}{\|\mathbf{w}\|}$$

- So w_0 determines the location of the decision surface.

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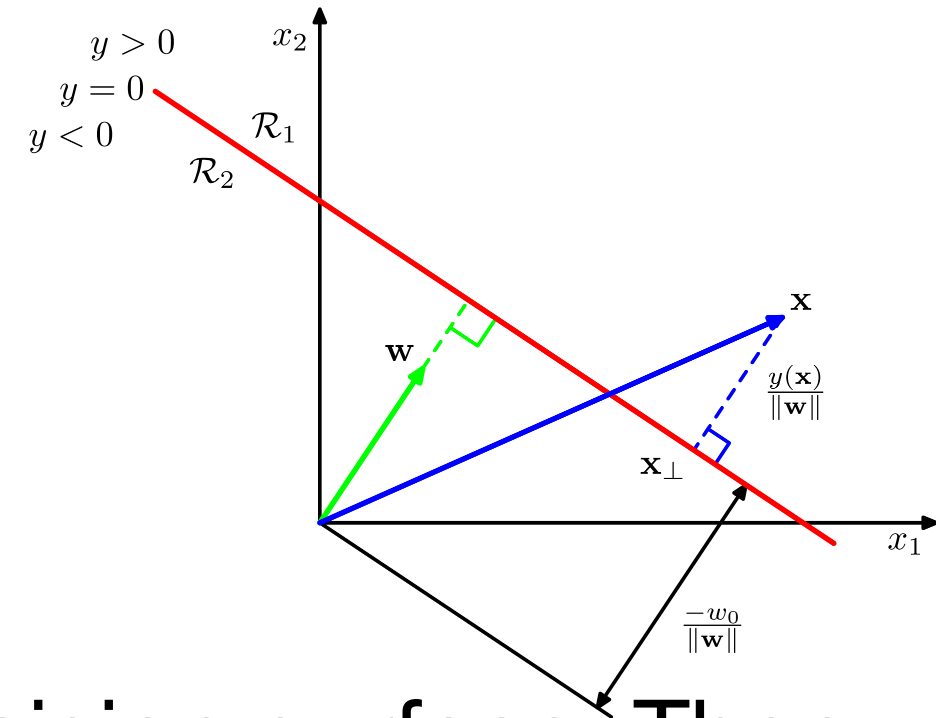
Properties of Linear Discriminant Functions



- Let

$$\mathbf{x} = \mathbf{x}_\perp + r\frac{\mathbf{w}}{\|\mathbf{w}\|}$$

where $\mathbf{x}_\perp$ is the projection $\mathbf{x}$ on the decision surface. Then

$$\mathbf{w}^T\mathbf{x} = \mathbf{w}^T\mathbf{x}_\perp + r\frac{\mathbf{w}^T\mathbf{w}}{\|\mathbf{w}\|}$$

$$\mathbf{w}^T\mathbf{x} + w_0 = \mathbf{w}^T\mathbf{x}_\perp + w_0 + r\|\mathbf{w}\|$$

$$y(\mathbf{x}) = r\|\mathbf{w}\|$$

$$r = \frac{y(\mathbf{x})}{\|\mathbf{w}\|}$$

- Simpler notion: define $\widetilde{\mathbf{w}} = (w_0, \mathbf{w})$ and $\widetilde{\mathbf{x}} = (1, \mathbf{x})$ so that

$$y(\mathbf{x}) = \widetilde{\mathbf{w}}^T\widetilde{\mathbf{x}}$$

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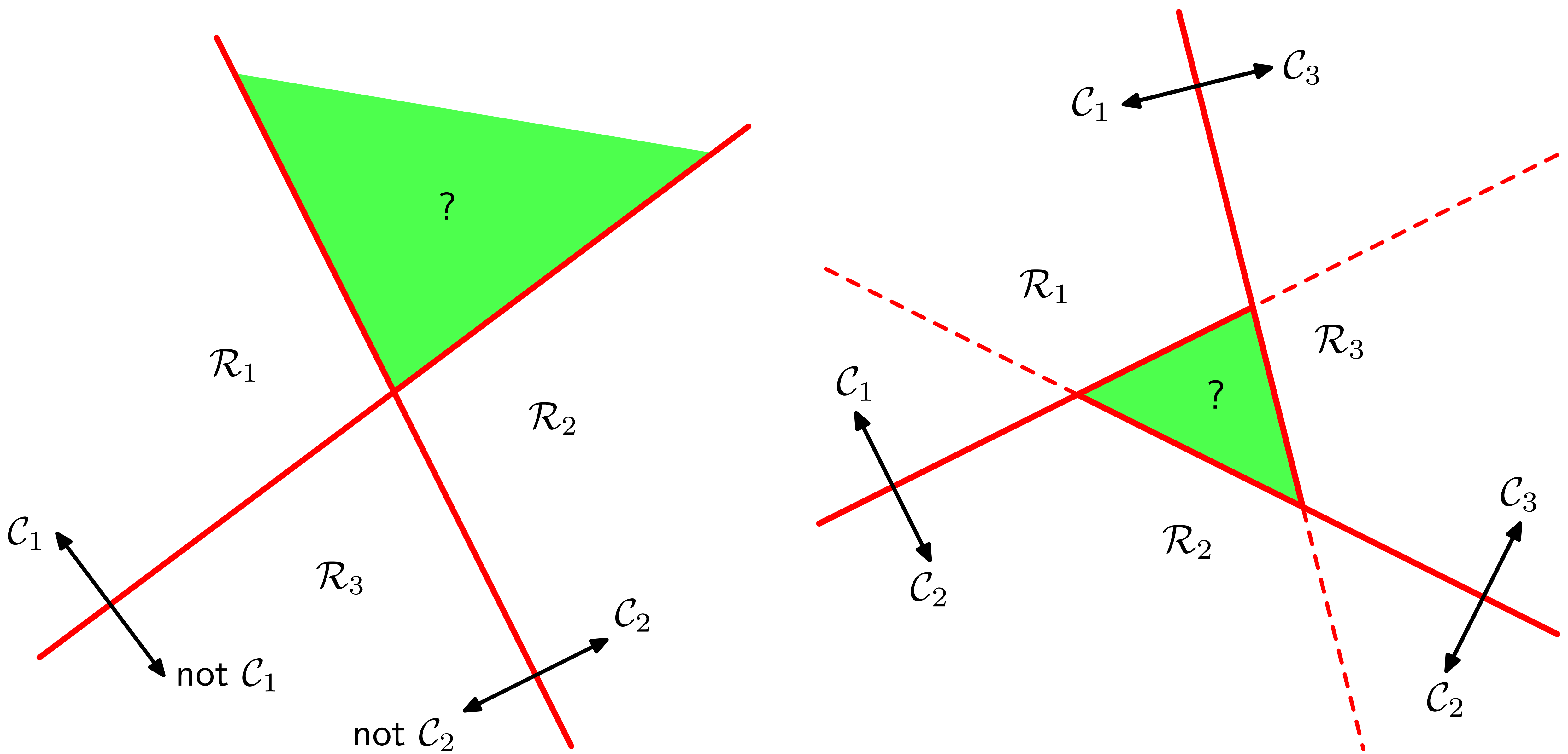
Multiple Classes: Simple Extension

- **One-versus-the-rest** classifier: classify C_k and samples not in C_k.
- **One-versus-one** classifier: classify every pair of classes.



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Multiple Classes: K-Class Discriminant

- A single K-class discriminant comprising K linear functions

$$y_k(\mathbf{x}) = \mathbf{w}_k^T \mathbf{x} + w_{k0}$$

- Decision function

$$\mathcal{C}(\mathbf{x}) = k, \text{ if } y_k(\mathbf{x}) > y_j(\mathbf{x}) \; \forall j \neq k$$

- The decision boundary between class C_k and C_j is given by $y_k(\mathbf{x}) = y_j(\mathbf{x})$

$$(\mathbf{w}_k - \mathbf{w}_j)^T \mathbf{x} + (w_{k0} - w_{j0}) = 0$$

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Fisher’s Linear Discriminant

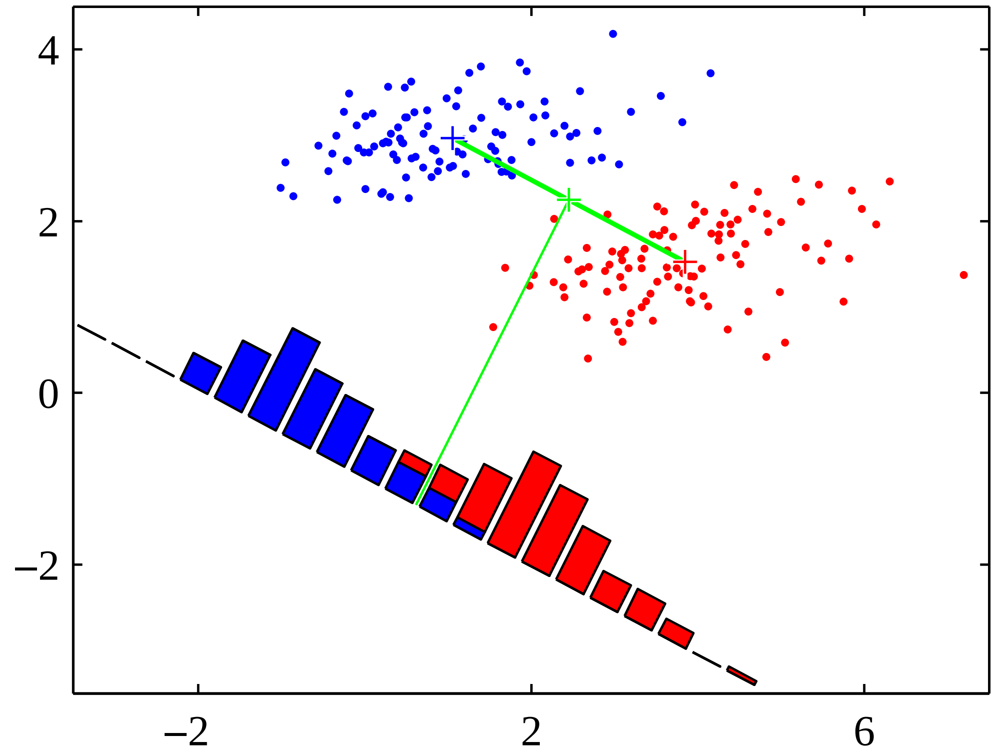
- Pursue the optimal linear projection on which the two classes can be maximally separated

$$y = \mathbf{w}^T \mathbf{x}$$

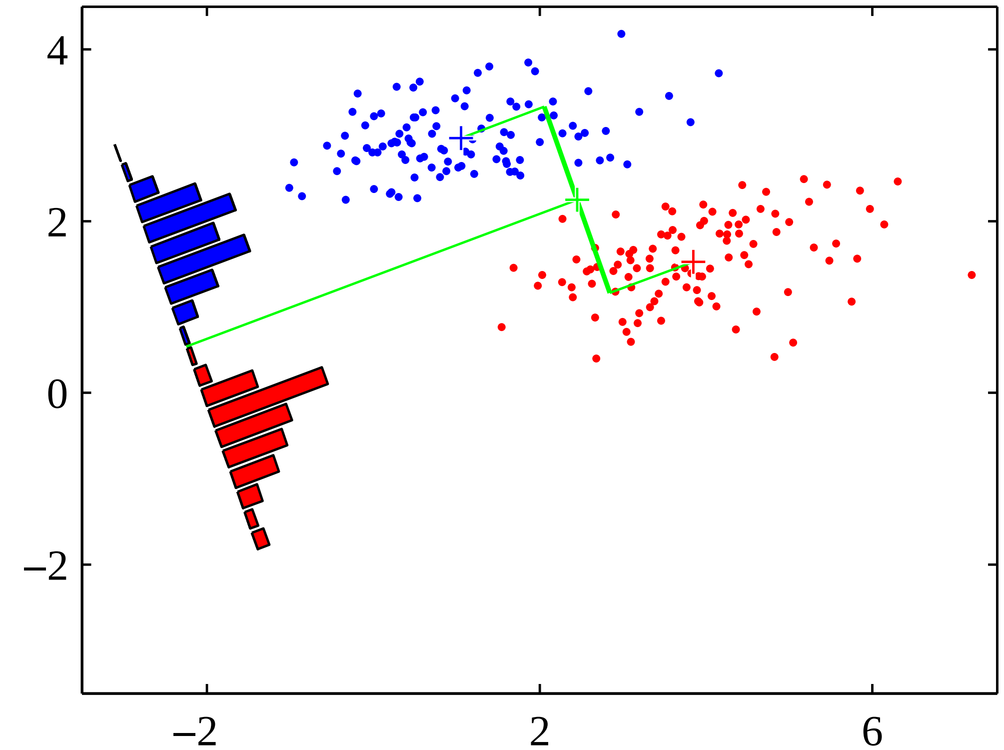
- The mean vectors of the two classes

$$\mathbf{m}_1 = \frac{1}{N_1} \sum_{n \in \mathcal{C}_1} \mathbf{x}_n, \quad \mathbf{m}_2 = \frac{1}{N_2} \sum_{n \in \mathcal{C}_2} \mathbf{x}_n$$

A way to view a linear classification model is in terms of dimensionality reduction.



Difference of means



Fisher’s Linear Discriminant

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What's a Good Projection?

- After projection, the two classes are separated as much as possible. Measured by the distance between projected center

$$\left(\mathbf{w}^T(\mathbf{m}_1 - \mathbf{m}_2)\right)^2 = \mathbf{w}^T(\mathbf{m}_1 - \mathbf{m}_2)(\mathbf{m}_1 - \mathbf{m}_2)^T\mathbf{w}$$
$$= \mathbf{w}^T\mathbf{S}_B\mathbf{w}$$

where $\mathbf{S}_B = (\mathbf{m}_1 - \mathbf{m}_2)(\mathbf{m}_1 - \mathbf{m}_2)^T$ is called **between-class** covariance matrix.

- After projection, the variances of the two classes are as small as possible. Measured by the within-class covariance

$$\mathbf{w}^T\mathbf{S}_W\mathbf{w}$$

where

$$\mathbf{S}_W = \sum_{n\in\mathcal{C}_1}(\mathbf{x}_n - \mathbf{m}_1)(\mathbf{x}_n - \mathbf{m}_1)^T + \sum_{n\in\mathcal{C}_2}(\mathbf{x}_n - \mathbf{m}_2)(\mathbf{x}_n - \mathbf{m}_2)^T$$

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Fisher's Linear Discriminant

- Fisher criterion: maximize the ratio w.r.t. $\mathbf{w}$

$$J(\mathbf{w}) = \frac{\texttt{Between-class variance}}{\texttt{Within-class variance}} = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_W \mathbf{w}}$$

- Recall the quotient rule: for $f(x) = \frac{g(x)}{h(x)}$

$$f'(x) = \frac{g'(x)h(x) - g(x)h'(x)}{h^2(x)}$$

- Setting $\nabla J(\boldsymbol{w}) = 0$, we obtain

$$(\mathbf{w}^T \mathbf{S}_B \mathbf{w})\mathbf{S}_W \mathbf{w} = (\mathbf{w}^T \mathbf{S}_W \mathbf{w})\mathbf{S}_B \mathbf{w}$$

$$(\mathbf{w}^T \mathbf{S}_B \mathbf{w})\mathbf{S}_W \mathbf{w} = (\mathbf{w}^T \mathbf{S}_W \mathbf{w})(\mathbf{m}_2 - \mathbf{m}_1)\Big((\mathbf{m}_2 - \mathbf{m}_1)^T \mathbf{w}\Big)$$

- Terms $\mathbf{w}^T\mathbf{S}_B\mathbf{w}$, $\mathbf{w}^T\mathbf{S}_W\mathbf{w}$ and $(\mathbf{m}_2 - \mathbf{m}_1)^T\mathbf{w}$ are scalars, and we only care about directions. So the scalars are dropped. Therefore

$$\mathbf{w} \propto \mathbf{S}_W^{-1}(\mathbf{m}_2 - \mathbf{m}_1)$$

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From Fisher's Linear Discriminant to Classifiers

- Fisher's Linear Discriminant is not a classifier; it only decides on an optimal projection to convert high-dimensional classification problem to 1D.

- A bias (threshold) is needed to form a linear classifier (multiple thresholds lead to nonlinear classifiers). The final classifier has the form

$$y(\mathbf{x}) = \mathrm{sign}(\mathbf{w}^T\mathbf{x} + w_0)$$

  where the nonlinear activation function sign(·) is a step function

$$\mathrm{sign}(a) = \begin{cases} +1, & a \geqslant 0 \\ -1, & a < 0 \end{cases}$$

- How to decide the bias w_0?

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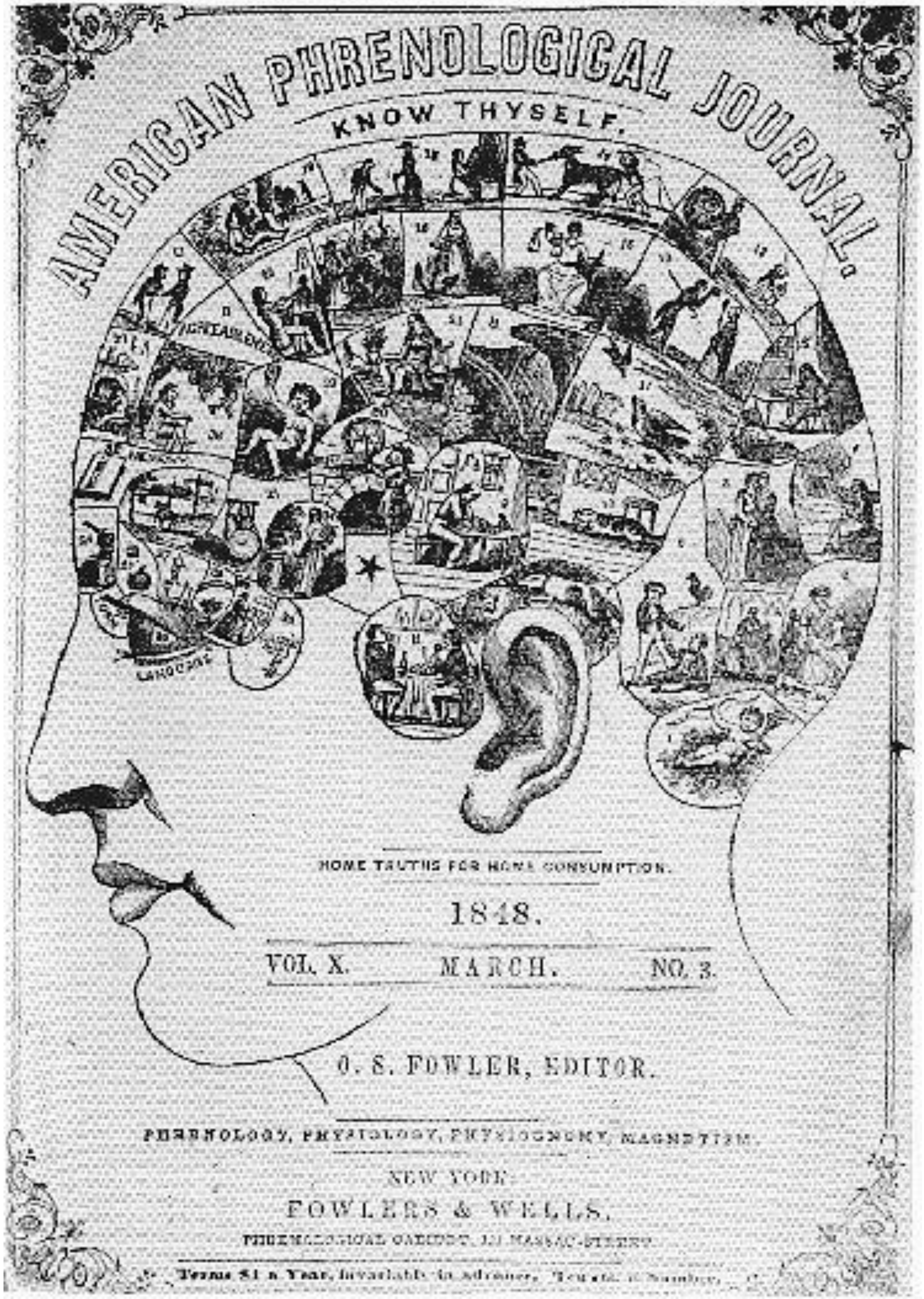
Perceptron



early theories
of the brain

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Biology and Learning

- Basic Idea
  - Good behavior should be rewarded, bad behavior punished (or not rewarded). This improves system fitness.
  - Killing a sabertooth tiger should be rewarded ...
  - Correlated events should be combined.
  - Pavlov's salivating dog.
- Training mechanisms
  - Behavioral modification of individuals (learning) Successful behavior is rewarded (e.g. food).
  - Hard-coded behavior in the genes (instinct) The wrongly coded animal does not reproduce.

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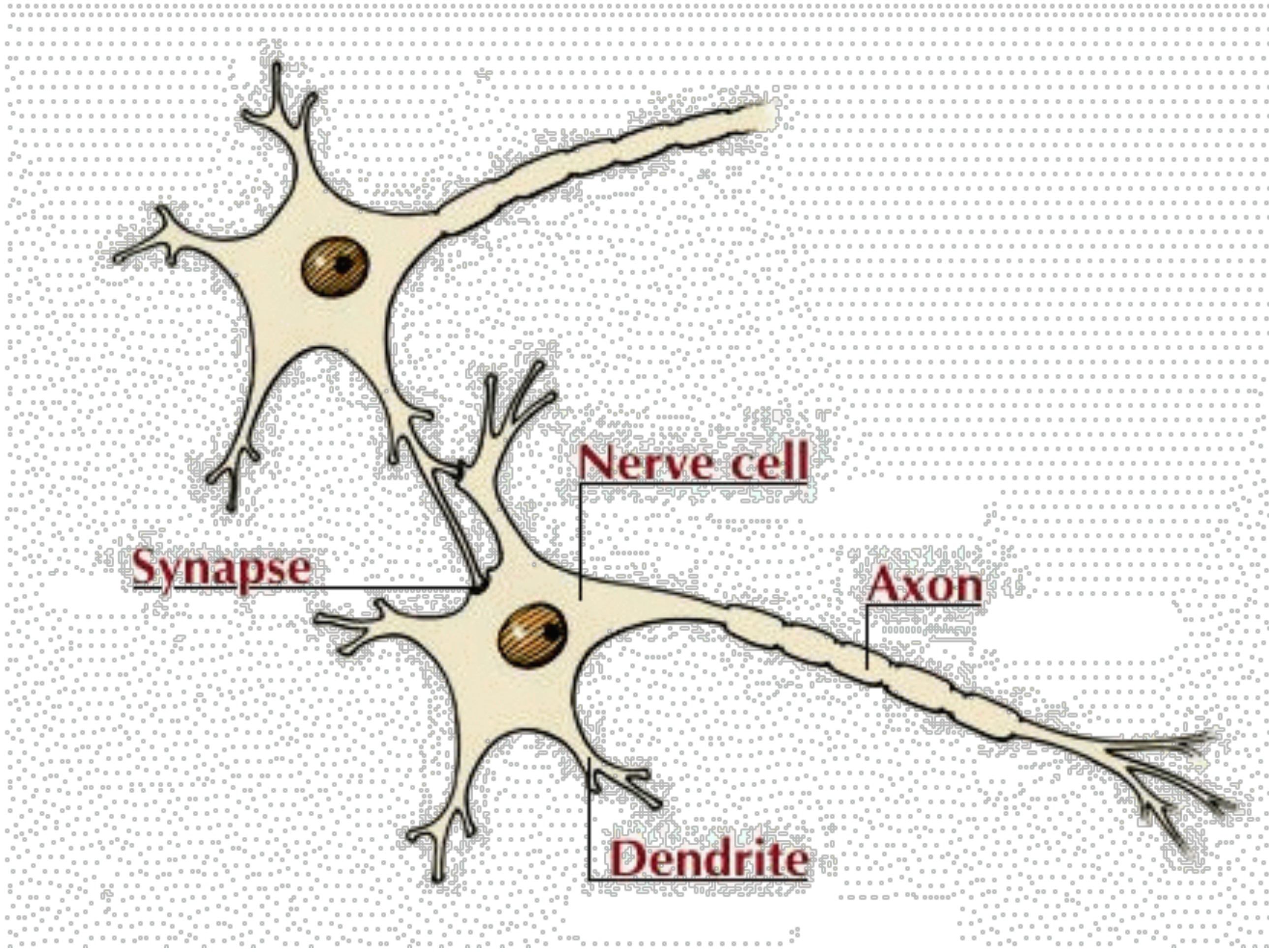
Neurons



- Soma (CPU)
  Cell body - combines signals
- Dendrite (input bus)
  Combines the inputs from several other nerve cells
- Synapse (interface)
  Interface and parameter store between neurons
- Axon (cable)
  May be up to 1m long and will transport the activation signal to neurons at different locations

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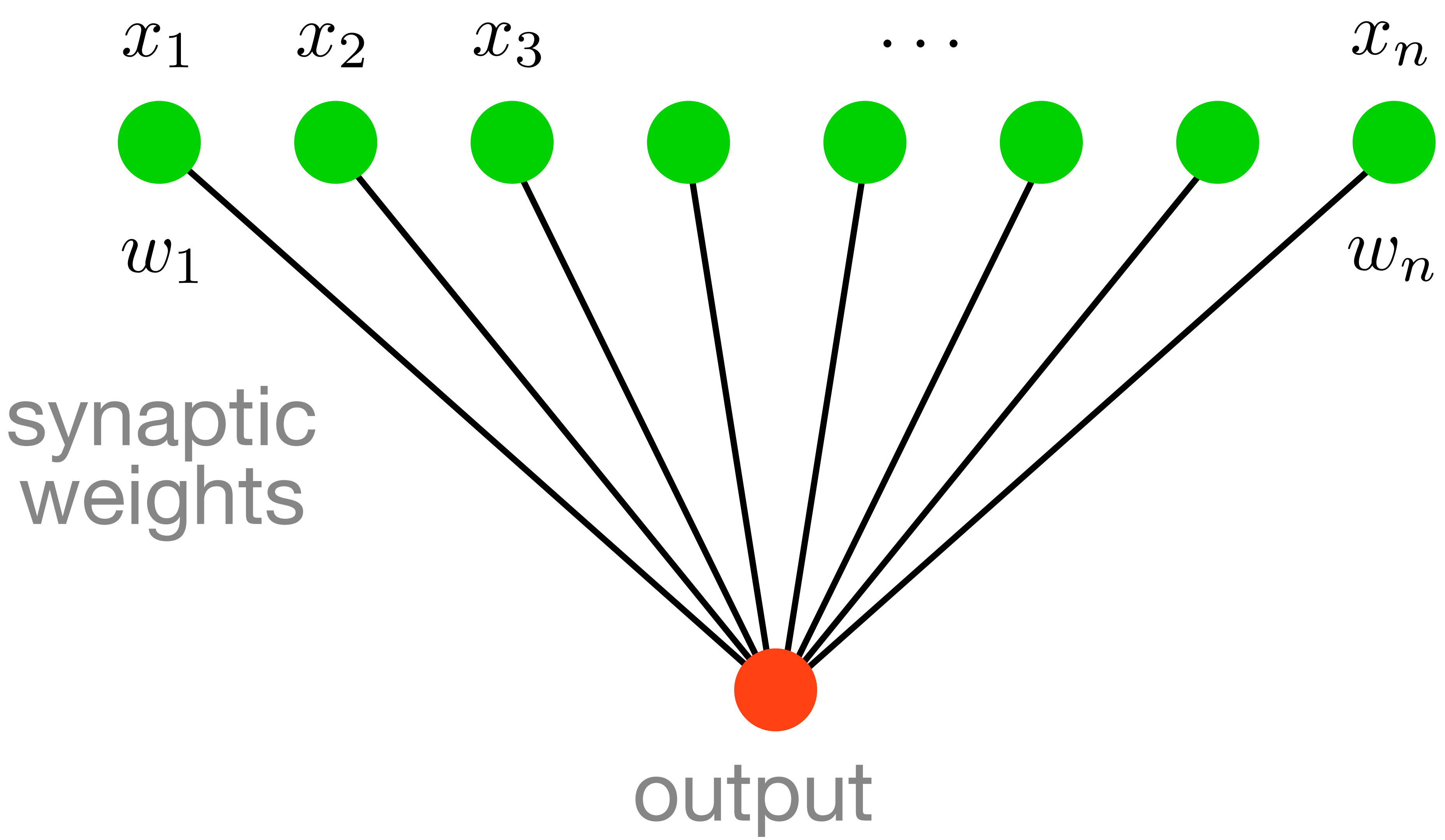
Neurons



$$f(x) = \sum_i w_i x_i = \langle w, x \rangle$$

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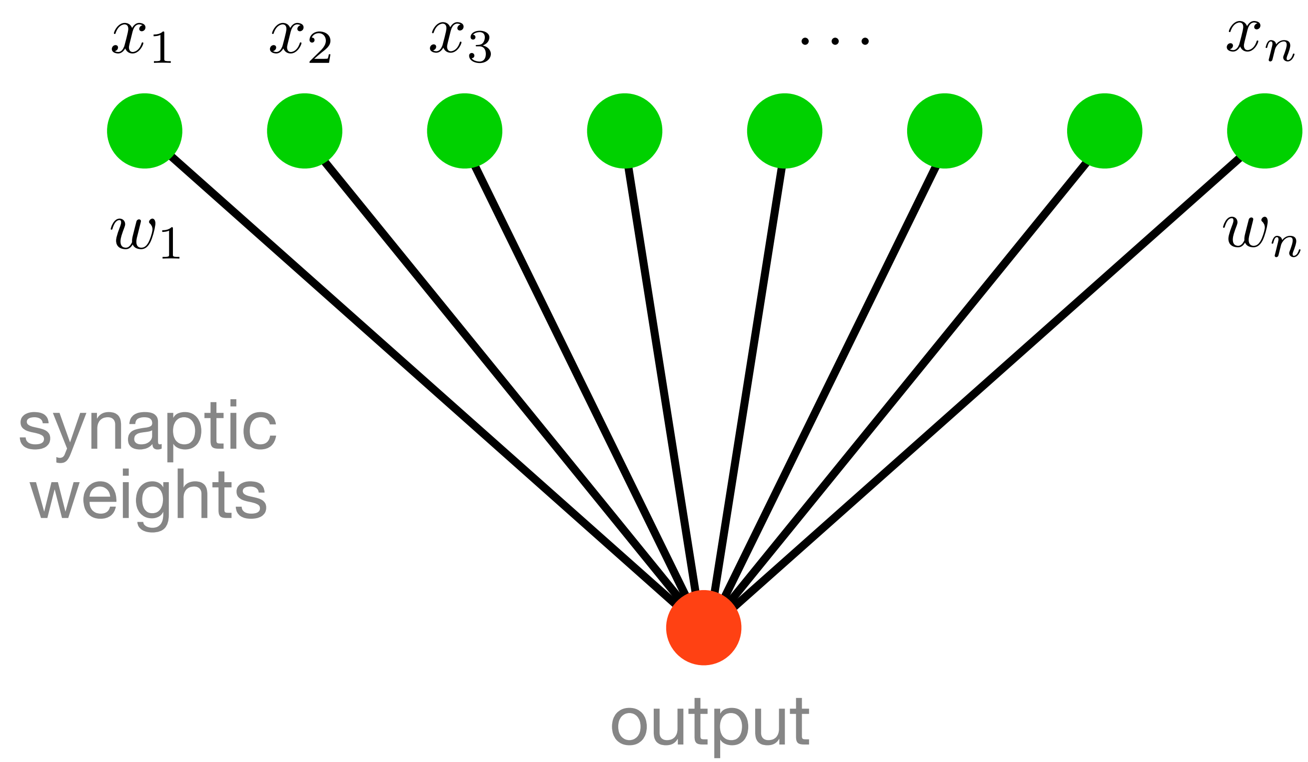
Perceptron

- Weighted linear combination
- Nonlinear decision function
- Linear offset (bias)



$$f(x) = \sigma\left(\langle w, x \rangle + b\right)$$

- Linear separating hyperplanes (spam/ham, novel/typical, click/no click)
- Learning
  Estimating the parameters w and b

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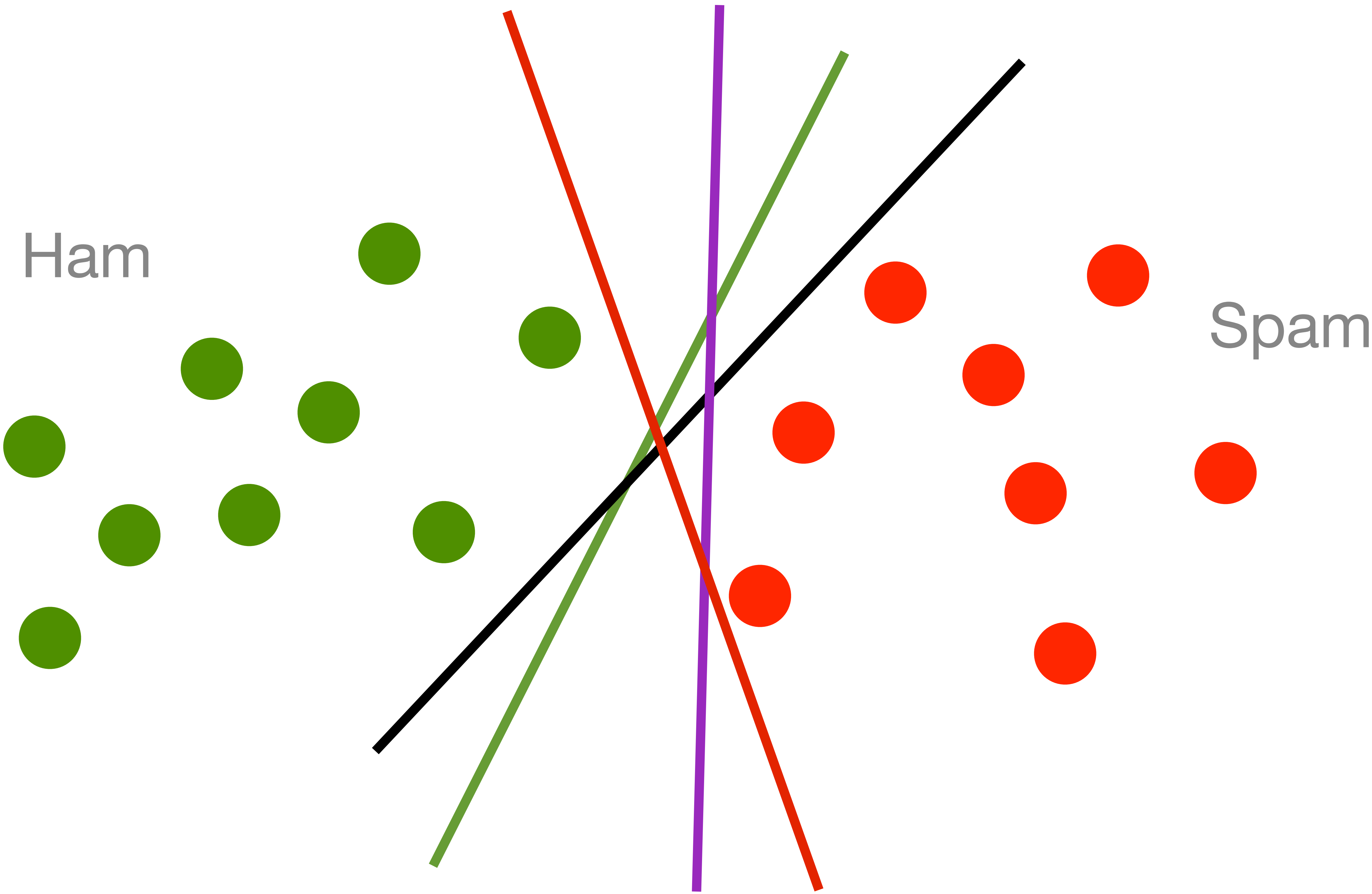
Perceptron



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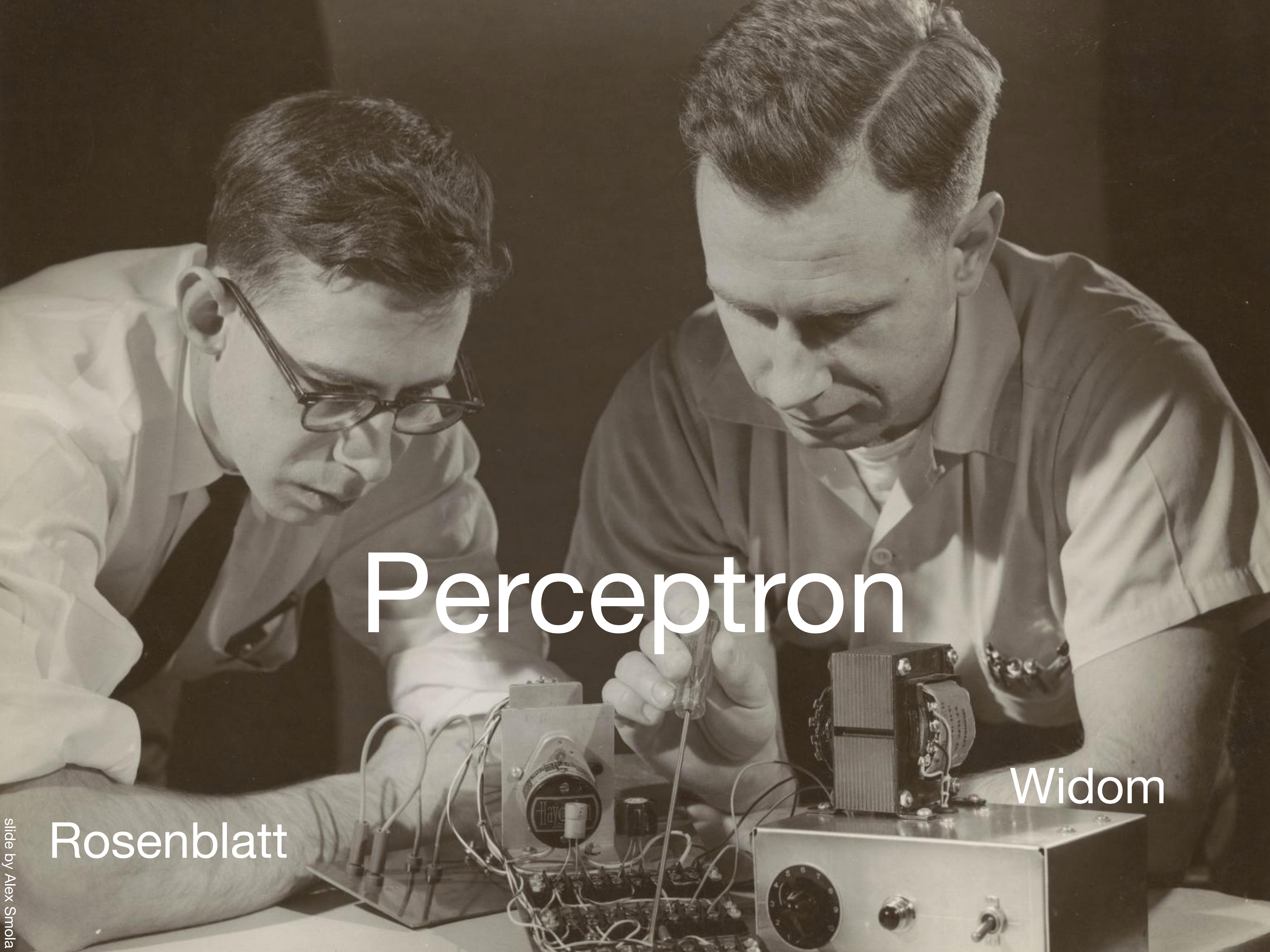
Perceptron
Widom
Rosenblatt
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The Perceptron

initialize $w = 0$ and $b = 0$
repeat
  if $y_i [\langle w, x_i \rangle + b] \leq 0$ **then**
    $w \leftarrow w + y_i x_i$ and $b \leftarrow b + y_i$
  end if
until all classified correctly

- Nothing happens if classified correctly
- Weight vector is linear combination $w = \sum_{i \in I} y_i x_i$
- Classifier is linear combination of inner products $f(x) = \sum_{i \in I} y_i \langle x_i, x \rangle + b$

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Convergence Theorem

- If there exists some (w^*, b^*) with unit length and
$$y_i \left[\langle x_i, w^* \rangle + b^*\right] \geq \rho \text{ for all } i$$
then the perceptron converges to a linear separator after a number of steps bounded by
$$\left({b^*}^2 + 1\right)\left(r^2 + 1\right)\rho^{-2} \text{ where } \|x_i\| \leq r$$

- Dimensionality independent
- Order independent (i.e. also worst case)
- Scales with 'difficulty' of problem

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Consequences

- Only need to store errors.
  This gives a compression bound for perceptron.
- Stochastic gradient descent on hinge loss

$$l(x_i, y_i, w, b) = \max\left(0, 1 - y_i\left[\langle w, x_i\rangle + b\right]\right)$$

- Fails with noisy data

do NOT train your
avatar with perceptrons

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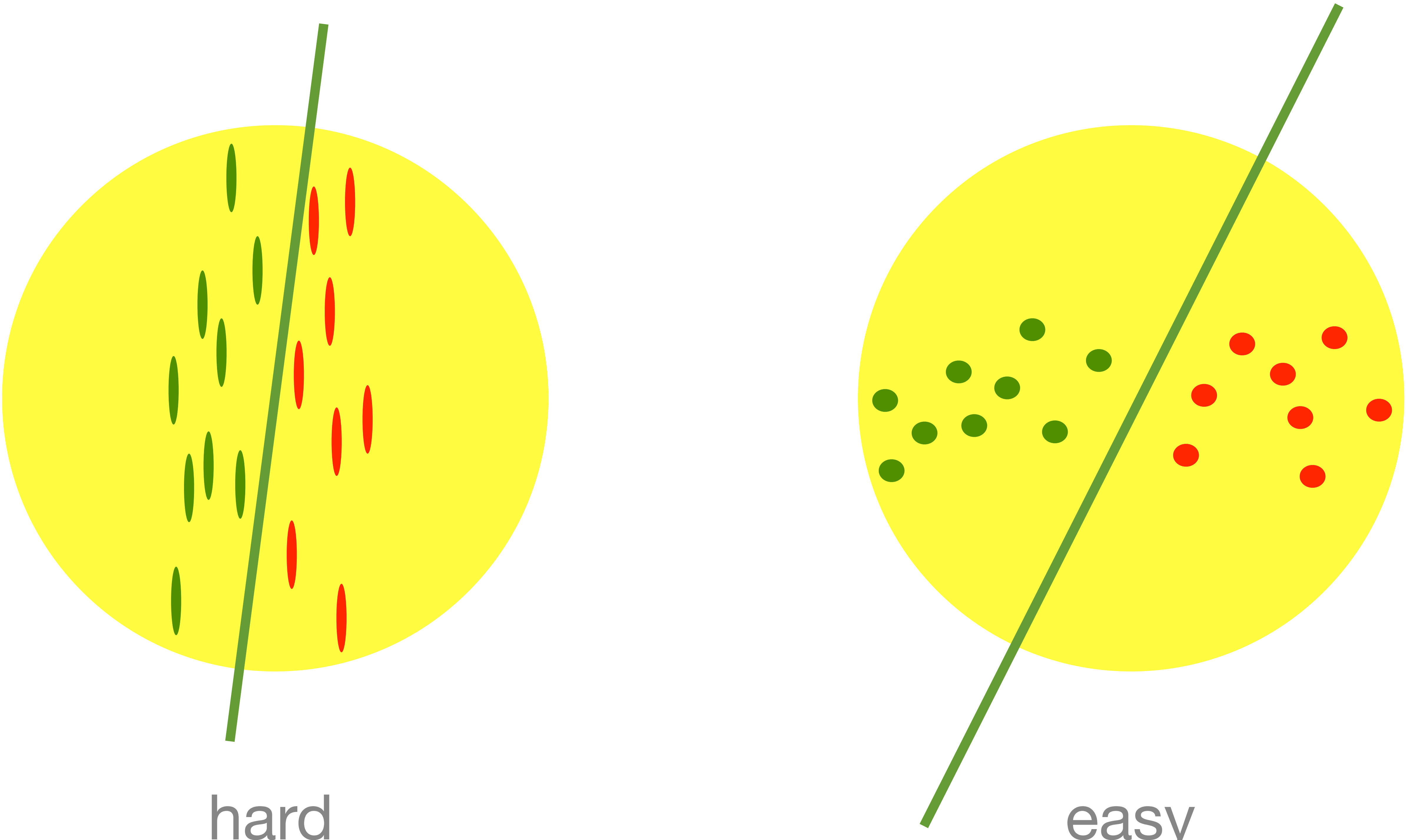
Hardness: margin vs. size



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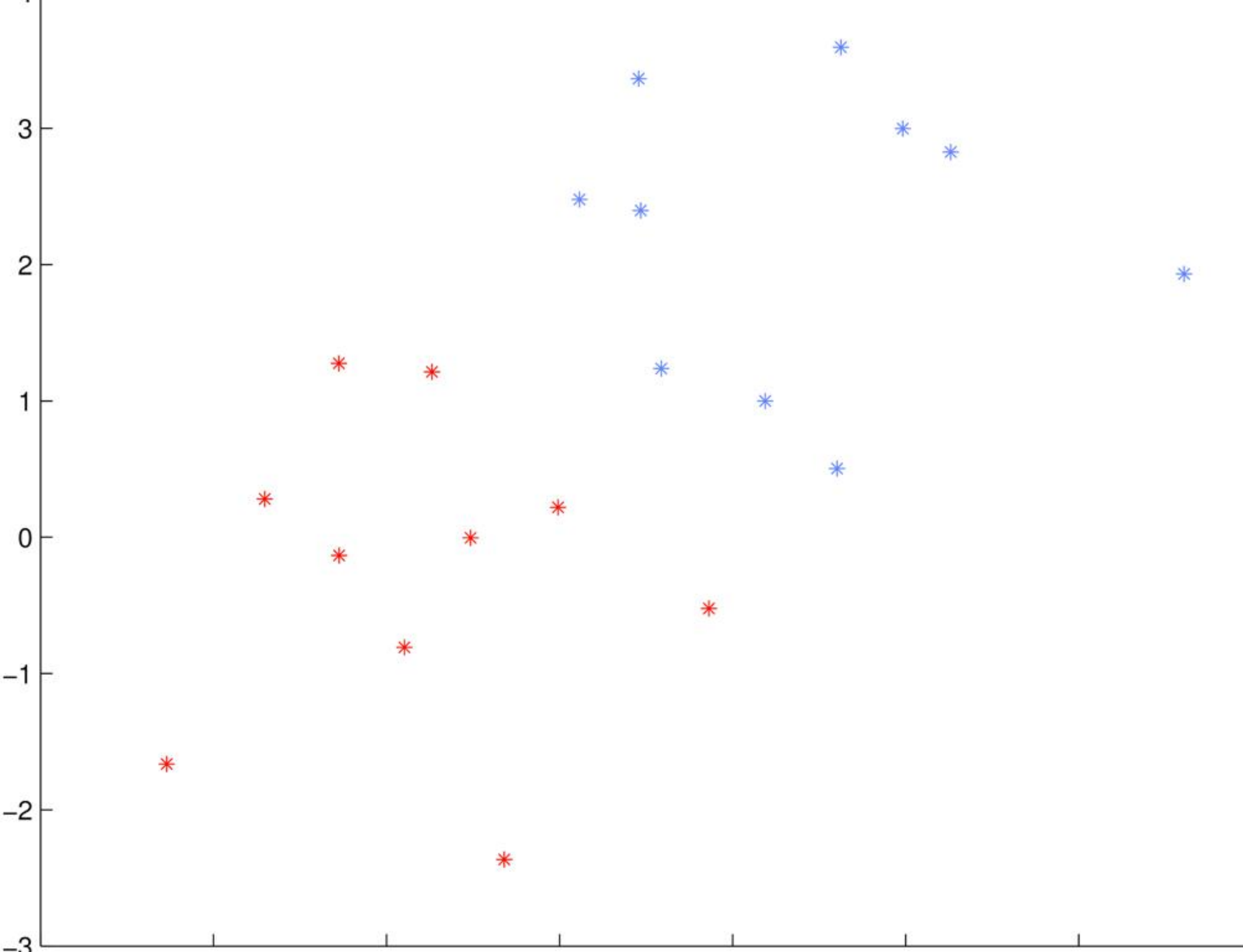

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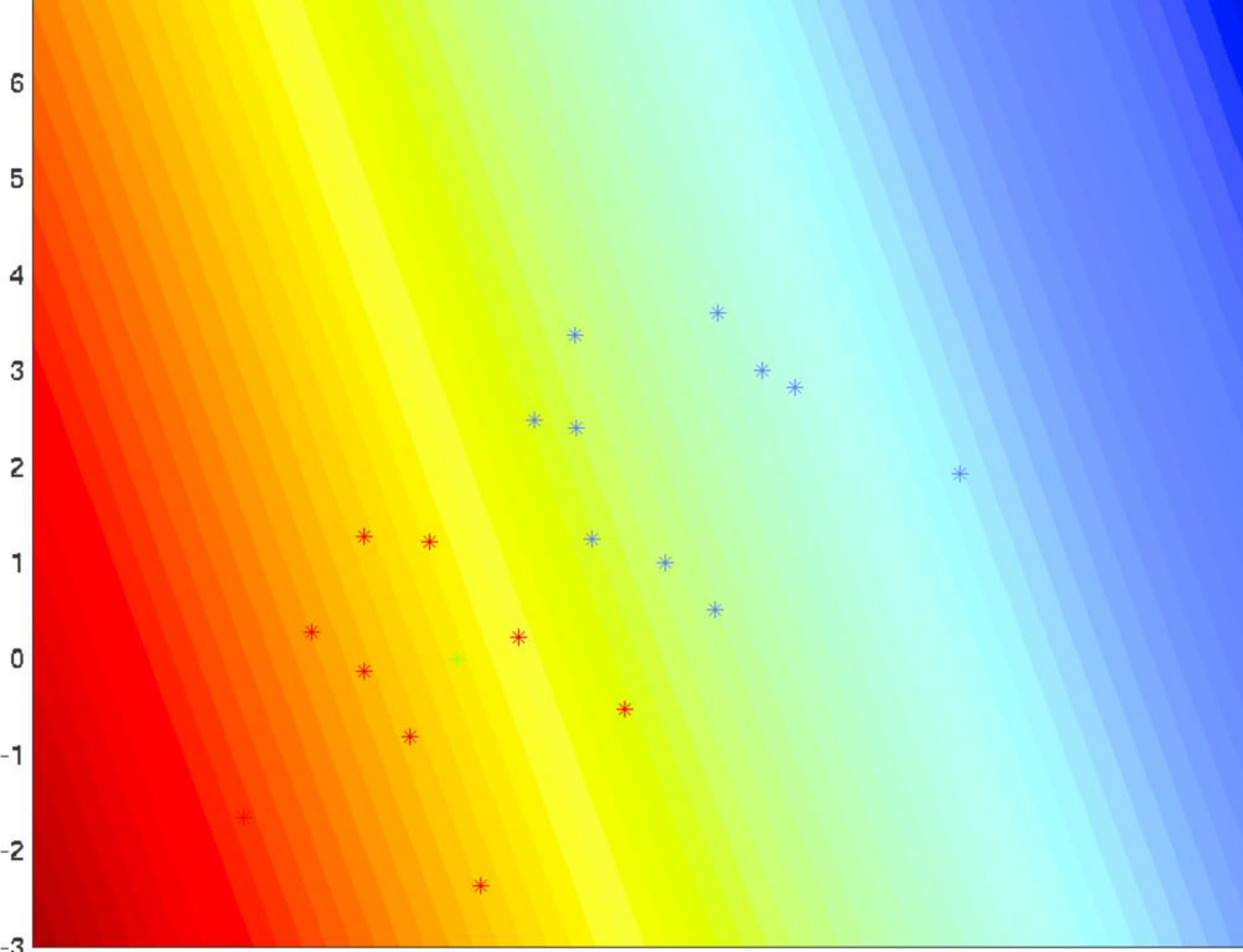

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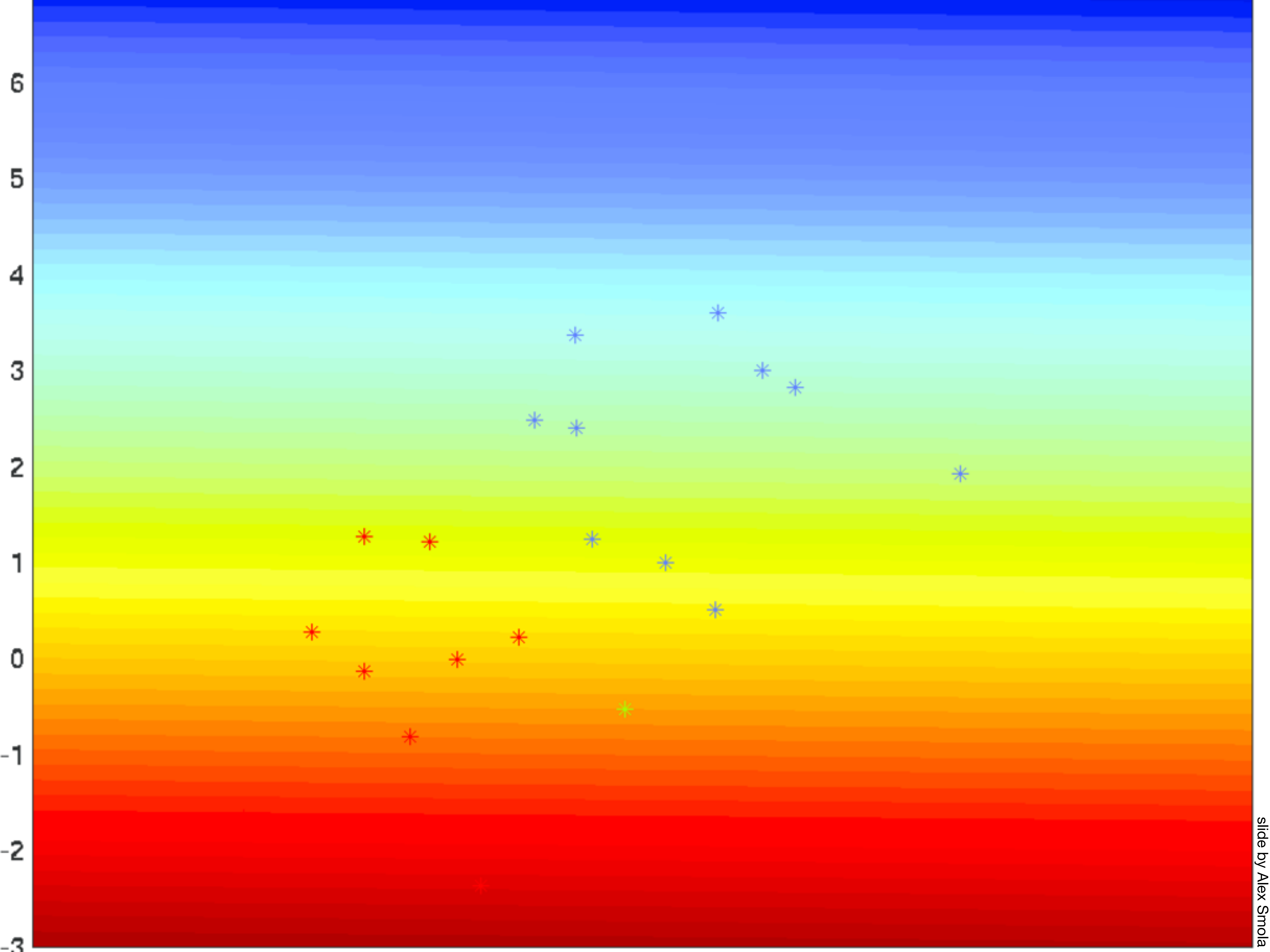

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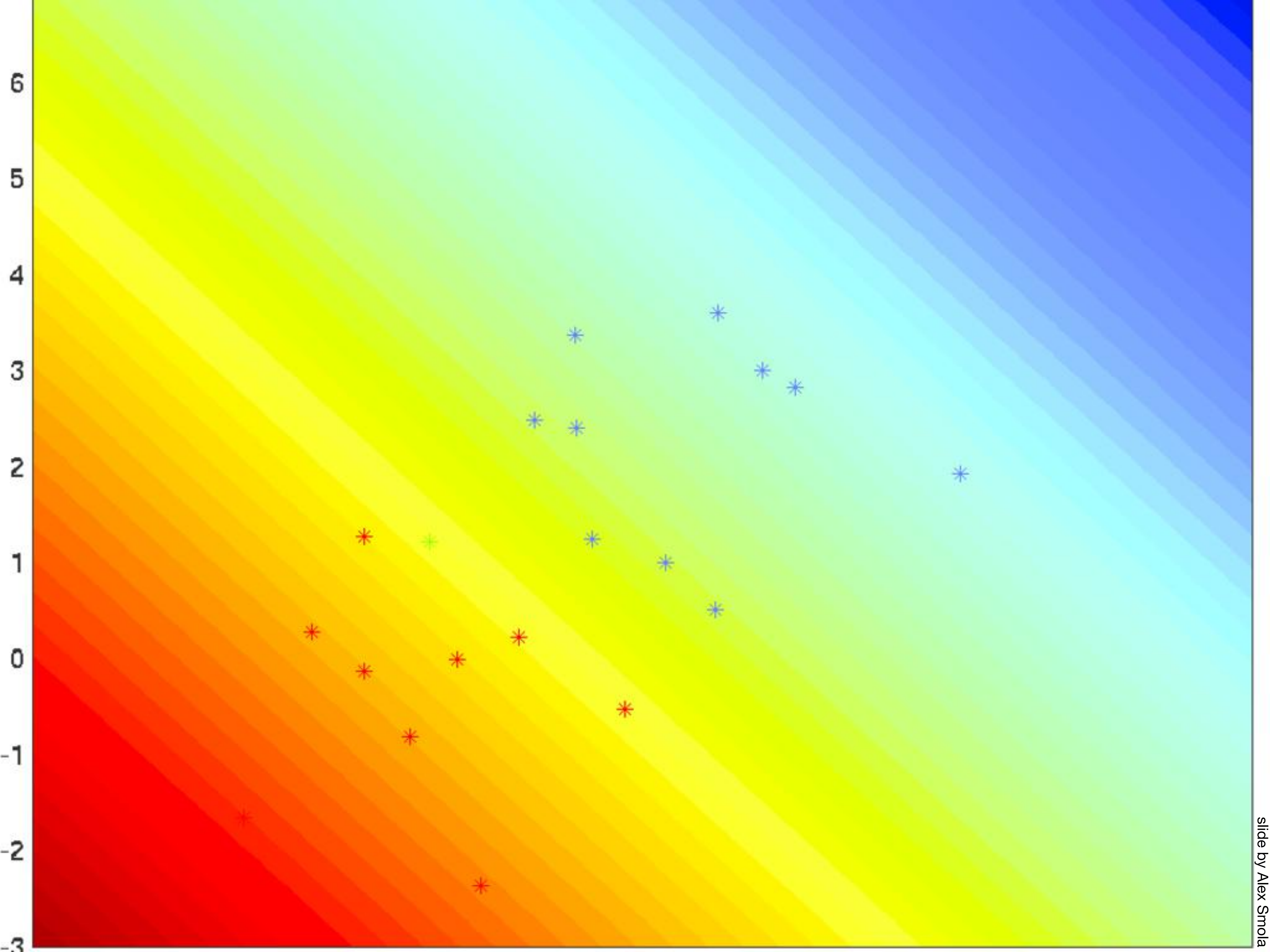
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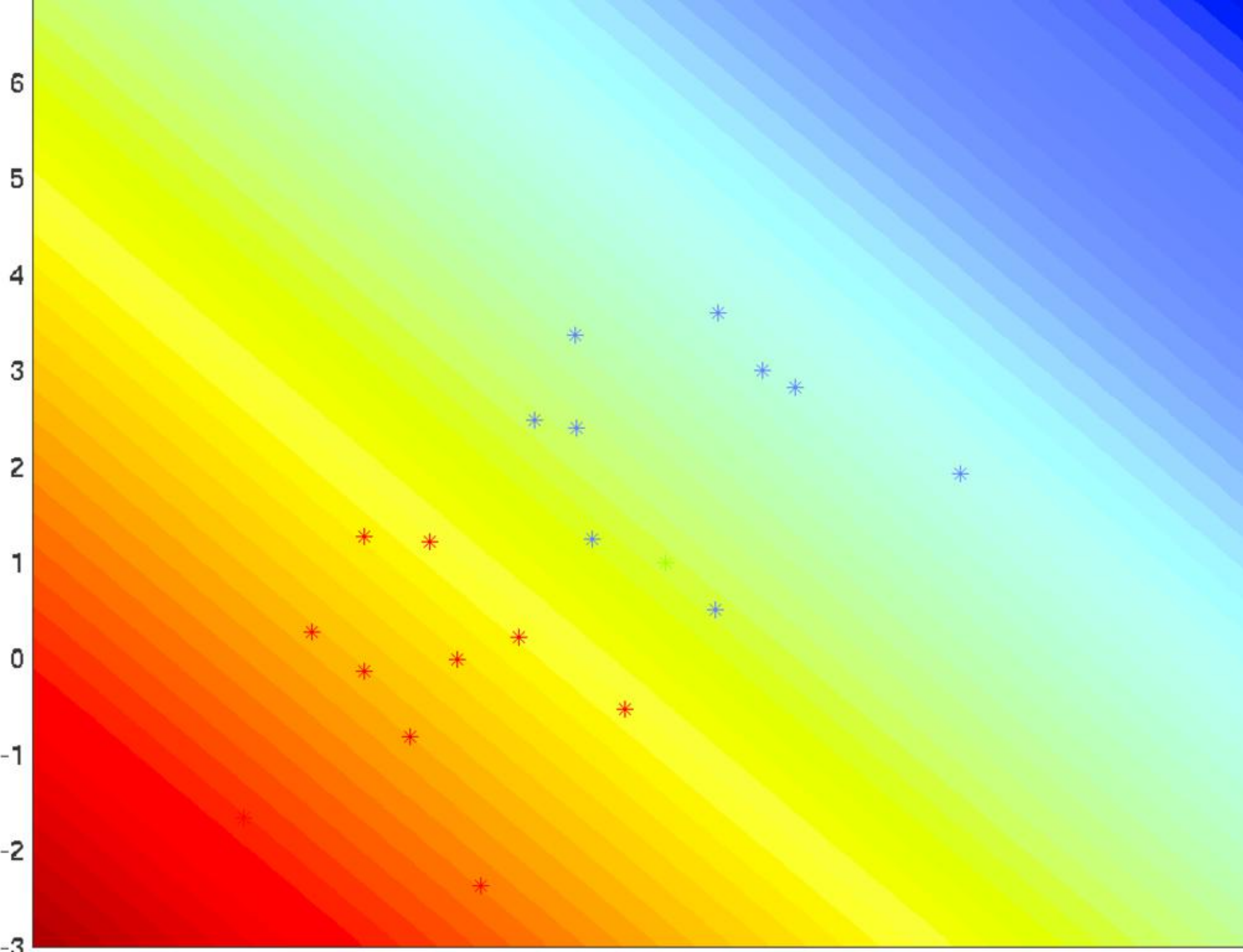

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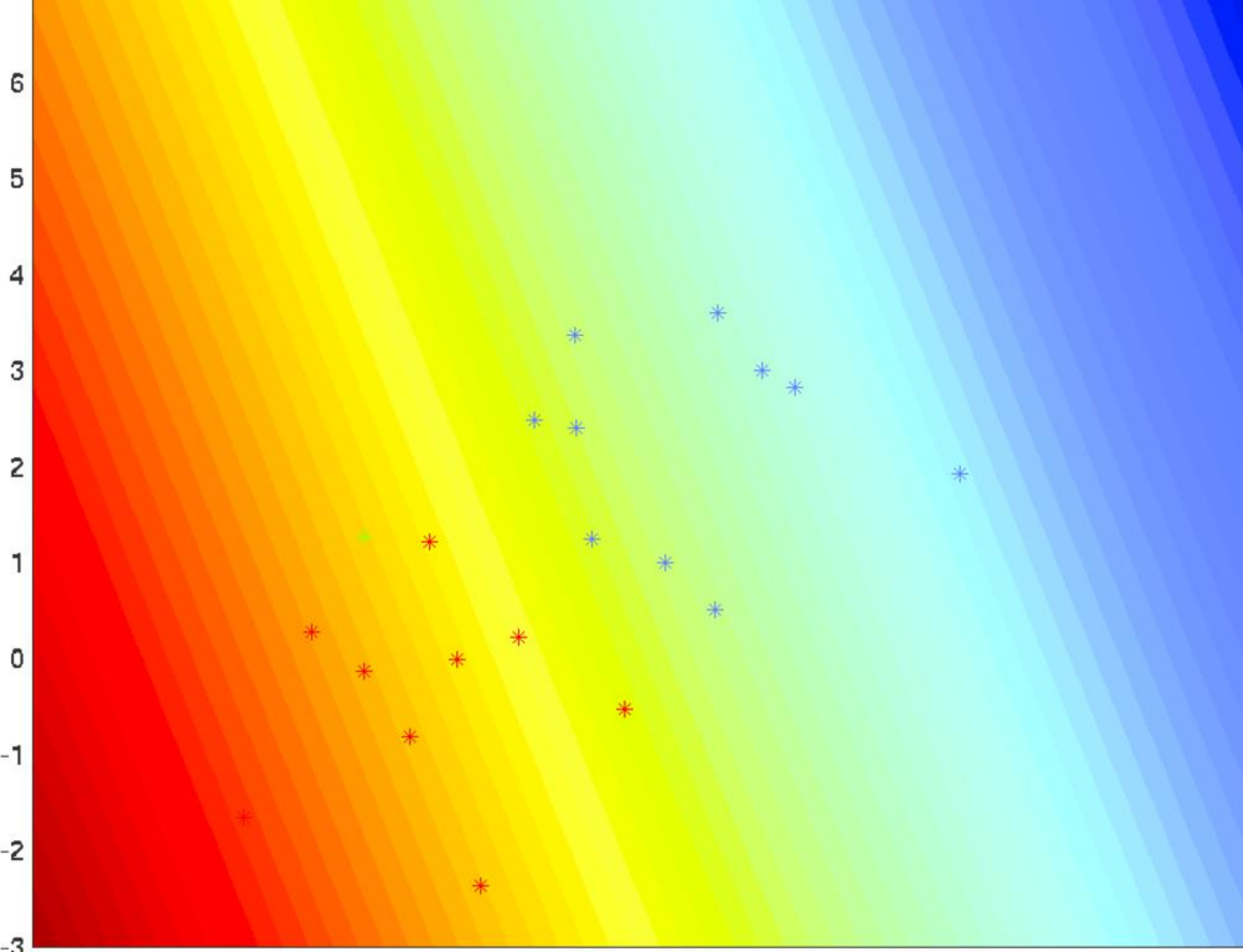

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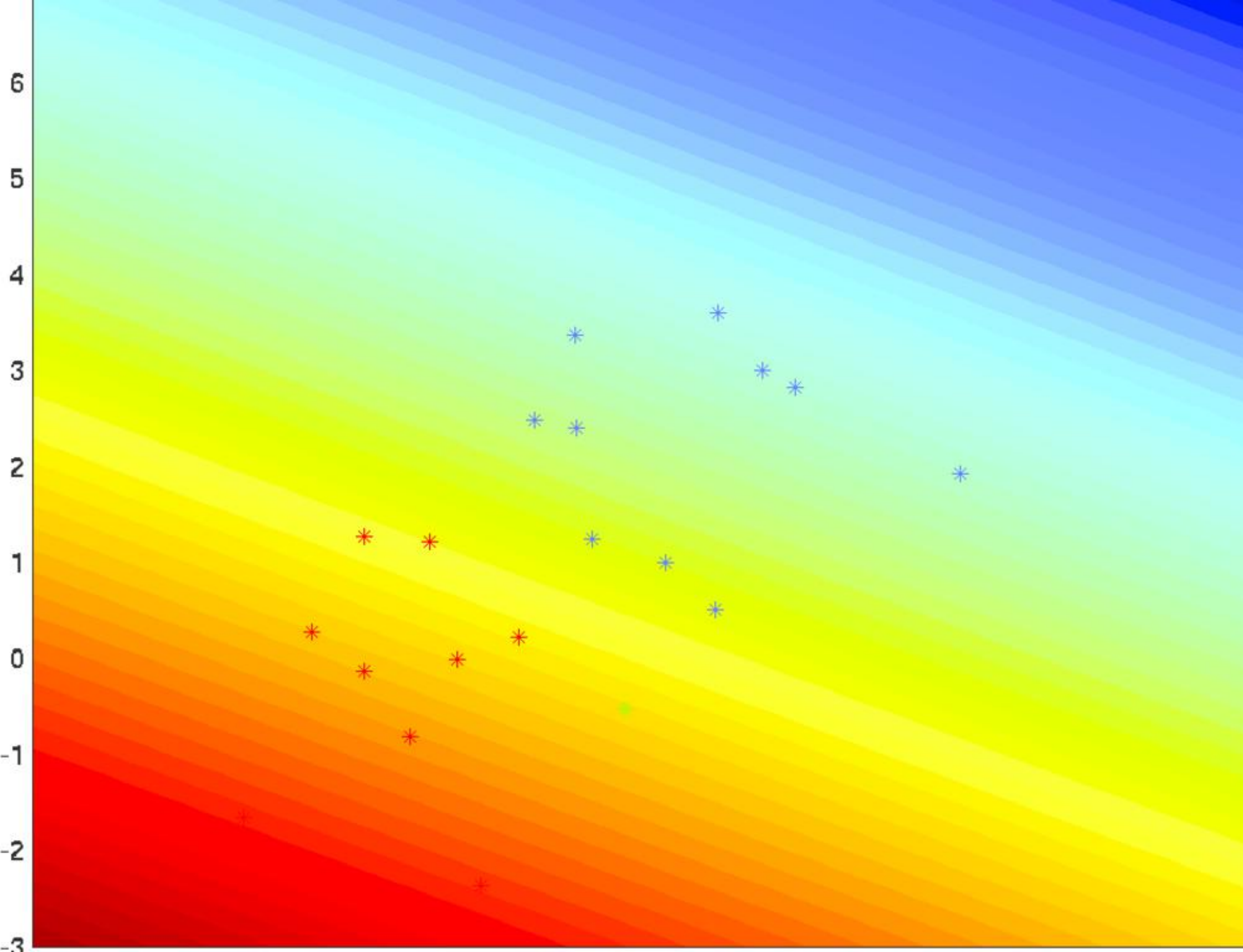

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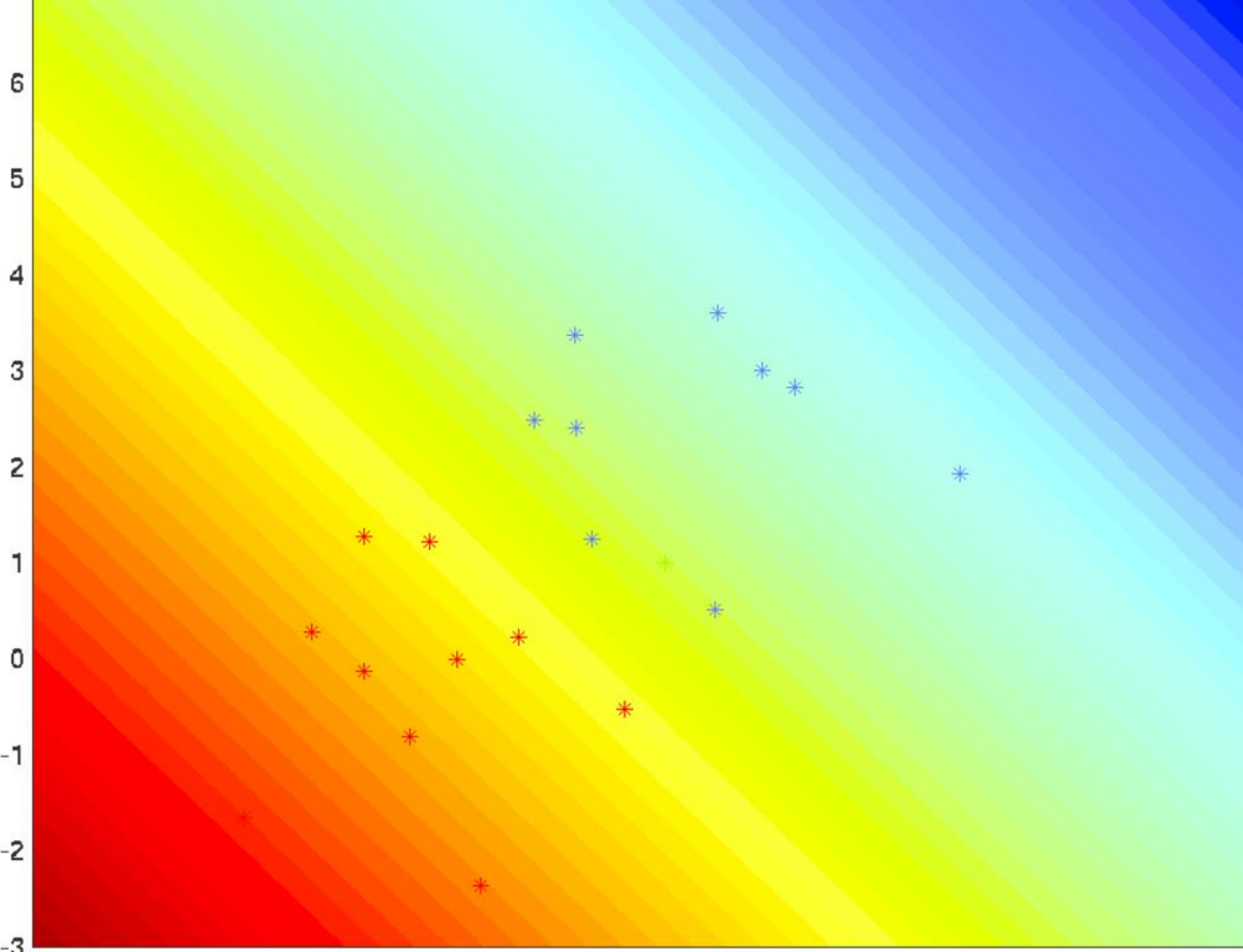

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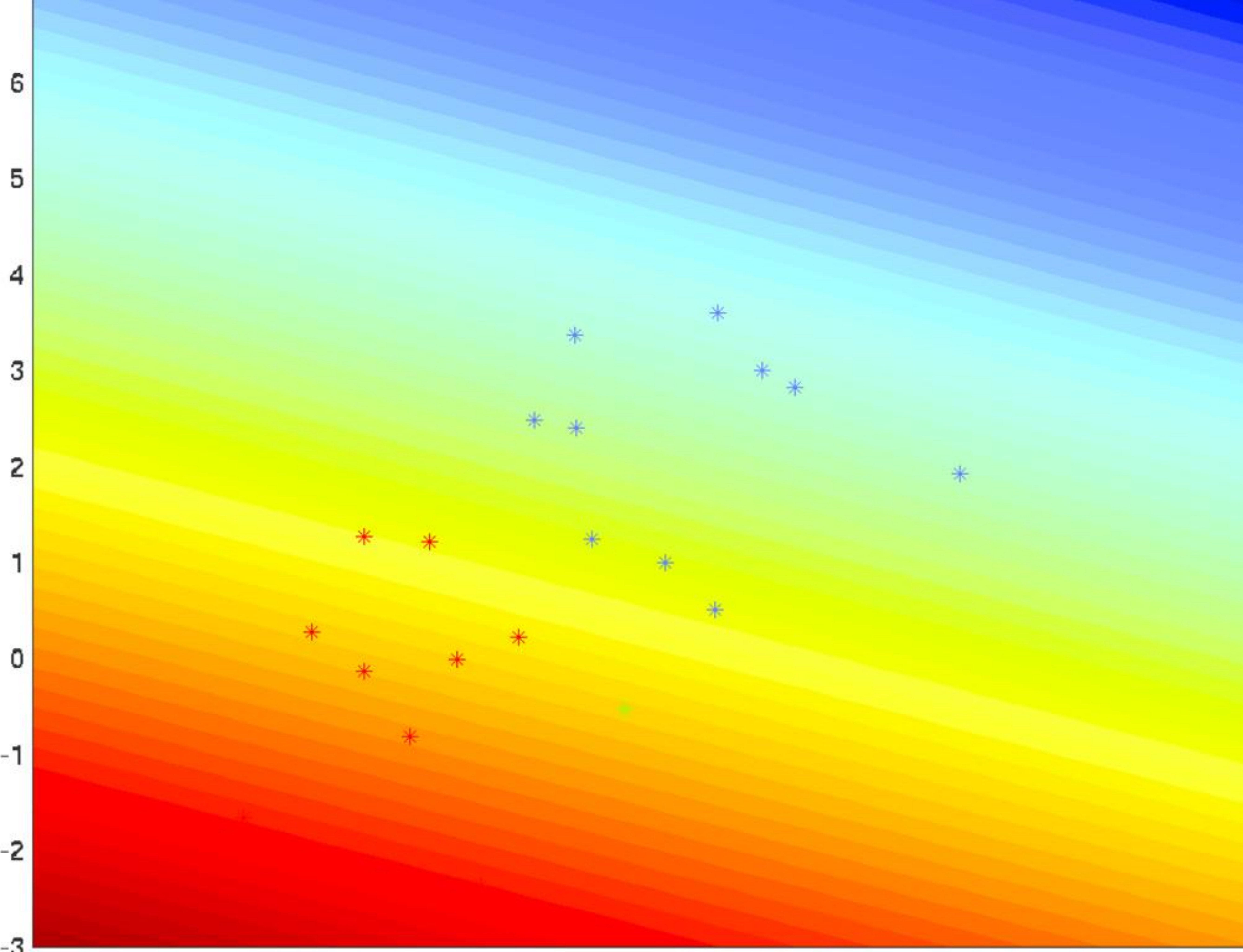

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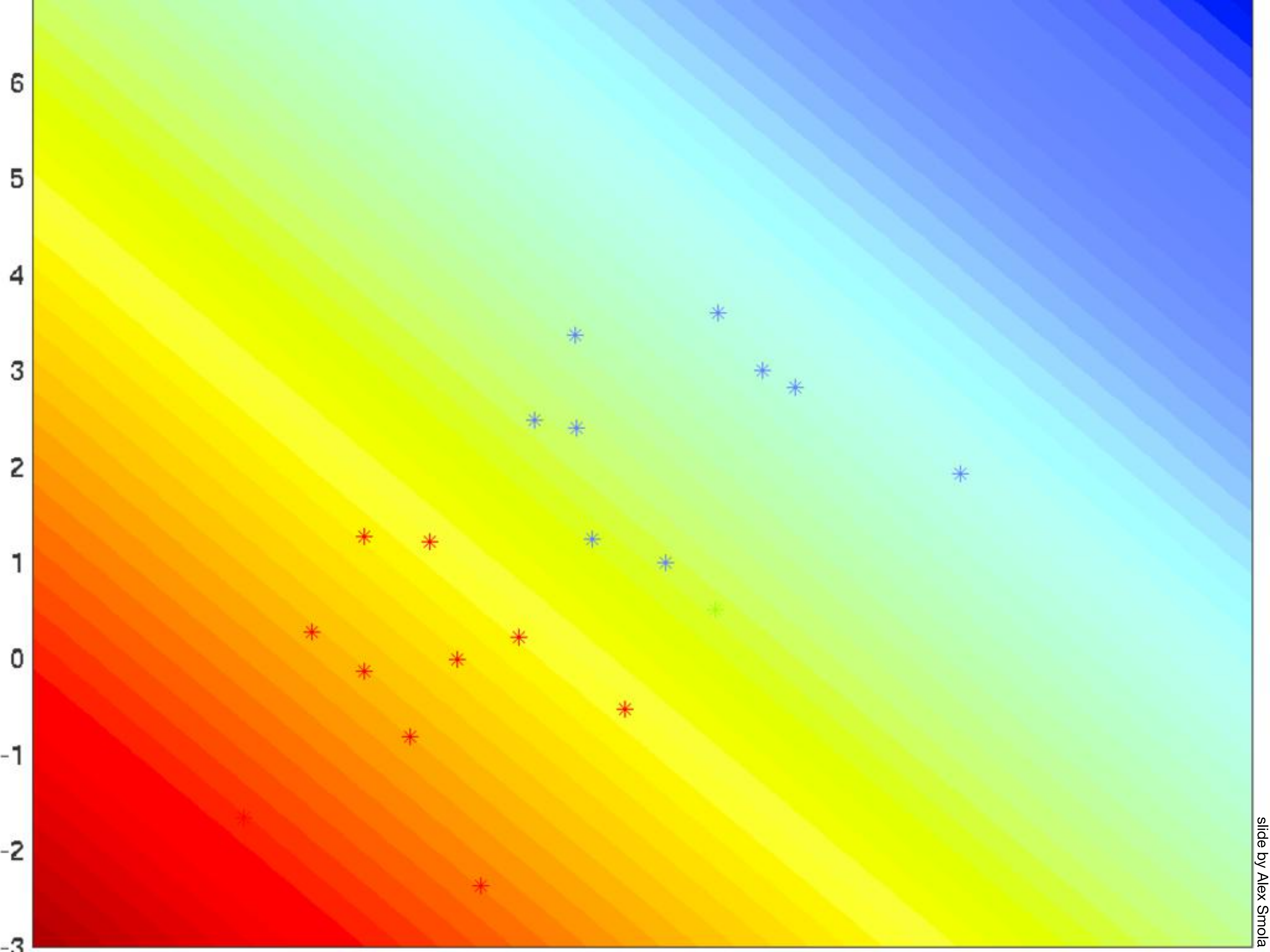
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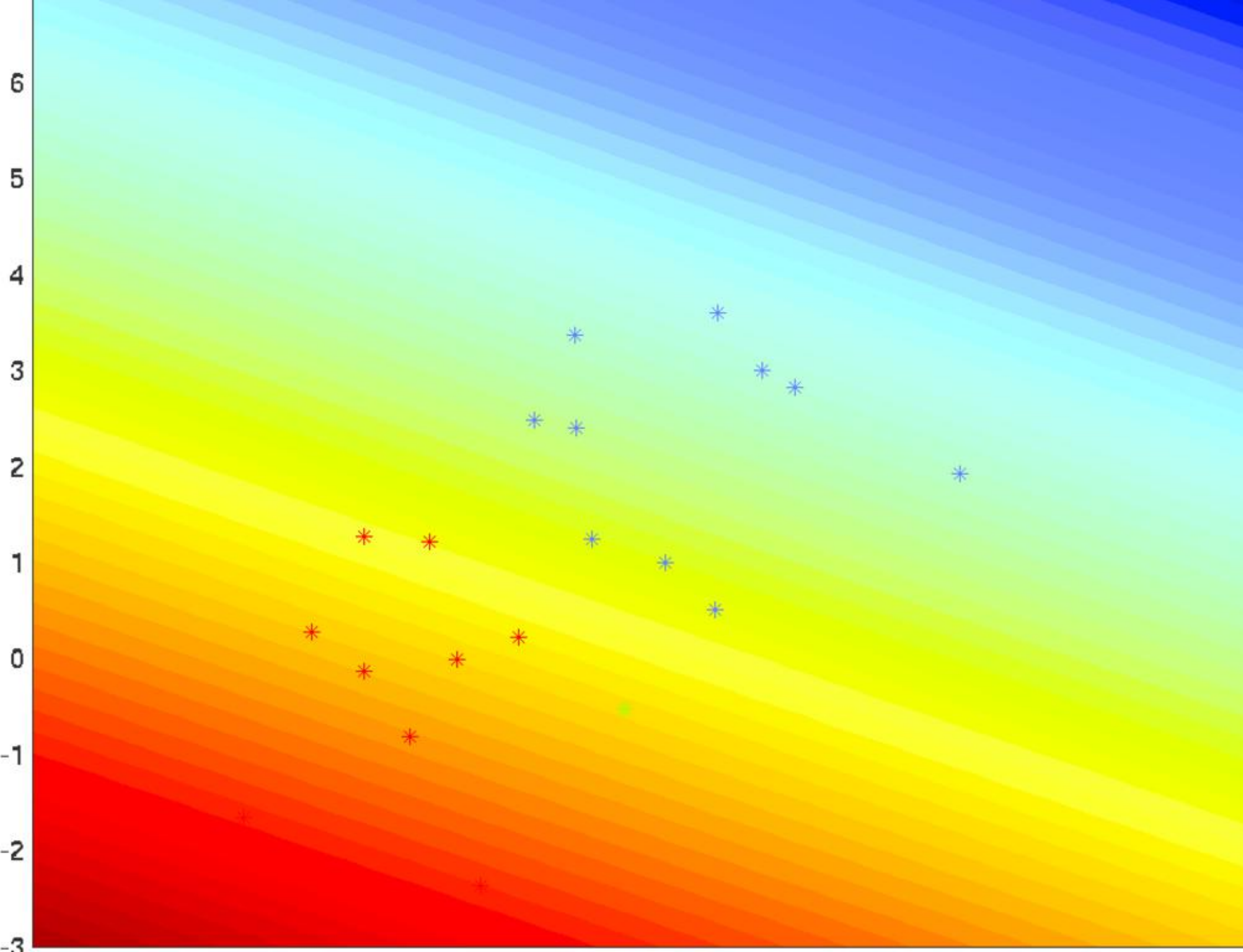

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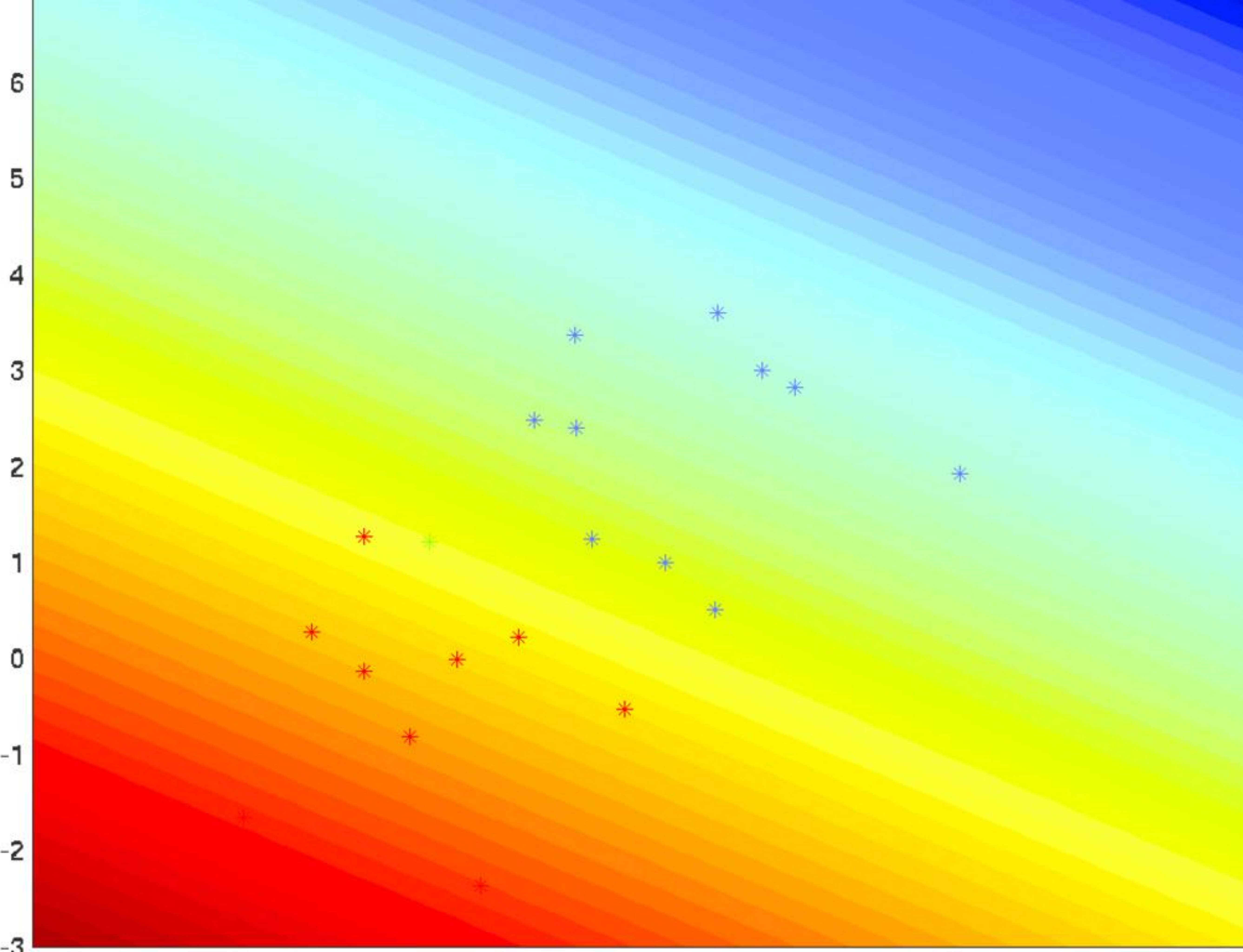

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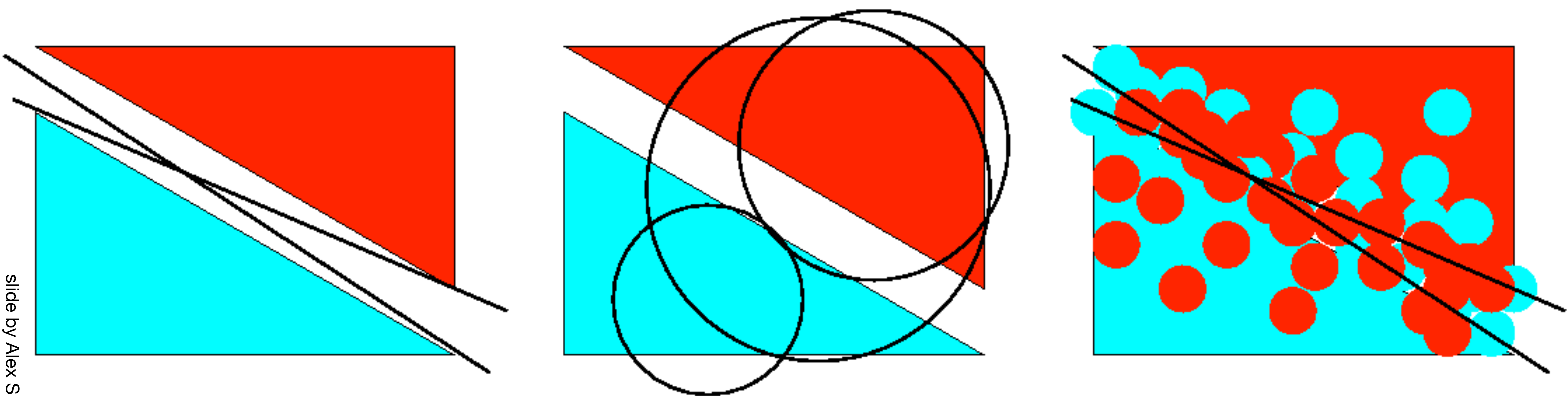
Concepts & version space

- Realizable concepts
  - Some function exists that can separate data and is included in the concept space
  - For perceptron - data is linearly separable
- Unrealizable concept
  - Data not separable
  - We don't have a suitable function class (often hard to distinguish)



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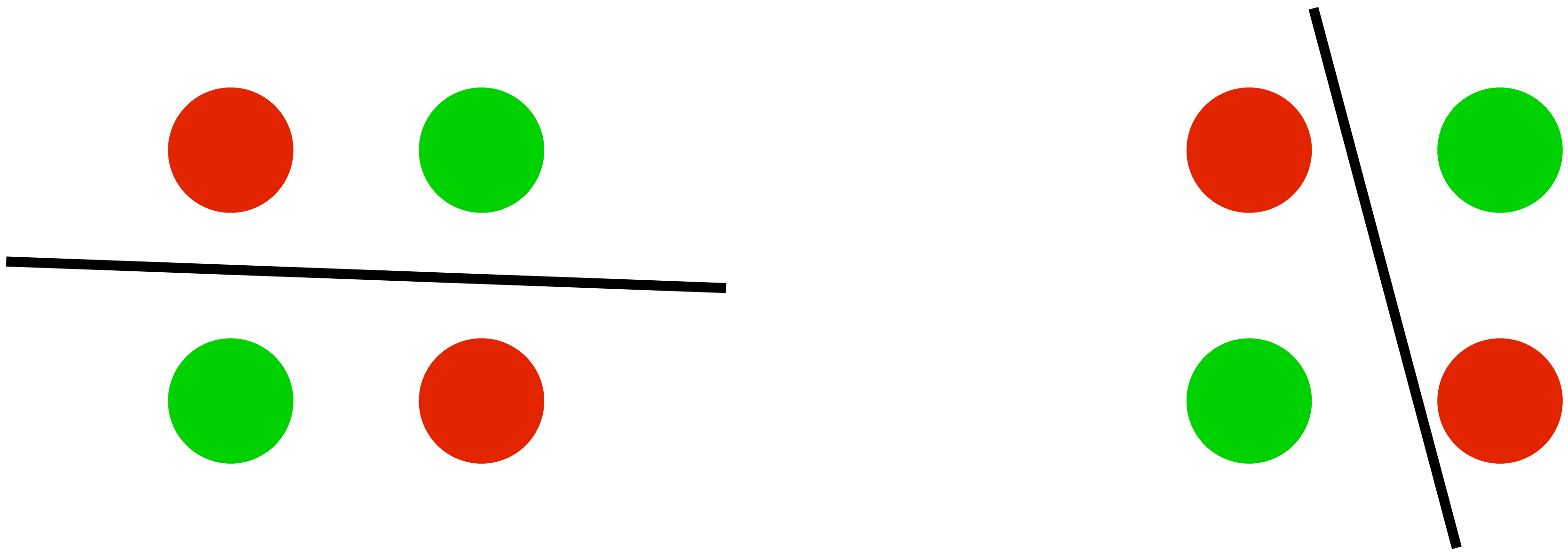
Minimum error separation



- XOR - not linearly separable
- Nonlinear separation is trivial
- Caveat (Minsky & Papert)
  Finding the minimum error linear separator
  is NP hard (this killed Neural Networks in the 70s).

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Nonlinear Features

- Regression
  We got nonlinear functions by preprocessing
- Perceptron
  - Map data into feature space $x \to \phi(x)$
  - Solve problem in this space
  - Query replace $\langle x, x' \rangle$ by $\langle \phi(x), \phi(x') \rangle$ for code
- Feature Perceptron
  - Solution in span of $\phi(x_i)$

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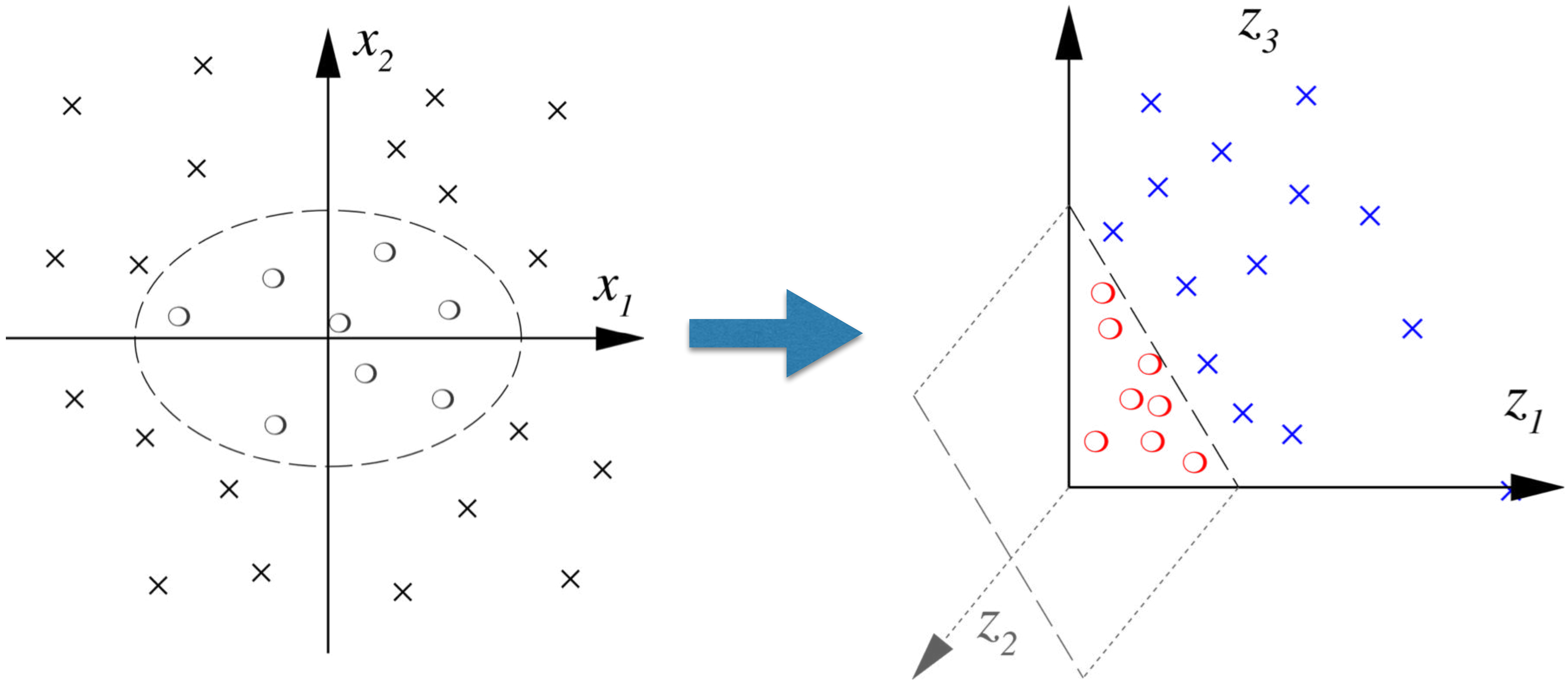
Quadratic Features



- Separating surfaces are
  Circles, hyperbolae, parabolae

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Constructing Features (very naive OCR system)

	1	2	3	4	5	6	7	8	9	0
Loops	0	0	0	1	0	1	0	2	1	1
3 Joints	0	0	0	0	0	1	0	0	1	0
4 Joints	0	0	0	1	0	0	0	1	0	0
Angles	0	1	1	1	1	0	1	0	0	0
Ink	1	2	2	2	2	2	1	3	2	2

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Feature Engineering for Spam Filtering

```
Delivered-To: alex.smola@gmail.com
Received: by 10.216.47.73 with SMTP id s51cs361171web;
        Tue, 3 Jan 2012 14:17:53 -0800 (PST)
Received: by 10.213.17.145 with SMTP id s17mr2519891eba.147.1325629071725;
        Tue, 03 Jan 2012 14:17:51 -0800 (PST)
Return-Path: <alex+caf_=alex.smola=gmail.com@smola.org>
Received: from mail-ey0-f175.google.com (mail-ey0-f175.google.com [209.85.215.175])
        by mx.google.com with ESMTPS id n4si29264232eef.57.2012.01.03.14.17.51
        (version=TLSv1/SSLv3 cipher=OTHER);
        Tue, 03 Jan 2012 14:17:51 -0800 (PST)
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permitted nor denied by best guess record for domain of
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209.85.220.179 as permitted sender) client-ip=209.85.220.179;
Received: by vcbf13 with SMTP id f13so11295098vcb.10
        for <alex@smola.org>; Tue, 03 Jan 2012 14:17:48 -0800 (PST)
DKIM-Signature: v=1; a=rsa-sha256; c=relaxed/relaxed;
        d=googlemail.com; s=gamma;
        h=mime-version:sender:date:x-google-sender-auth:message-id:subject
         :from:to:content-type;
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        b=WK2B2+ExWnf/gvTkw6uUvKuP4XeoKnlJq3USYTm0RARK8dSFjyOQsIHeAP9Yssxp6O
         7ngGoTzYqd+ZsyJfvQcLAWp1PCJhG8AMcnqWkx0NMeoFvIp2HQooZwxSOCx5ZRgY+7qX
         uIbbdna4lUDXj6UFe16SpLDCkptd8OZ3gr7+o=
MIME-Version: 1.0
Received: by 10.220.108.81 with SMTP id e17mr24104004vcp.67.1325629067787;
 Tue, 03 Jan 2012 14:17:47 -0800 (PST)
Sender: althoff.tim@googlemail.com
Received: by 10.220.17.129 with HTTP; Tue, 3 Jan 2012 14:17:47 -0800 (PST)
Date: Tue, 3 Jan 2012 14:17:47 -0800
X-Google-Sender-Auth: 6bwi6D17HjZIkxOEol38NZzyeHs
Message-ID: <CAFJJHDGPBW+SdZg0MdAABiAKydDk9tpeMoDijYGjoGO-WC7osg@mail.gmail.com>
Subject: CS 281B. Advanced Topics in Learning and Decision Making
From: Tim Althoff <althoff@eecs.berkeley.edu>
To: alex@smola.org
Content-Type: multipart/alternative; boundary=f46d043c7af4b07e8d04b5a7113a

--f46d043c7af4b07e8d04b5a7113a
Content-Type: text/plain; charset=ISO-8859-1
```

- bag of words
- pairs of words
- date & time
- recipient path
- IP number
- sender
- encoding
- links
- ... secret sauce ...

slide by Alex Smola

More feature engineering

- Two Interlocking Spirals
  Transform the data into a radial and angular part
  $$(x_1, x_2) = (r \sin \phi, r \cos \phi)$$
- Handwritten Japanese Character Recognition
  - Break down the images into strokes and recognize it
  - Lookup based on stroke order
- Medical Diagnosis
  - Physician's comments
  - Blood status / ECG / height / weight / temperature ...
  - Medical knowledge
- Preprocessing
  - Zero mean, unit variance to fix scale issue (e.g. weight vs. income)
  - Probability integral transform (inverse CDF) as alternative

slide by Alex Smola

The Perceptron on features

initialize $w, b = 0$
repeat
    Pick (x_i, y_i) from data
    if $y_i(w \cdot \Phi(x_i) + b) \leq 0$ then
$$\begin{aligned} w' &= w + y_i \Phi(x_i) \\ b' &= b + y_i \end{aligned}$$
until $y_i(w \cdot \Phi(x_i) + b) > 0$ for all i

- Nothing happens if classified correctly
- Weight vector is linear combination $w = \sum_{i \in I} y_i \phi(x_i)$
- Classifier is linear combination of inner products $f(x) = \sum_{i \in I} y_i \langle \phi(x_i), \phi(x) \rangle + b$

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Problems

- Problems
  - Need domain expert (e.g. Chinese OCR)
  - Often expensive to compute
  - Difficult to transfer engineering knowledge
- Shotgun Solution
  - Compute many features
  - Hope that this contains good ones
  - Do this efficiently

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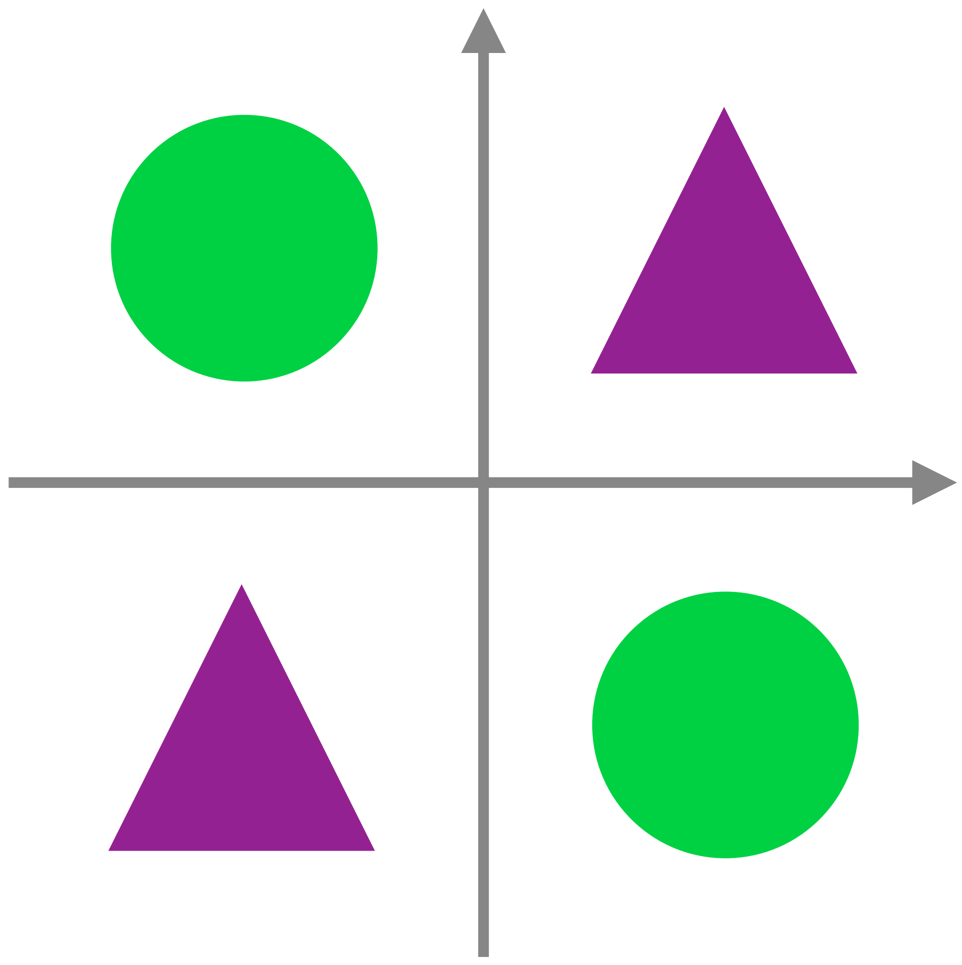
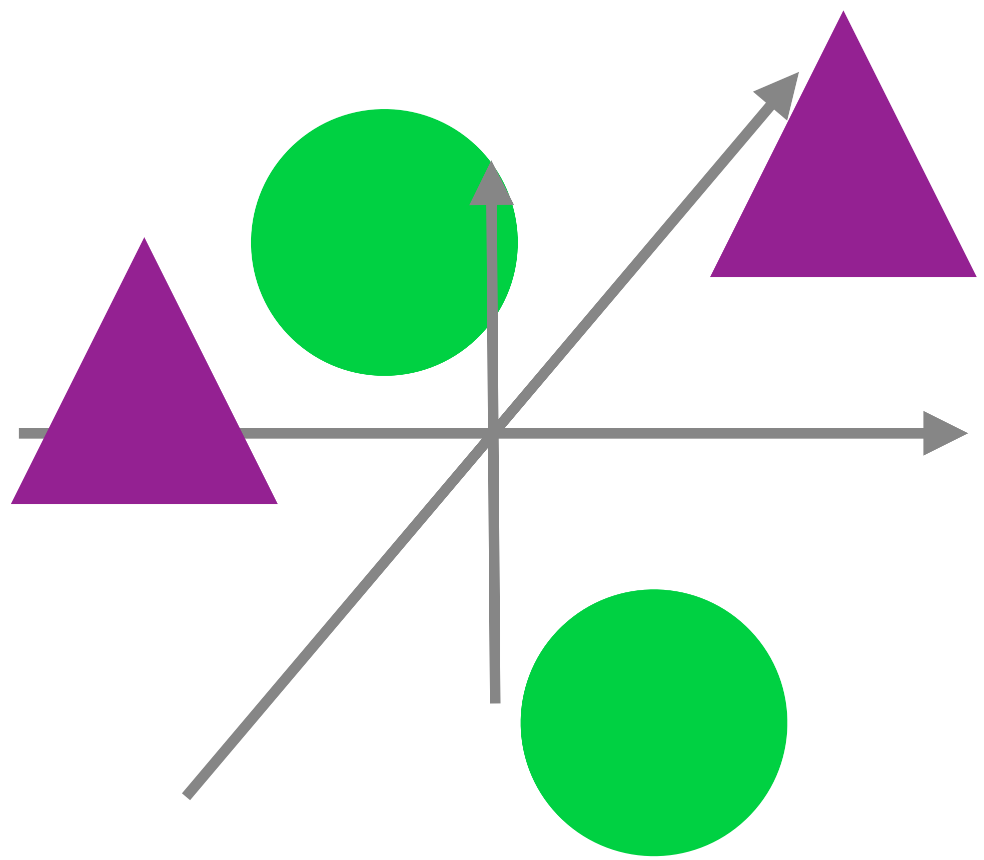
Solving XOR



(x_1, x_2)



$(x_1, x_2, x_1 x_2)$

- XOR not linearly separable
- Mapping into 3 dimensions makes it easily solvable

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Next Lecture:

Multi-layer Perceptron