Gradient Descent; Word Vectors

LING 574 Deep Learning for NLP

Shane Steinert-Threlkeld

Announcements

- Office hours:
  - Shane:
    - Wed 3-5PM
    - GUG 415K + https://washington.zoom.us/my/shanest
  - Saiya:
    - Tuesday 3:30 - 5:30PM
    - GUG 407 + https://washington.zoom.us/s/92010041700
- HW1 now **due April 6** (as opposed to April 4), i.e. free late submission
  - Dropbox folder for the course on patas is delayed
  - Sign up for patas account ASAP if you have not done so already: list “575” as course

Today’s Plan

- Terminology / Notation
- Gradient Descent
- Word Vectors, intro
- Homework 1

Basic Terminology / Notation

Supervised Learning

Supervised Learning

- Given: a dataset $\mathscr{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$
  - $x_i \in X$: input for i-th example
  - $y_i \in Y$: output for i-th example

Supervised Learning

- Given: a dataset $\mathscr{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$
  - $x_i \in X$: input for i-th example
  - $y_i \in Y$: output for i-th example

- For example:
  - Sentiment analysis:
    - Input: bag of words representation of “This movie was great.”
    - Output: 4 [on a scale 1-5]
  - Language modeling:
    - Input: “This movie was”
    - Output: “great”

Supervised Learning

Supervised Learning

- Given: a dataset $\mathscr{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$
  - $x_i \in X$: input for i-th example
  - $y_i \in Y$: output for i-th example

Supervised Learning

- Given: a dataset $\mathscr{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$
  - $x_i \in X$: input for i-th example
  - $y_i \in Y$: output for i-th example

- Goal: *learn* a function $f : X \to Y$ which:
  - "Does well" on the given data $\mathscr{D}$
  - Generalizes well to unseen data

Parameterized Functions

- A learning algorithm searches for a function f amongst a space of possible functions
- Parameters define a family of functions
  - θ: general symbol for parameters
  - $\hat{y} = f(x; \theta)$: input x, parameters θ; model/function output $\hat{y}$
- Example: the family of linear functions $f(x) = mx + b$
  - $\theta = \{m, b\}$
- Later: neural network architecture defines the family of functions

Loss Minimization

- General form of optimization problem
- $\mathscr{L}(\hat{Y}, Y)$: loss function ("objective function"); $\mathscr{L}(\hat{Y}, Y) = \frac{1}{|Y|}\sum_i \ell(\hat{y}(x_i), y_i)$
  - How "close" are the model's outputs to the true outputs
  - $\ell(\hat{y}, y)$: local (per-instance) loss, averaged over training instances
  - More later: depends on the particular task, among other things
- View the loss *as a function of the model's parameters*

$$\mathscr{L}(\theta) := \mathscr{L}(\hat{Y}, Y) = \mathscr{L}(f(X; \theta), Y)$$

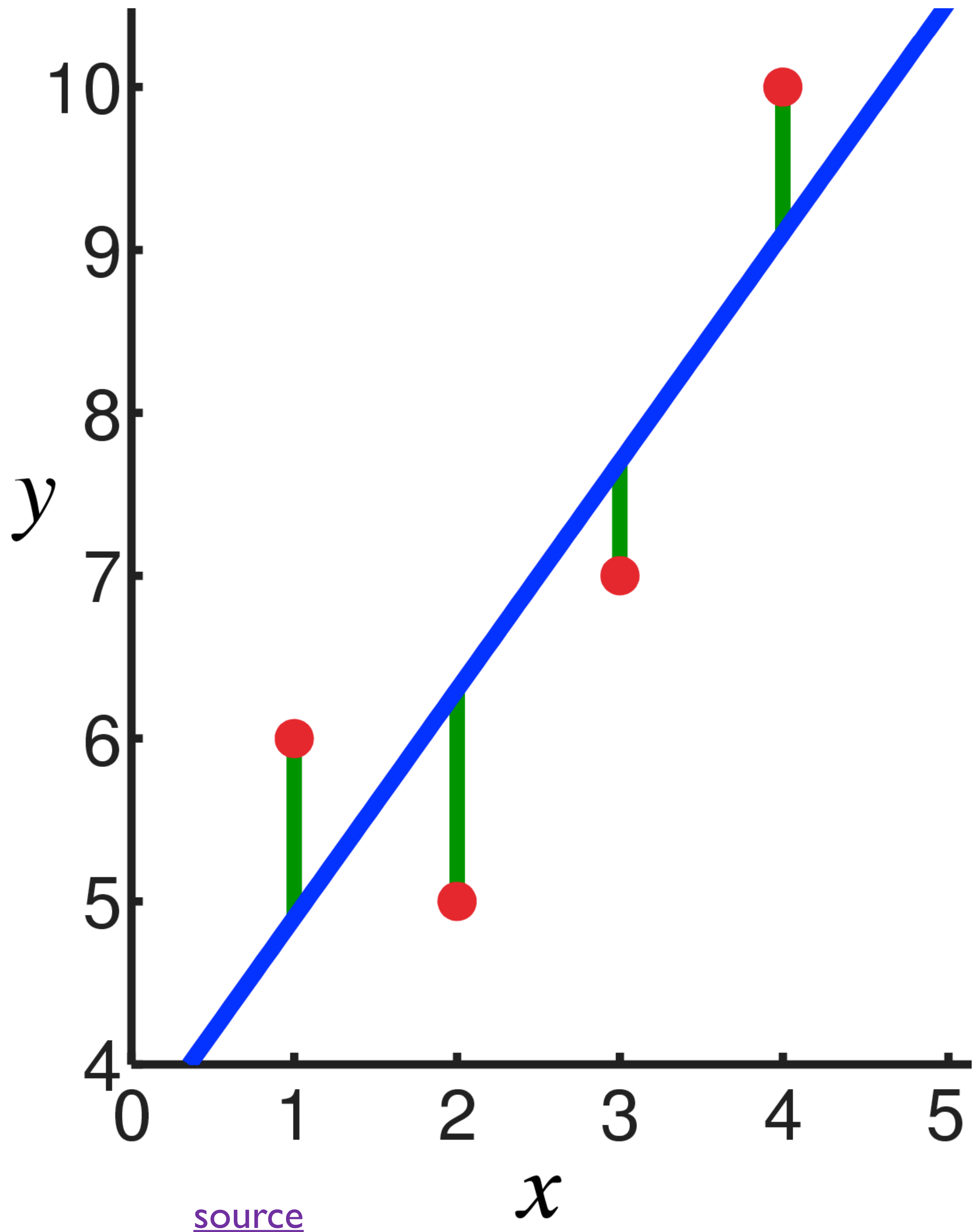
Loss Minimization

- The optimization problem:

$$\theta^* = \arg\min_{\theta} \mathcal{L}(\theta)$$

- Example: (least-squares) linear regression
  - $\ell(\hat{y}, y) = (\hat{y} - y)^2$

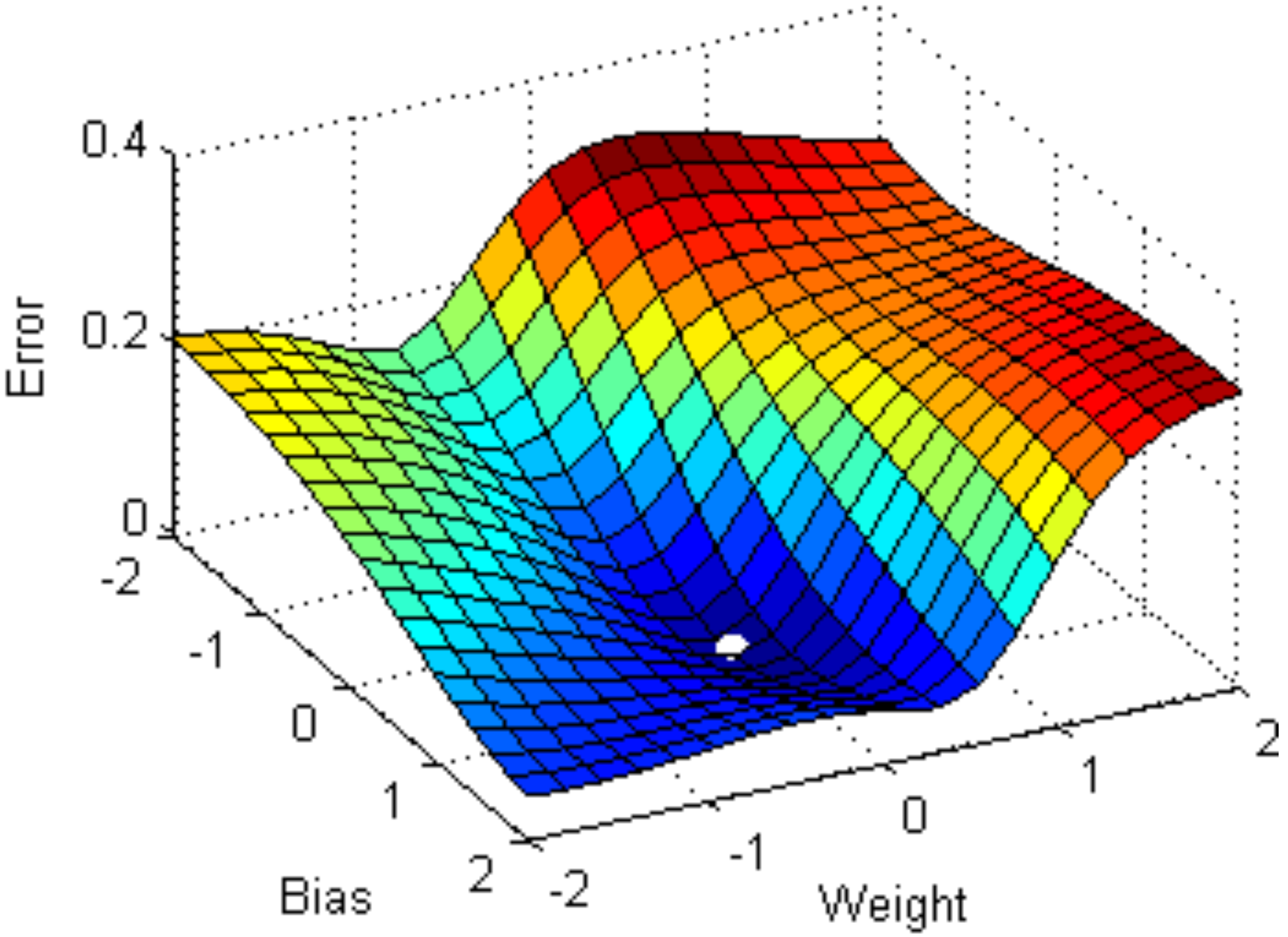
$$m^*, b^* = \arg\min_{m,b} \sum_i ((mx_i + b) - y_i)^2$$



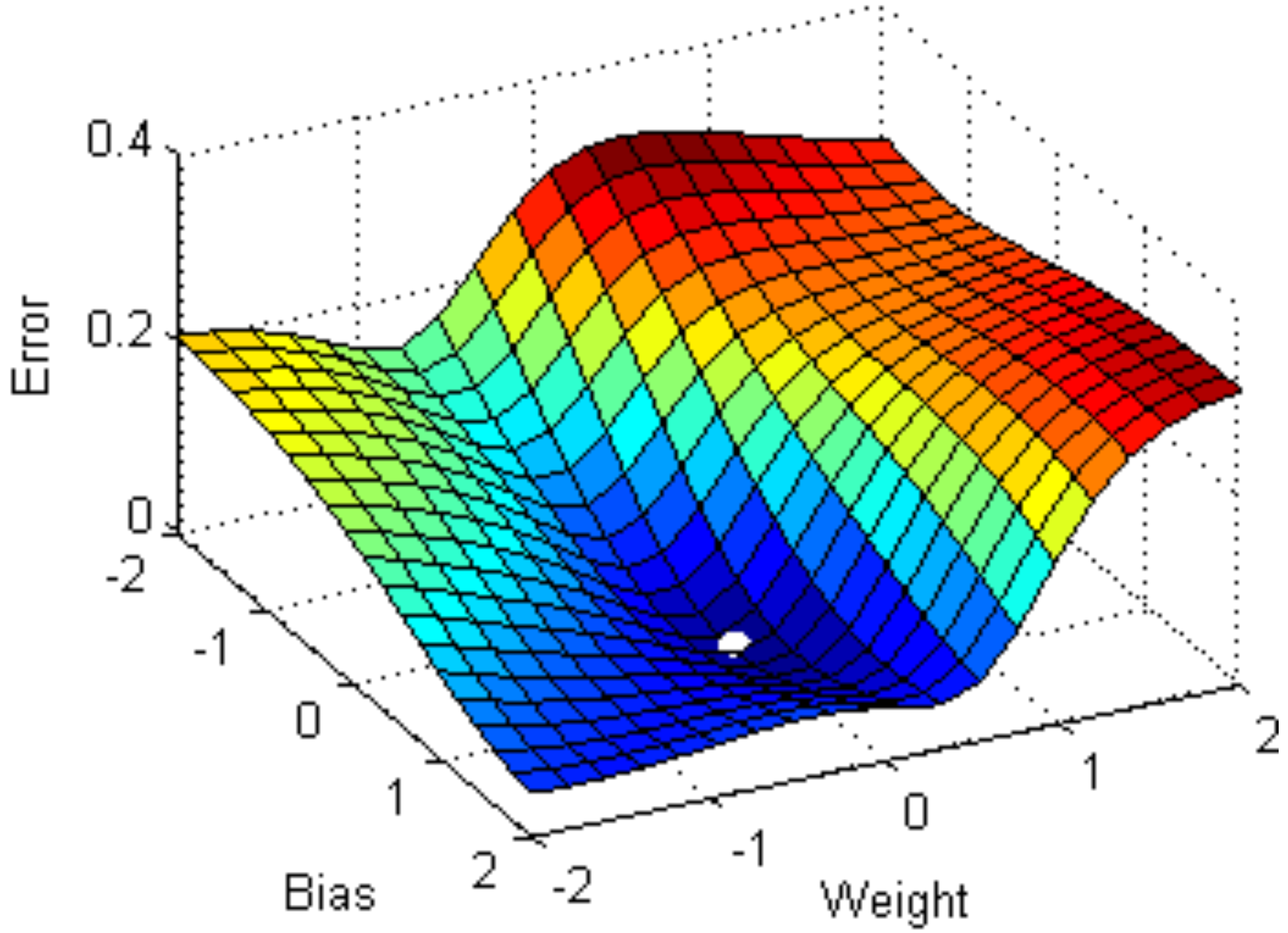
source

Learning: (Stochastic) Gradient Descent

Gradient Descent: Basic Idea



Gradient Descent: Basic Idea



source

Gradient Descent: Basic Idea

- The *gradient* of the loss w/r/t parameters tells which direction in parameter space to "walk" to make the loss smaller (i.e. to improve model outputs)
- Guaranteed to work in linear model case
  - Can get stuck in local minima for non-linear functions, like NNs
  - [More precisely: if loss is a *convex* function of the parameters, gradient descent is guaranteed to find an optimal solution. For non-linear functions, the loss will generally *not* be convex.]

Derivatives

- The derivative of a function of one real variable measures how much the output changes with respect to a change in the input variable

Derivatives

- The derivative of a function of one real variable measures how much the output changes with respect to a change in the input variable

$$f(x) = x^2 + 35x + 12$$

$$\frac{df}{dx} = 2x + 35$$

Derivatives

- The derivative of a function of one real variable measures how much the output changes with respect to a change in the input variable

$$f(x) = x^2 + 35x + 12$$

$$\frac{df}{dx} = 2x + 35$$

$$f(x) = e^x$$

$$\frac{df}{dx} = e^x$$

Partial Derivatives

- A partial derivative of a function of several variables measures its derivative with respect one of those variables, with the others held constant.

Partial Derivatives

- A partial derivative of a function of several variables measures its derivative with respect one of those variables, with the others held constant.

$$f(x, y) = 10x^3y^2 + 5xy^3 + 4x + y$$

Partial Derivatives

- A partial derivative of a function of several variables measures its derivative with respect one of those variables, with the others held constant.

$$f(x, y) = 10x^3y^2 + 5xy^3 + 4x + y$$

$$\frac{\partial f}{\partial x} = 30x^2y^2 + 5y^3 + 4$$

Partial Derivatives

- A partial derivative of a function of several variables measures its derivative with respect one of those variables, with the others held constant.

$$f(x, y) = 10x^3y^2 + 5xy^3 + 4x + y$$

$$\frac{\partial f}{\partial x} = 30x^2y^2 + 5y^3 + 4$$

$$\frac{\partial f}{\partial y} = 20x^3y + 15xy^2 + 1$$

Gradient

Gradient

- The gradient of a function $f(x_1, x_2, \ldots x_n)$ is a vector function, returning all of the partial derivatives

Gradient

- The gradient of a function $f(x_1, x_2, \ldots x_n)$ is a vector function, returning all of the partial derivatives

$$\nabla f = \left\langle \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_n} \right\rangle$$

Gradient

- The gradient of a function $f(x_1, x_2, \ldots x_n)$ is a vector function, returning all of the partial derivatives

$$\nabla f = \left\langle \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_n} \right\rangle$$

$$f(x, y) = 4x^2 + y^2$$

$$\nabla f = \langle 8x, 2y \rangle$$

Gradient

- The gradient of a function $f(x_1, x_2, ... x_n)$ is a vector function, returning all of the partial derivatives

$$\nabla f = \left\langle \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_n} \right\rangle$$

$$f(x, y) = 4x^2 + y^2$$

$$\nabla f = \langle 8x, 2y \rangle$$

- The gradient is perpendicular to the *level curve* at a point

Gradient

- The gradient of a function $f(x_1, x_2, \ldots x_n)$ is a vector function, returning all of the partial derivatives

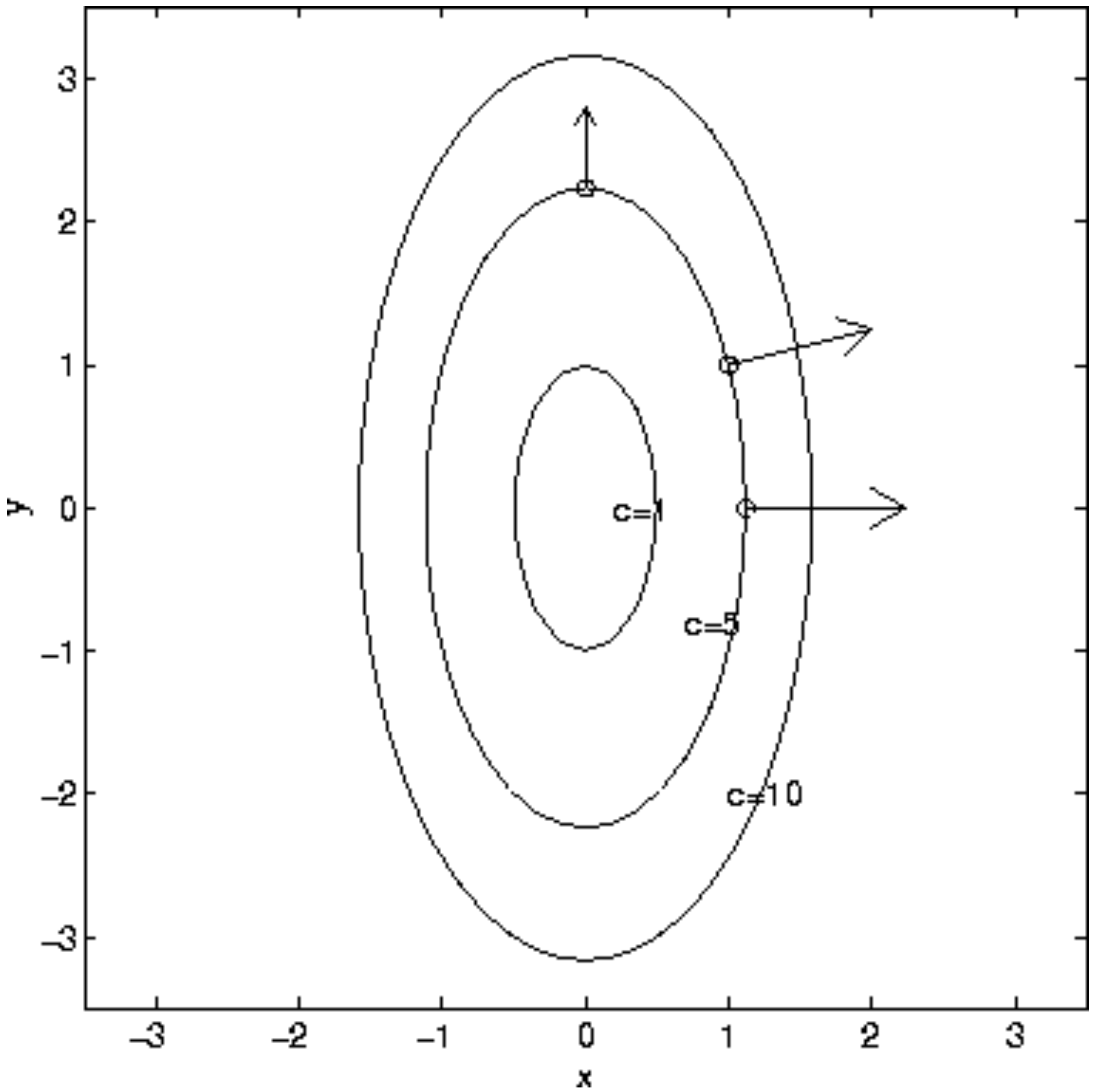
$$\nabla f = \left\langle \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_n} \right\rangle$$

$$f(x, y) = 4x^2 + y^2$$

$$\nabla f = \langle 8x, 2y \rangle$$

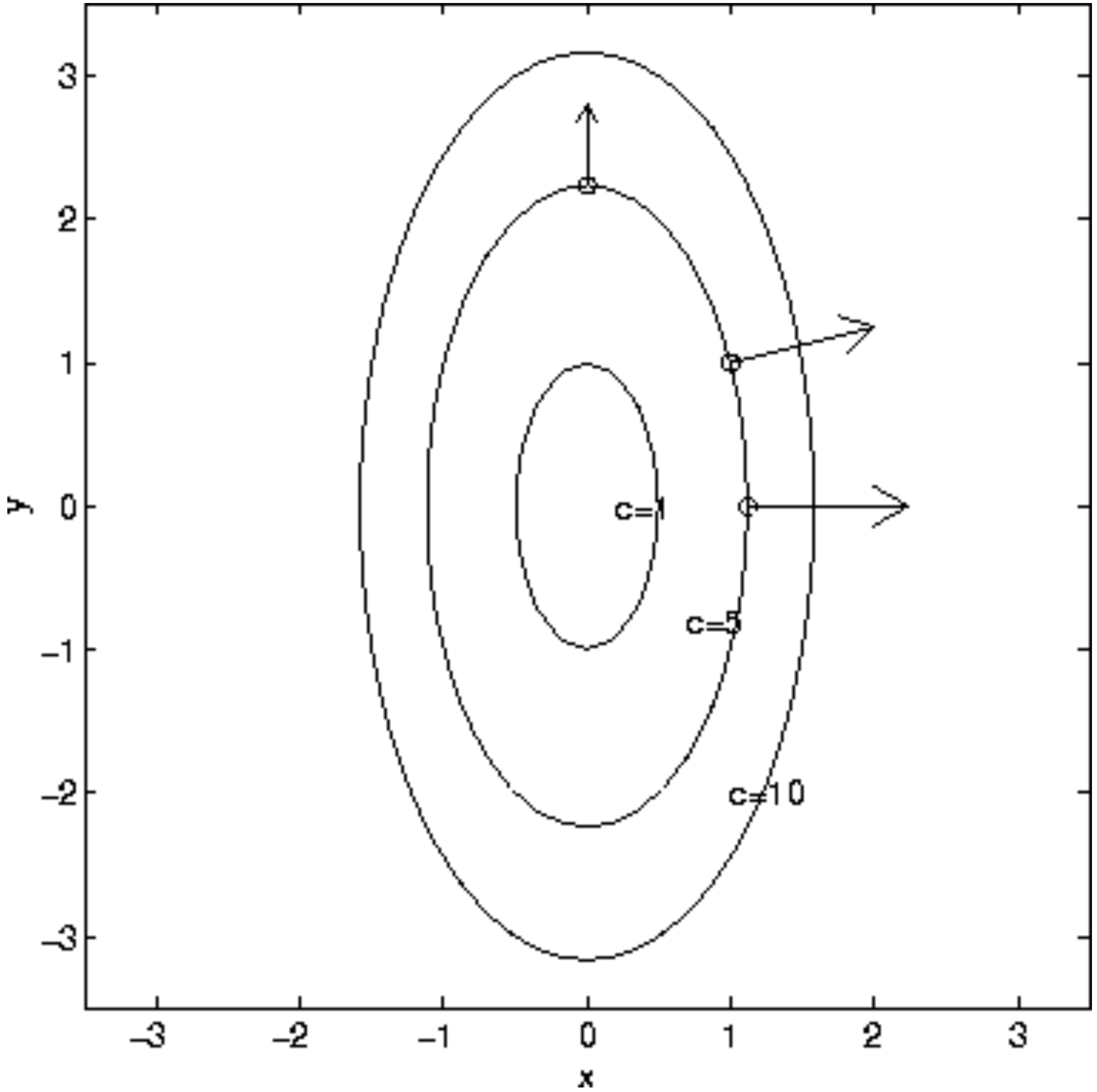
- The gradient is perpendicular to the *level curve* at a point
- The gradient points in the direction of greatest rate of increase of f

Gradient and Level Curves



Level curves: $f(x, y) = c$

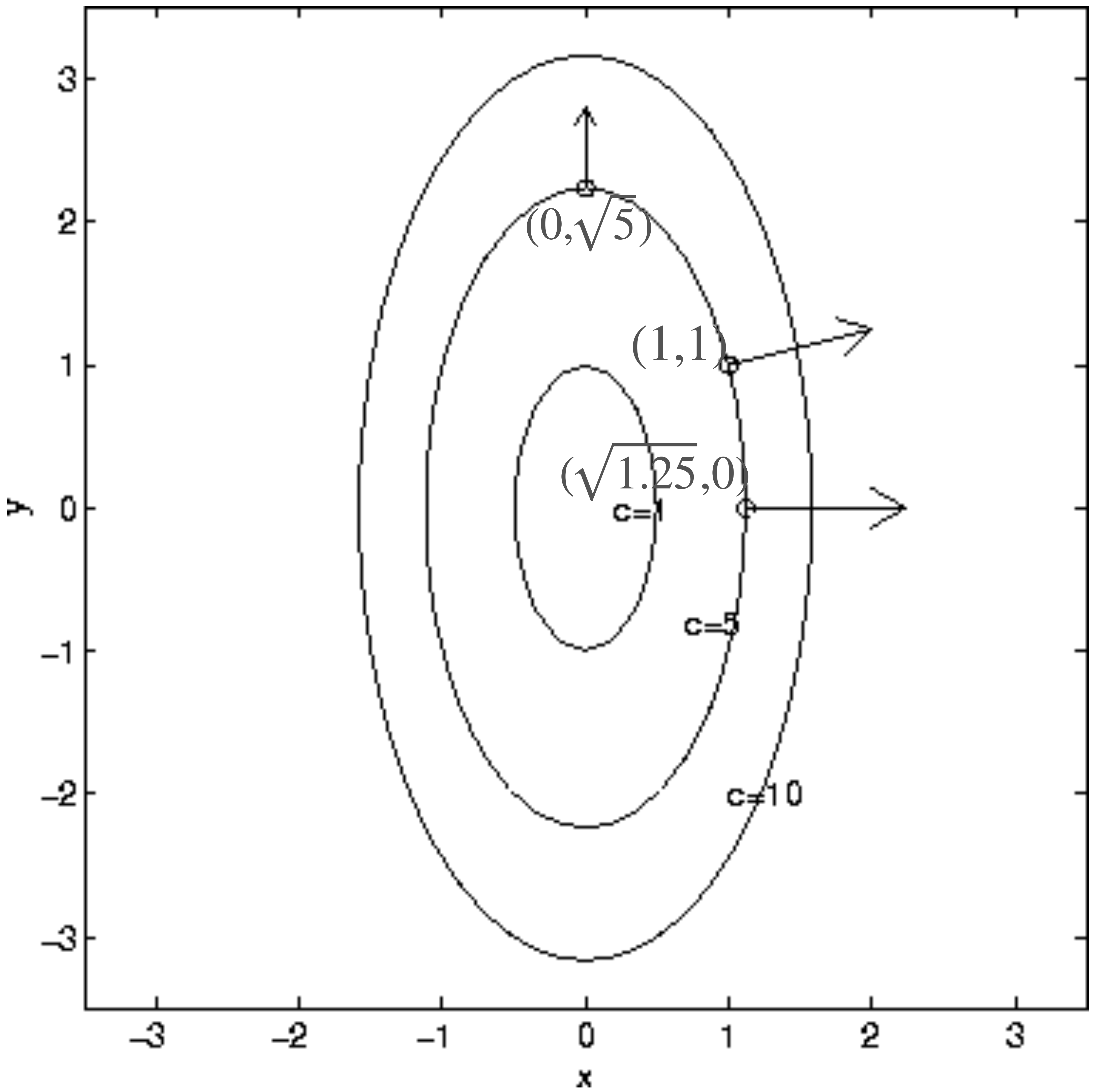
Gradient and Level Curves



$$f(x,y) = 4x^2 + y^2$$
$$\nabla f = \langle 8x, 2y \rangle$$

Level curves: $f(x,y) = c$

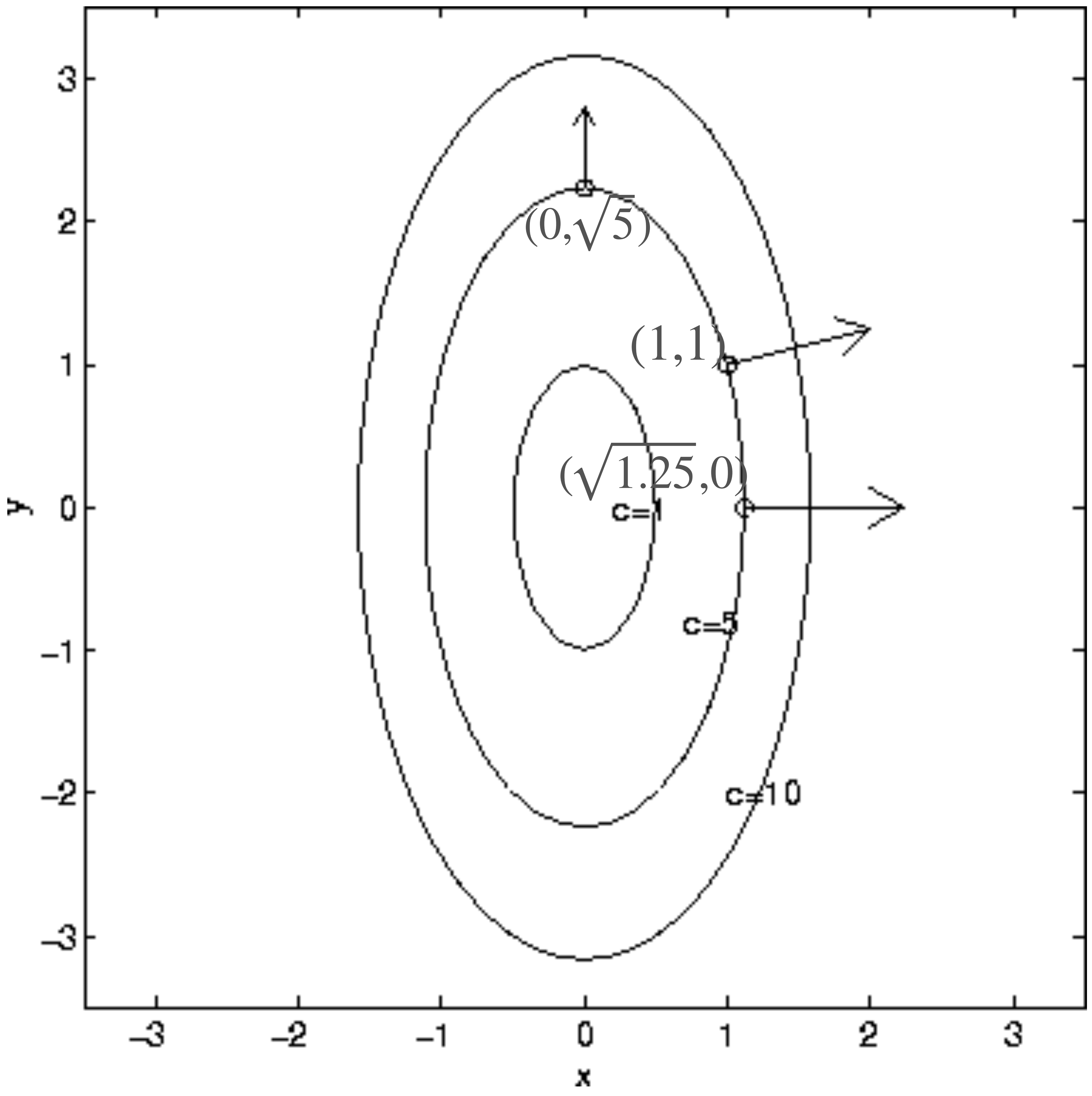
Gradient and Level Curves



$$f(x,y) = 4x^2 + y^2$$
$$\nabla f = \langle 8x, 2y \rangle$$

Level curves: $f(x,y) = c$

Gradient and Level Curves



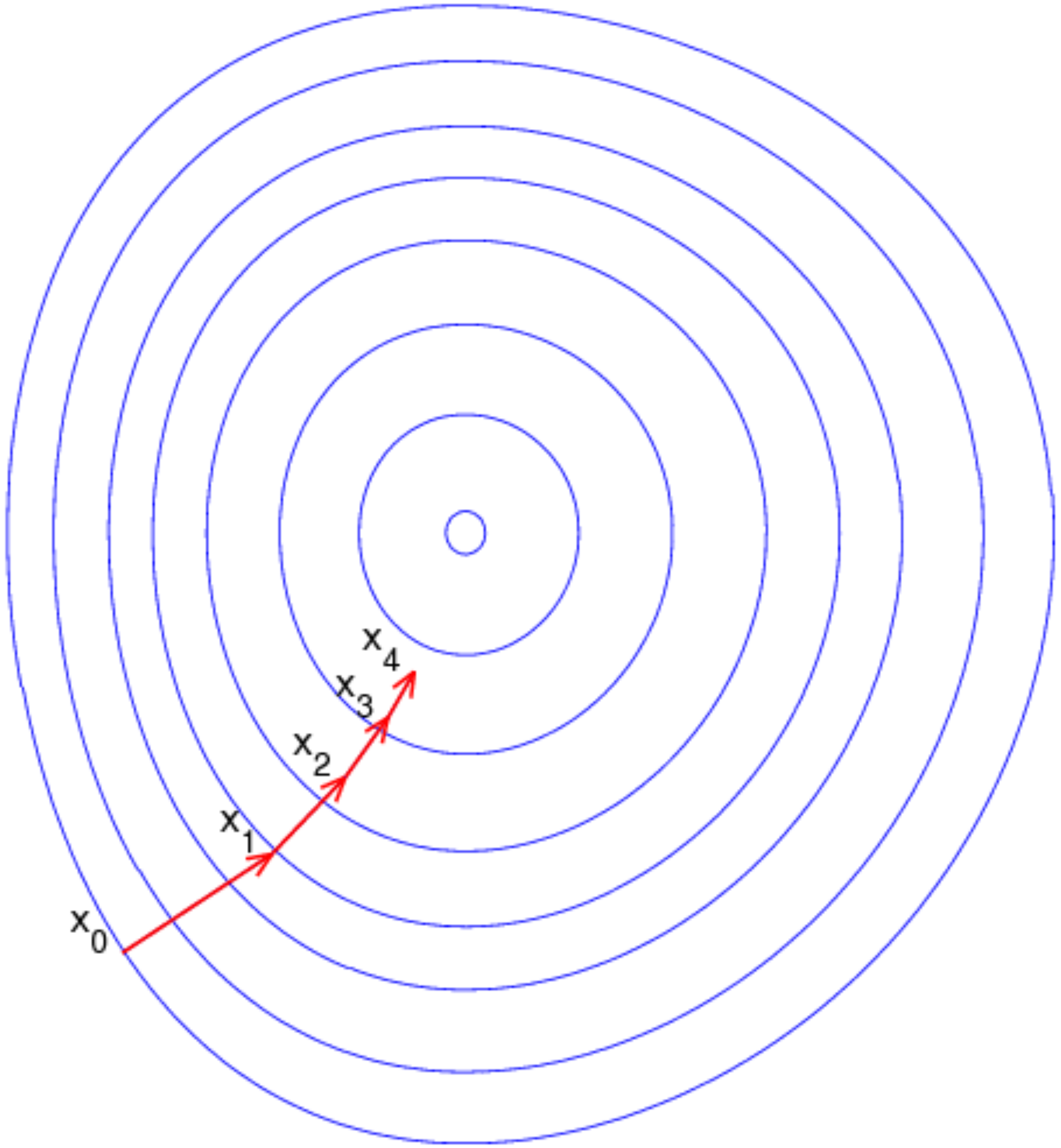
$$f(x, y) = 4x^2 + y^2$$

$$\nabla f = \langle 8x, 2y \rangle$$

Level curves: $f(x, y) = c$

Q: what are the actual gradients at those points?

Gradient Descent and Level Curves



source

Gradient Descent Algorithm

- Initialize θ_0
- Repeat until convergence:

$$\theta_{n+1} = \theta_n - \alpha \nabla \mathscr{L}(\hat{Y}(\theta_n), Y)$$

Gradient Descent Algorithm

- Initialize θ_0
- Repeat until convergence:

$$\theta_{n+1} = \theta_n - \underbrace{\alpha}_{\text{Learning rate}} \nabla \mathscr{L}(\hat{Y}(\theta_n), Y)$$

Gradient Descent Algorithm

- Initialize θ_0
- Repeat until convergence:

$$\theta_{n+1} = \theta_n - \alpha \nabla \mathscr{L}(\hat{Y}(\theta_n), Y)$$

Learning rate

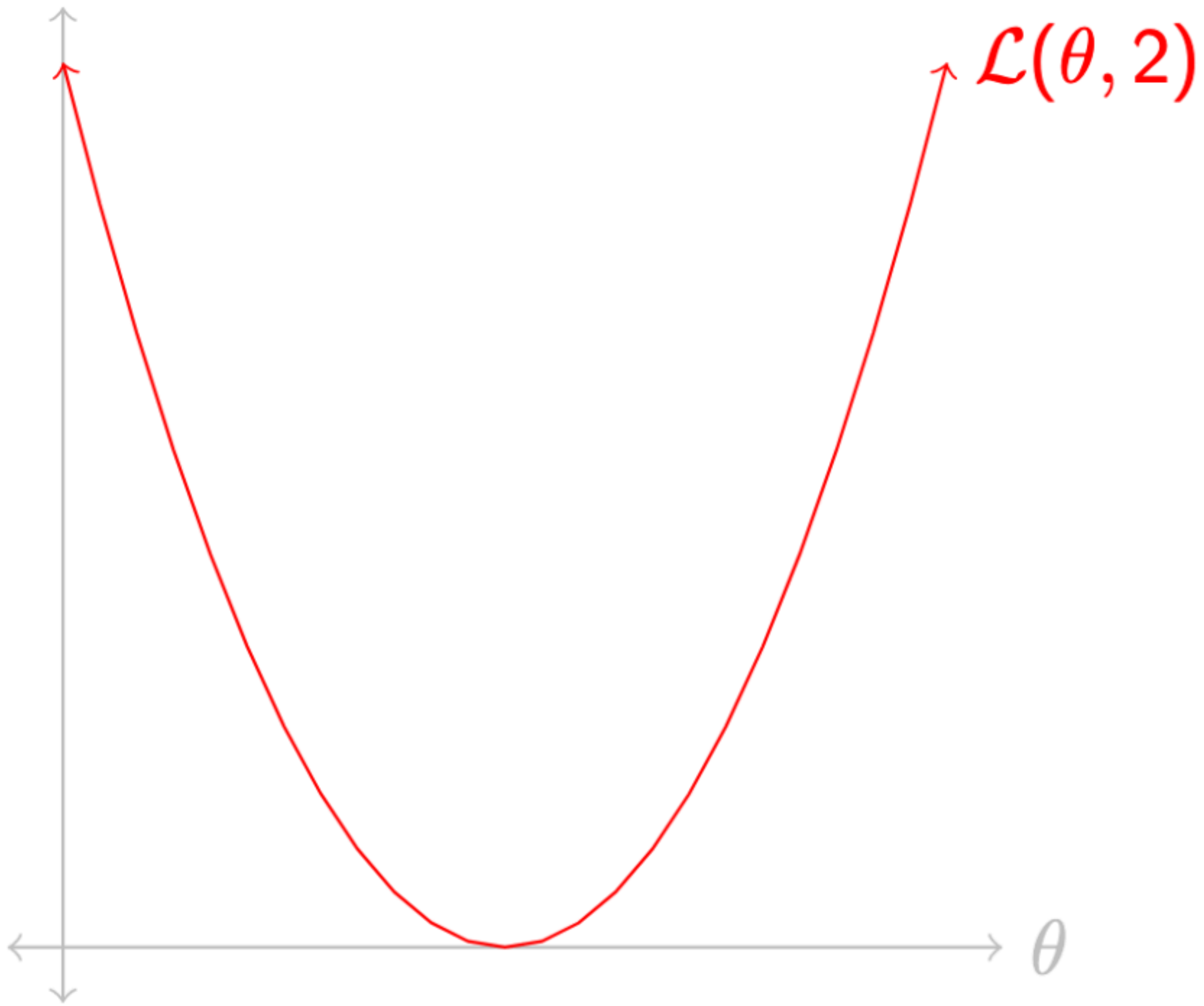
- High learning rate: big steps, may bounce and “overshoot” the target
- Low learning rate: small steps, smoother minimization of loss, but can be slow

Gradient Descent: Minimal Example

- Task: predict a target/true value $y = 2$
- "Model": $\hat{y}(\theta) = \theta$
  - A single parameter: the actual guess
- Loss: Euclidean distance

$$\mathscr{L}(\hat{y}(\theta), y) = (\hat{y} - y)^2 = (\theta - y)^2$$

Gradient Descent: Minimal Example



$$\frac{\partial}{\partial \theta} \mathcal{L}(\theta, y) = 2(\theta - y)$$

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\partial}{\partial \theta} \mathcal{L}(\theta, y)$$

Stochastic Gradient Descent

Stochastic Gradient Descent

- The above is called "batch" gradient descent
  - Updates *once per pass through the dataset*
  - Expensive, and slow; does not scale well

Stochastic Gradient Descent

- The above is called “batch” gradient descent
  - Updates *once per pass through the dataset*
  - Expensive, and slow; does not scale well
- *Stochastic* gradient descent: single example at a time; very noisy estimate of true gradient

Stochastic Gradient Descent

- The above is called “batch” gradient descent
  - Updates *once per pass through the dataset*
  - Expensive, and slow; does not scale well
- *Stochastic* gradient descent: single example at a time; very noisy estimate of true gradient
- Mini-batch gradient descent:
  - Break the data into “mini-batches”: small chunks of the data
  - Compute gradients and update parameters for each batch
  - Mini-batch of size 1 = single example = stochastic gradient descent
  - A *noisy estimate* of the true gradient, but works well in practice; more parameter updates

Stochastic Gradient Descent

- The above is called “batch” gradient descent
  - Updates *once per pass through the dataset*
  - Expensive, and slow; does not scale well
- *Stochastic* gradient descent: single example at a time; very noisy estimate of true gradient
- Mini-batch gradient descent:
  - Break the data into “mini-batches”: small chunks of the data
  - Compute gradients and update parameters for each batch
  - Mini-batch of size 1 = single example = stochastic gradient descent
  - A *noisy estimate* of the true gradient, but works well in practice; more parameter updates
- Epoch: one pass through the whole training data

Stochastic Gradient Descent

```
initialize parameters / build model

for each epoch:

  data = shuffle(data)
  batches = make_batches(data)

  for each batch in batches:

    outputs = model(batch)
    loss = loss_fn(outputs, true_outputs)
    compute gradients
    update parameters
```

Word Vectors, Intro

Distributional Similarity

- "You shall know a word by the company it keeps!" (*Firth, 1957*)

Distributional Similarity

- "You shall know a word by the company it keeps!" ([Firth, 1957])
  - A bottle of ***tezgüino*** is on the table.

Distributional Similarity

- “You shall know a word by the company it keeps!” (*Firth, 1957*)
  - A bottle of ***tezgüino*** is on the table.
  - Everybody likes ***tezgüino***.

Distributional Similarity

- “You shall know a word by the company it keeps!” (*Firth, 1957*)
  - A bottle of ***tezgüino*** is on the table.
  - Everybody likes ***tezgüino***.
  - ***Tezgüino*** makes you drunk.

Distributional Similarity

- "You shall know a word by the company it keeps!" (*Firth, 1957*)
  - A bottle of ***tezgüino*** is on the table.
  - Everybody likes ***tezgüino***.
  - ***Tezgüino*** makes you drunk.
  - We make ***tezgüino*** from corn.

Distributional Similarity

- “You shall know a word by the company it keeps!” ([Firth, 1957])
  - A bottle of ***tezgüino*** is on the table.
  - Everybody likes ***tezgüino***.
  - ***Tezgüino*** makes you drunk.
  - We make ***tezgüino*** from corn.
- Tezguino; corn-based alcoholic beverage. (From [Lin, 1998a])

Distributional Similarity

- How can we represent the “company” of a word?

Distributional Similarity

- How can we represent the “company” of a word?
- How can we make similar words have similar representations?

Why use word vectors?

- With words, a feature is a word identity
  - Feature 5: 'The previous word was "terrible"'
  - requires exact same word to be in training and test
  - **One-hot vectors:**
    - “terrible”: [0 0 0 0 0 0 1 0 0 0 … 0]
    - Length = size of vocabulary
  - All words are as different from each other
    - e.g. “terrible” is as different from “bad” as from “awesome”

Why use word vectors?

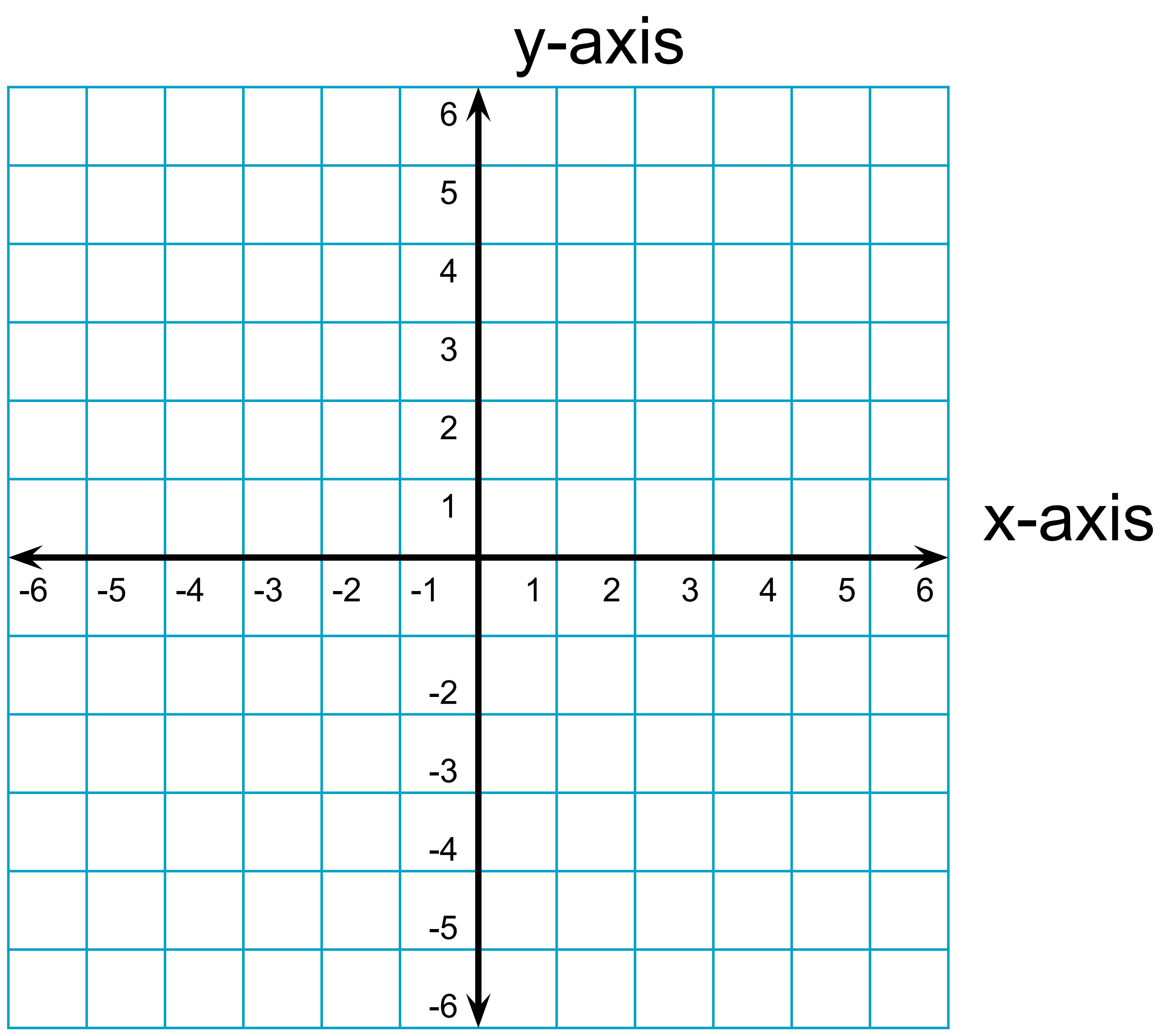
- With embeddings (= vectors):
  - Feature is a word vector
  - 'The previous word was vector [35,22,17, …]
  - Now in the test set we might see a similar vector [34,21,14, …]
  - We can generalize to similar but unseen words!

Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a “dimension”

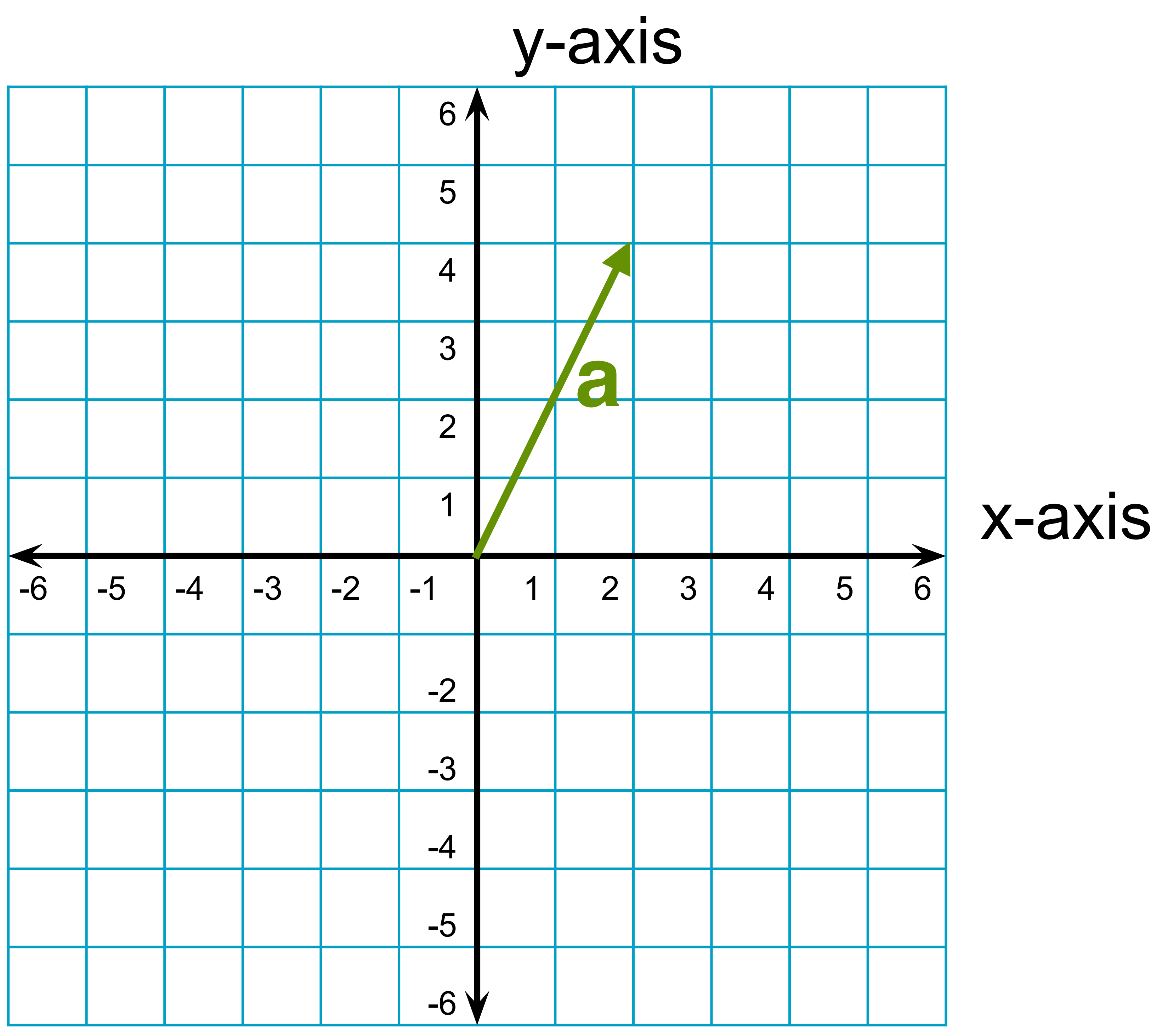
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a “dimension”



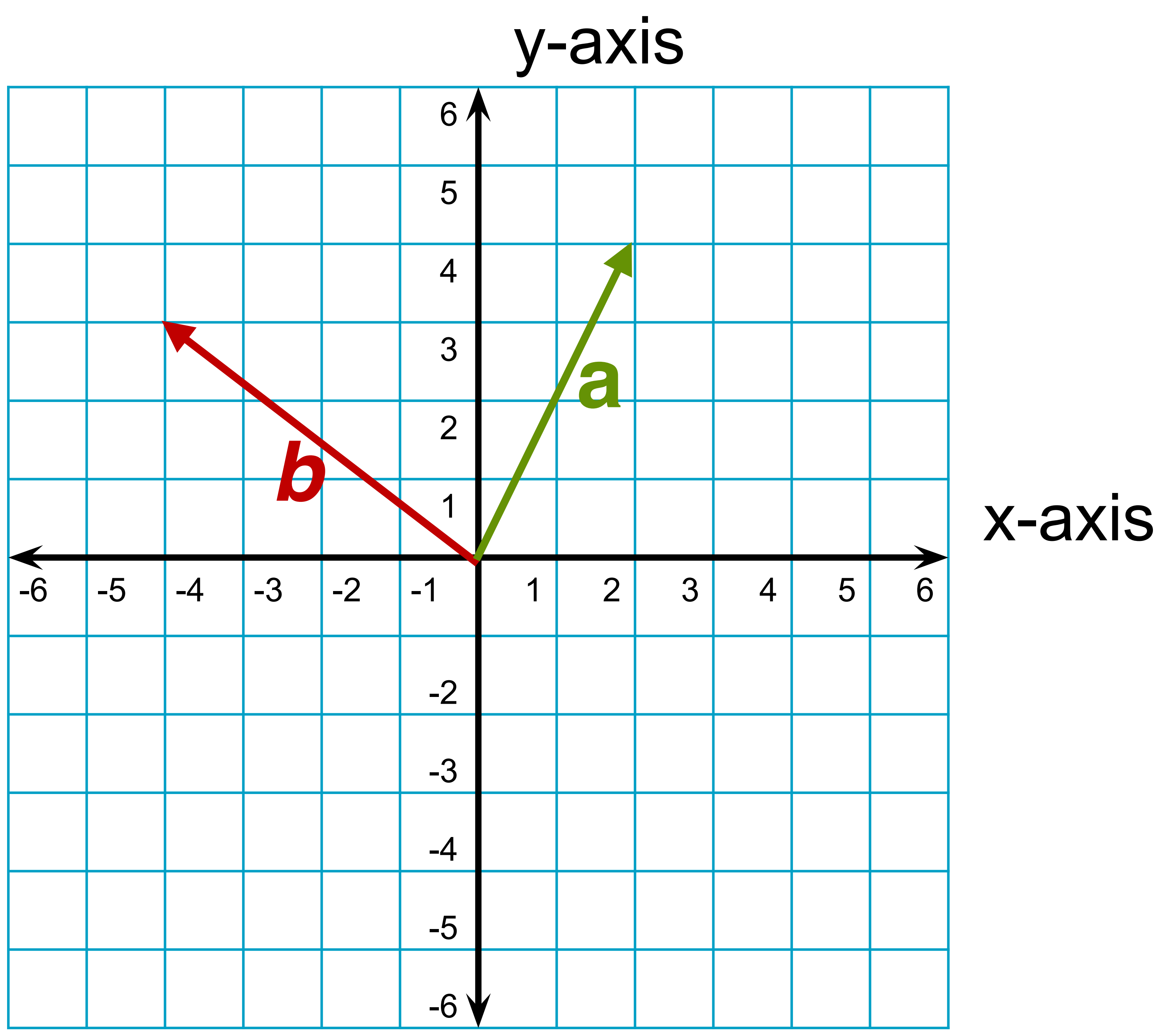
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a "dimension"
  - $\vec{a} = \langle 2,4 \rangle$



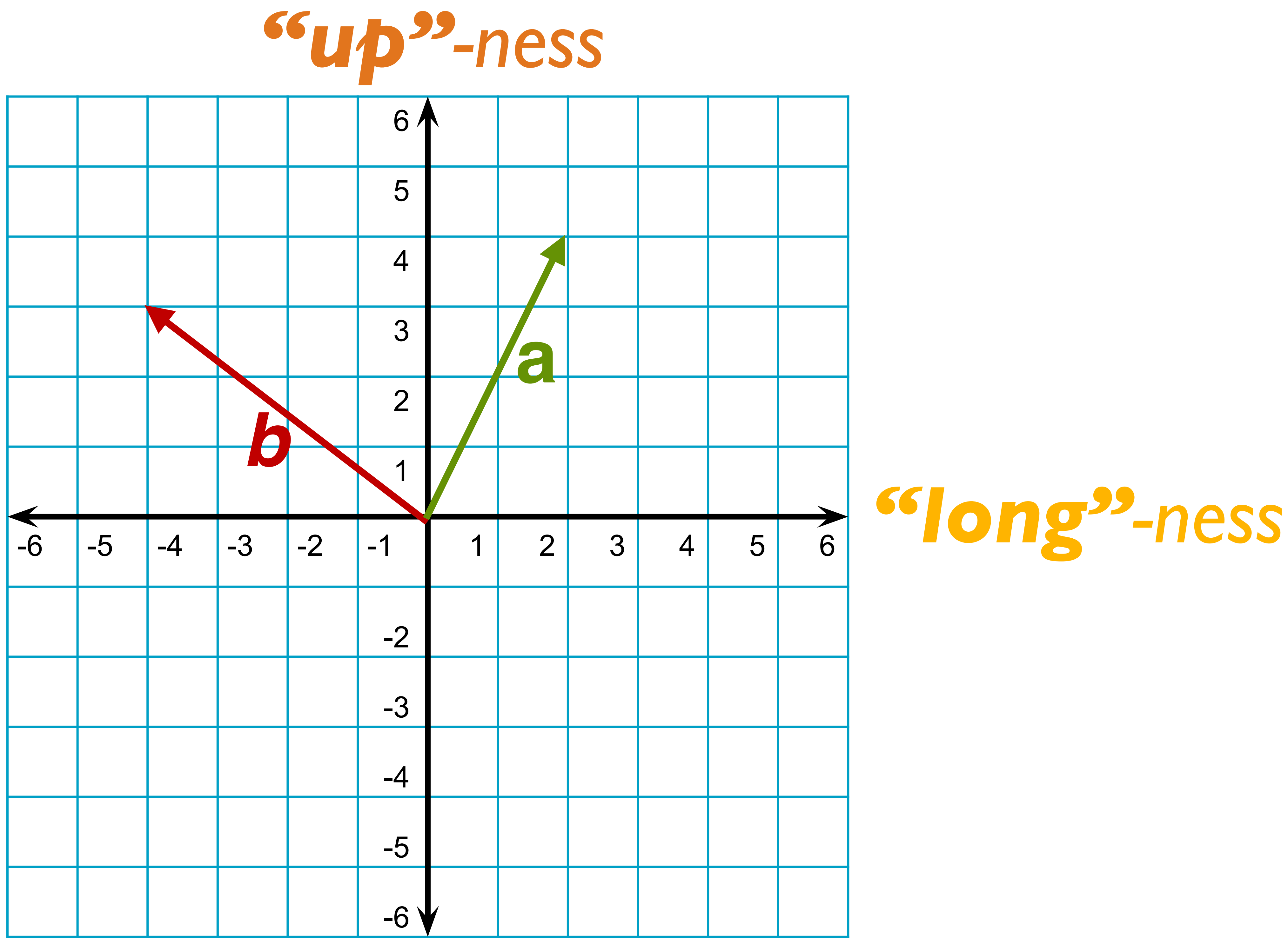
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a “dimension”
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$



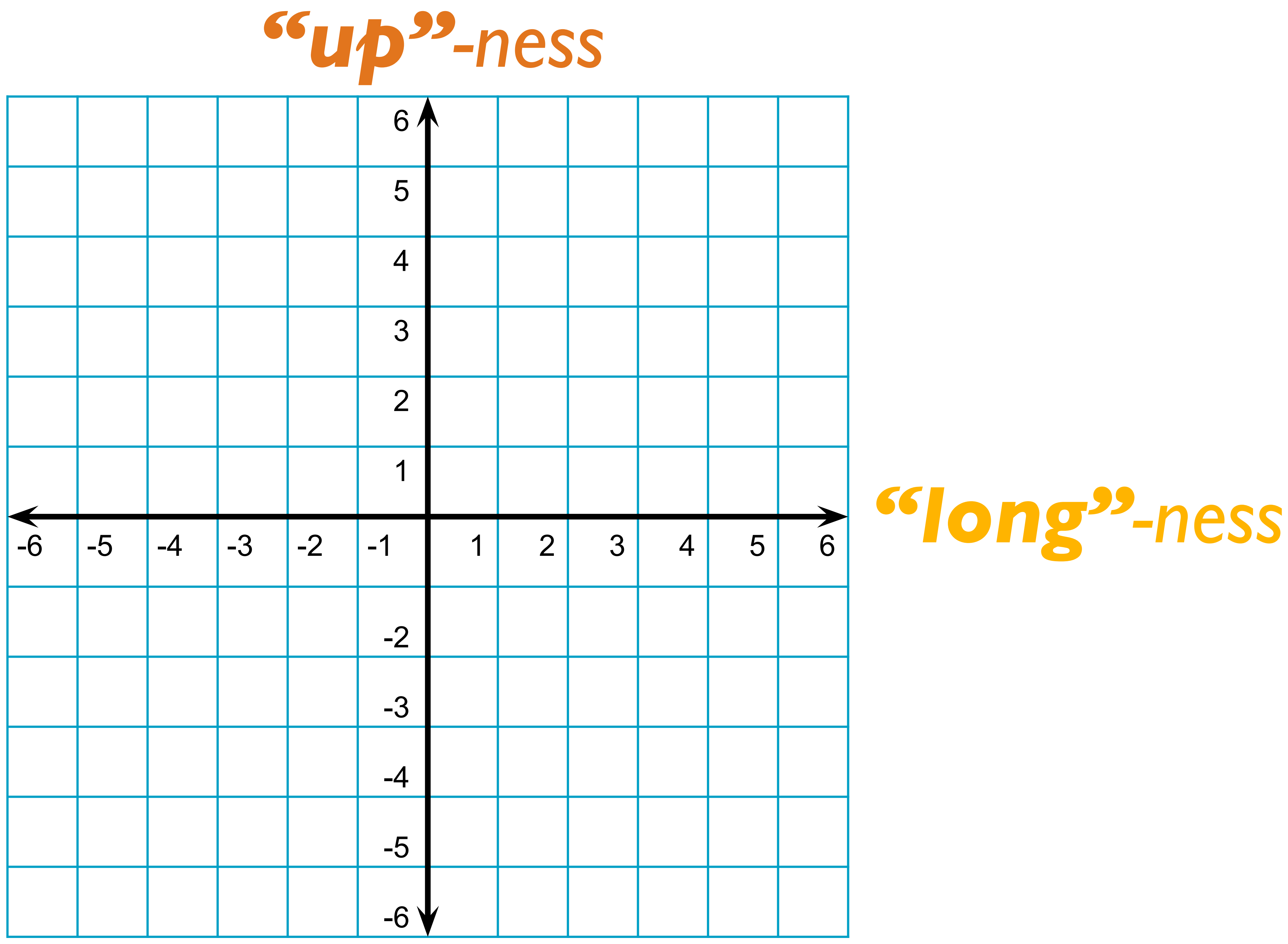
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a “dimension”
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$



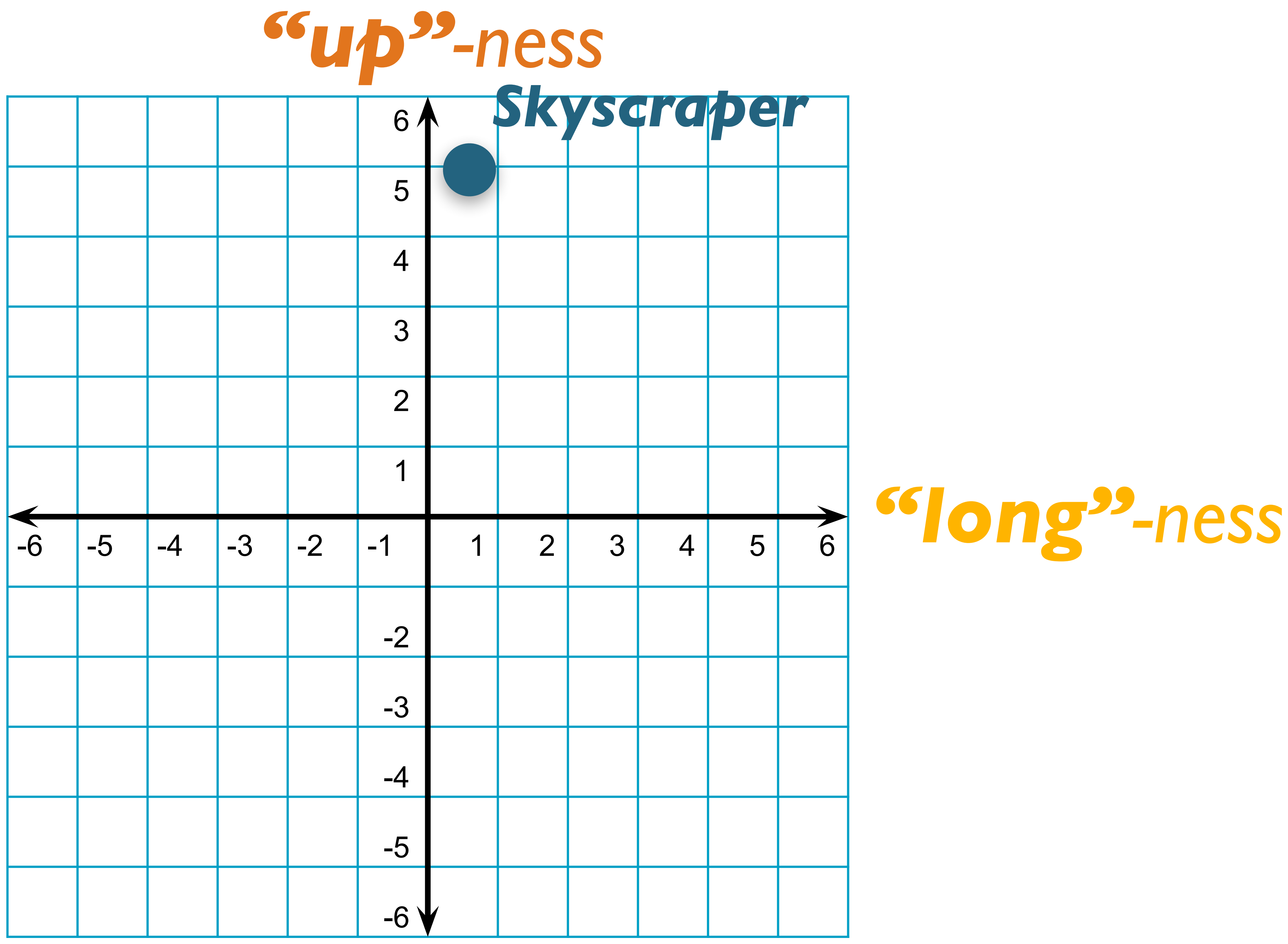
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a “dimension”
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$



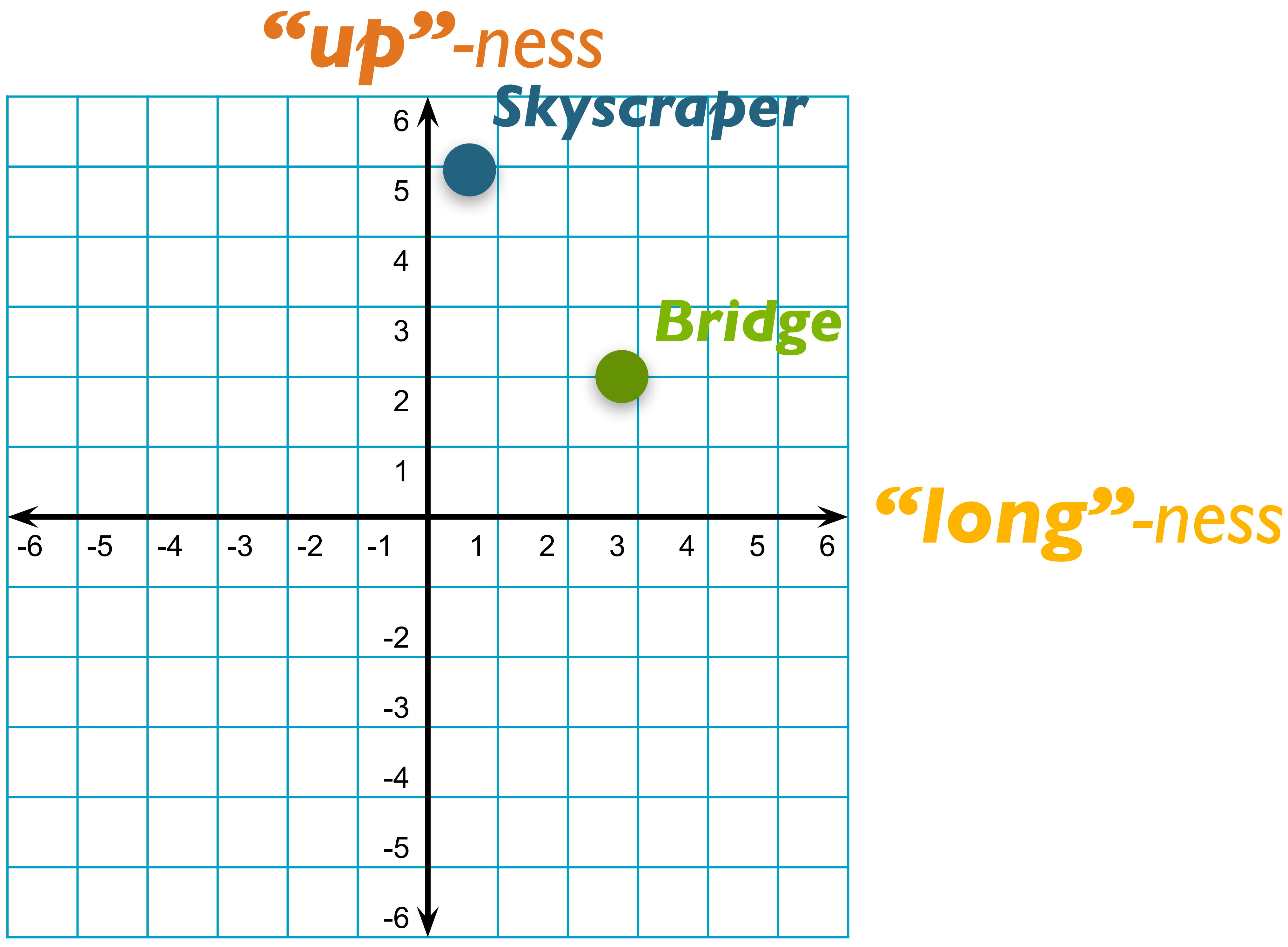
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a "dimension"
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$



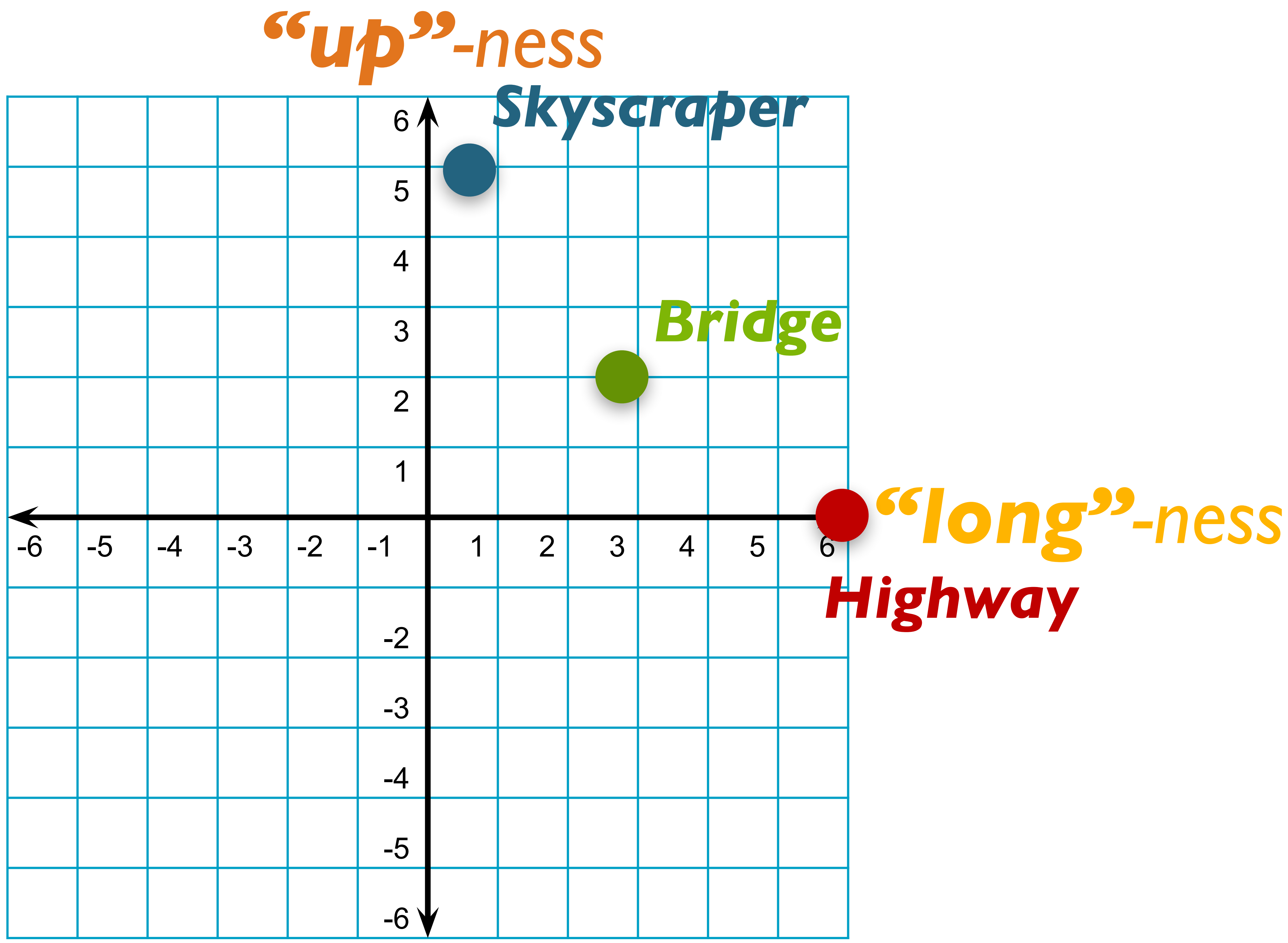
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a "dimension"
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$



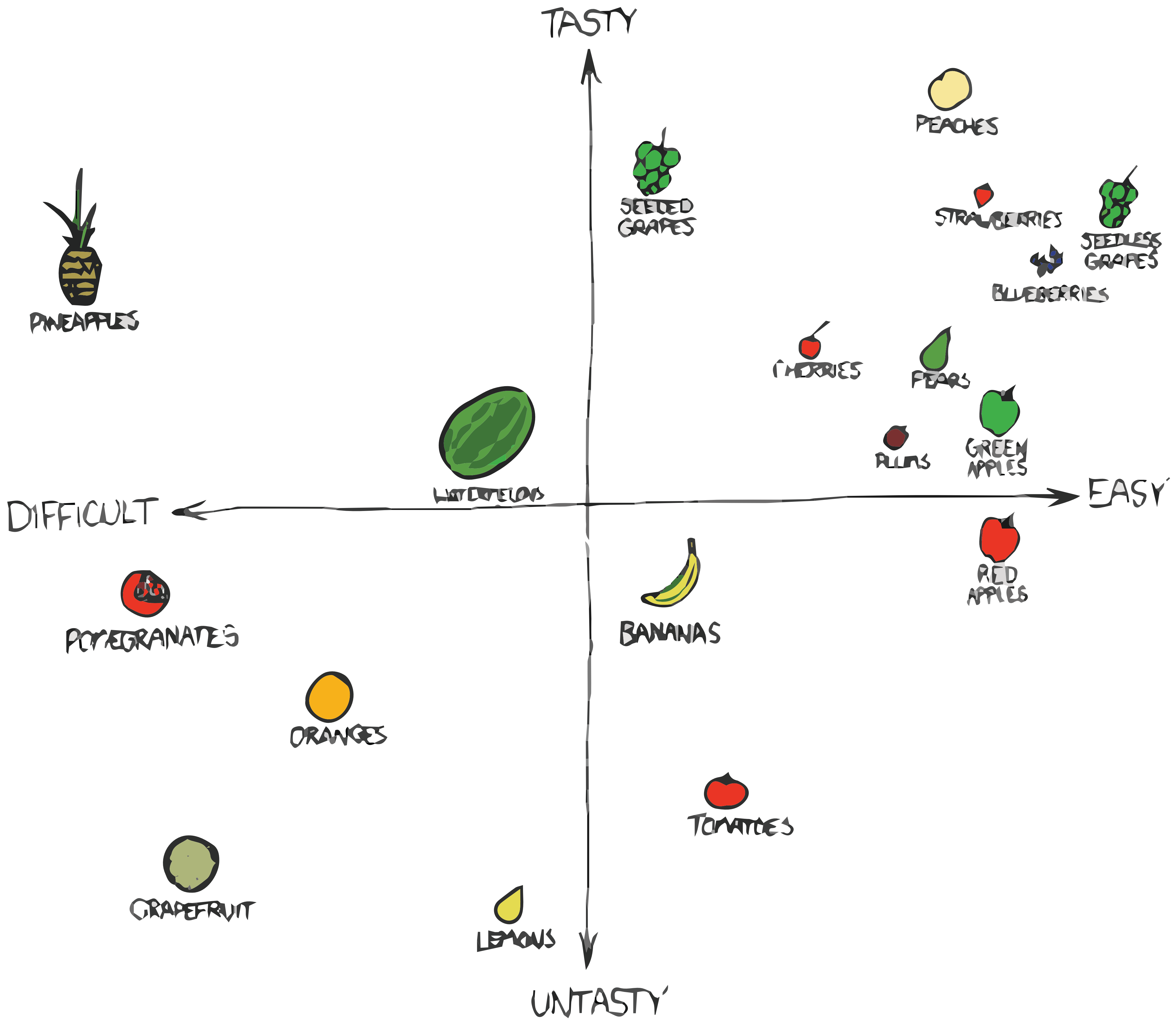
Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a “dimension”
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$



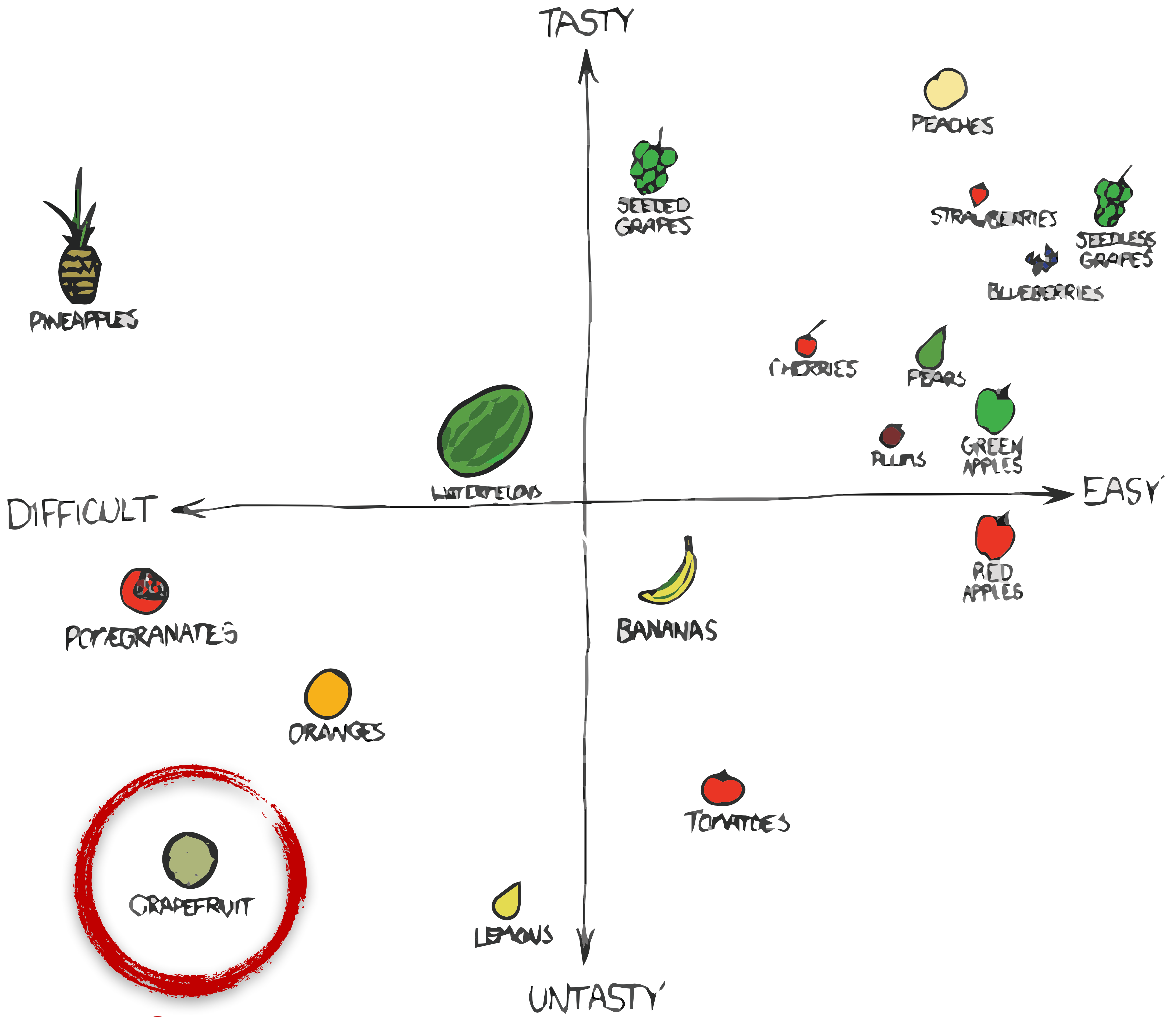
Vectors: A Refresher

xkcd.com/388



Vectors: A Refresher

xkcd.com/388



WTF, Grapefruit?

Basic vector operations

- Addition: $\mathbf{x} + \mathbf{y} = \langle \mathbf{x}_0 + \mathbf{y}_0, \ldots, \mathbf{x}_n + \mathbf{y}_n \rangle$
- Subtraction: $\mathbf{x} - \mathbf{y} = \langle \mathbf{x}_0 - \mathbf{y}_0, \ldots, \mathbf{x}_n - \mathbf{y}_n \rangle$
- Scalar multiplication: $k\mathbf{x} = \langle k\mathbf{x}_0, \ldots, k\mathbf{x}_n \rangle$
- Length: $||\mathbf{x}|| = \sqrt{\sum_i \mathbf{x}_i^2}$

Vector Distances: Manhattan & Euclidean

- **Manhattan Distance** $$d_{\text{manhattan}}(x, y) = \sum_i |x_i - y_i|$$
  - (Distance as cumulative horizontal + vertical moves)
- **Euclidean Distance**

$$d_{\text{euclidean}}(x, y) = \sum_i (x_i - y_i)^2$$

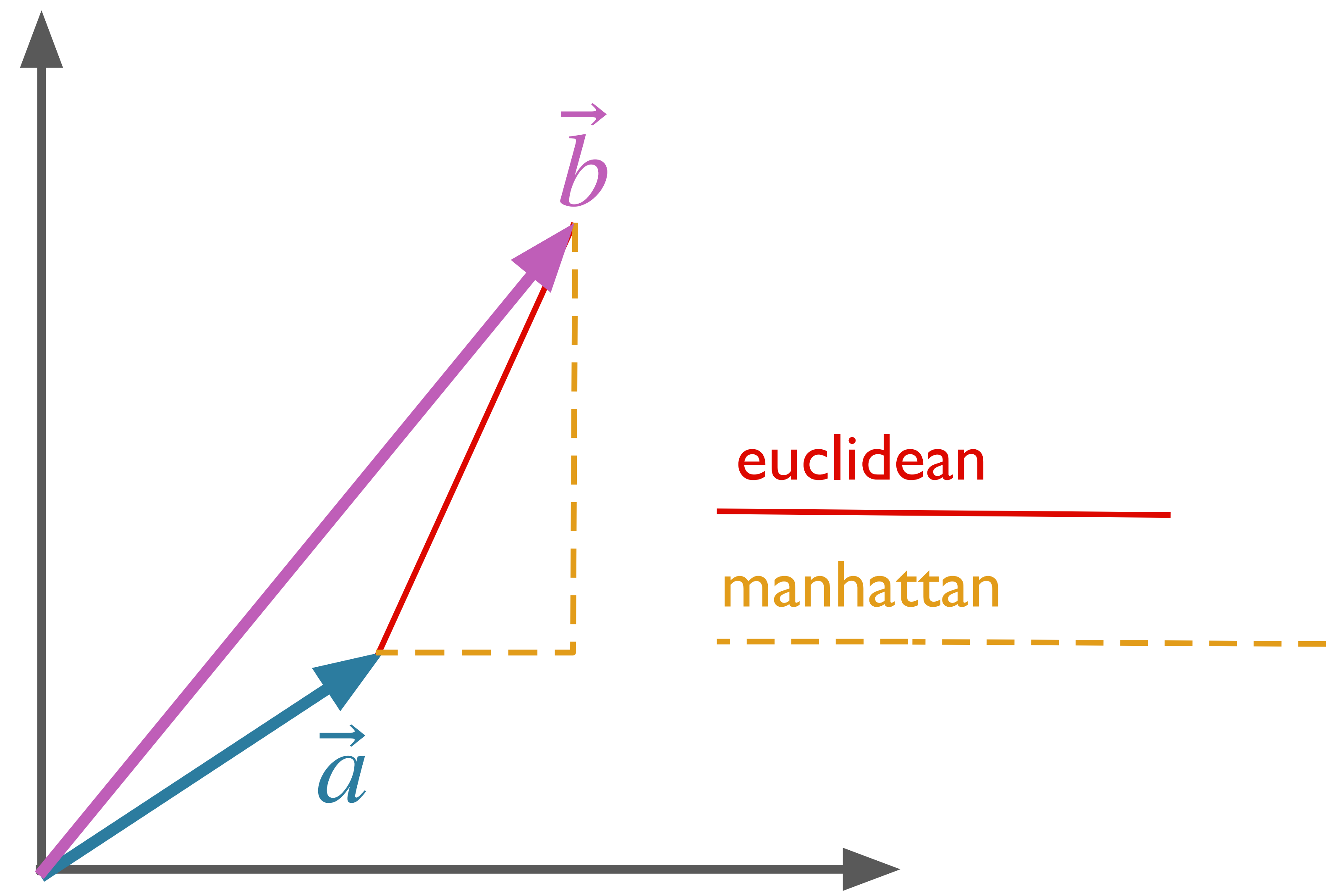
- Too sensitive to extreme values

Vector Distances: Manhattan & Euclidean

- **Manhattan Distance** $d_{\text{manhattan}}(x, y) = \sum_i |x_i - y_i|$
  - (Distance as cumulative horizontal + vertical moves)
- **Euclidean Distance**

$$d_{\text{euclidean}}(x, y) = \sum_i (x_i - y_i)^2$$

- Too sensitive to extreme values



Vector Similarity: Dot Product

- Produces real number scalar from product of vectors' components

$$\text{sim}_{\text{dot}}(x, y) = x \cdot y = \sum_i x_i \times y_i$$

- Biased toward ***longer*** (larger magnitude) vectors
  - In our case, vectors with fewer zero counts

Vector Similarity: Cosine

- If you normalize the dot product for vector magnitude…
- …result is same as cosine of angle between the vectors.

$$\text{sim}_{\text{cos}}(x, y) = \frac{x \cdot y}{\|x\| \, \|y\|} = \frac{\sum_i x_i \times y_i}{\sqrt{\sum_i x_i^2} \sqrt{\sum_i y_i^2}}$$

Bag of Words Vectors

- Represent ‘company’ of word such that similar words will have similar representations
  - ‘Company’ = context

Bag of Words Vectors

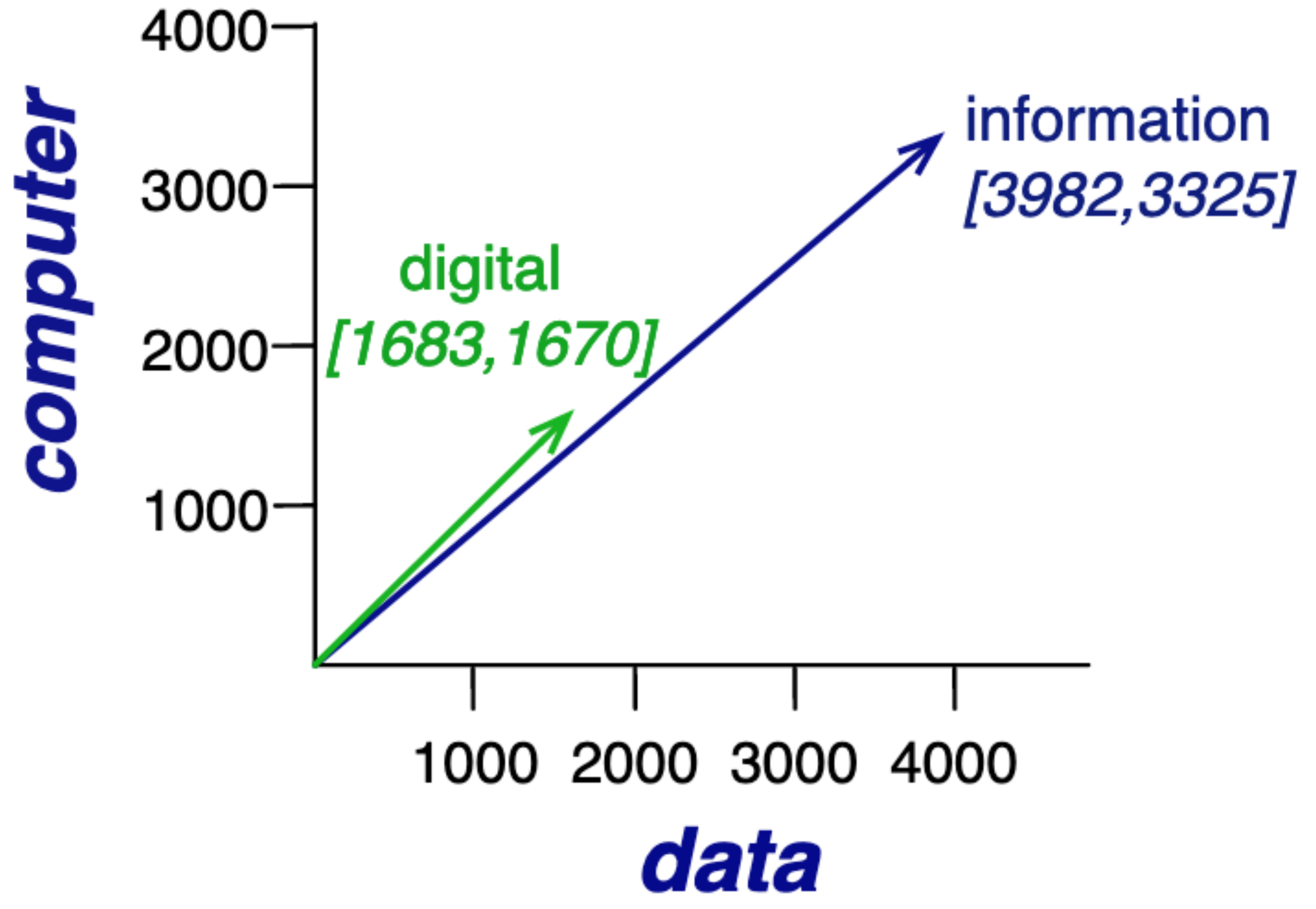
- Represent 'company' of word such that similar words will have similar representations
  - 'Company' = context
- Word represented by context feature vector
  - Many alternatives for vector

Bag of Words Vectors

- Represent 'company' of word such that similar words will have similar representations
  - 'Company' = context
- Word represented by context feature vector
  - Many alternatives for vector
- Initial representation:
  - 'Bag of words' feature vector
  - Feature vector length N, where N is size of vocabulary
    - f_i+=1 if $word_i$ within window size w of $word$

Bag of Words Vectors

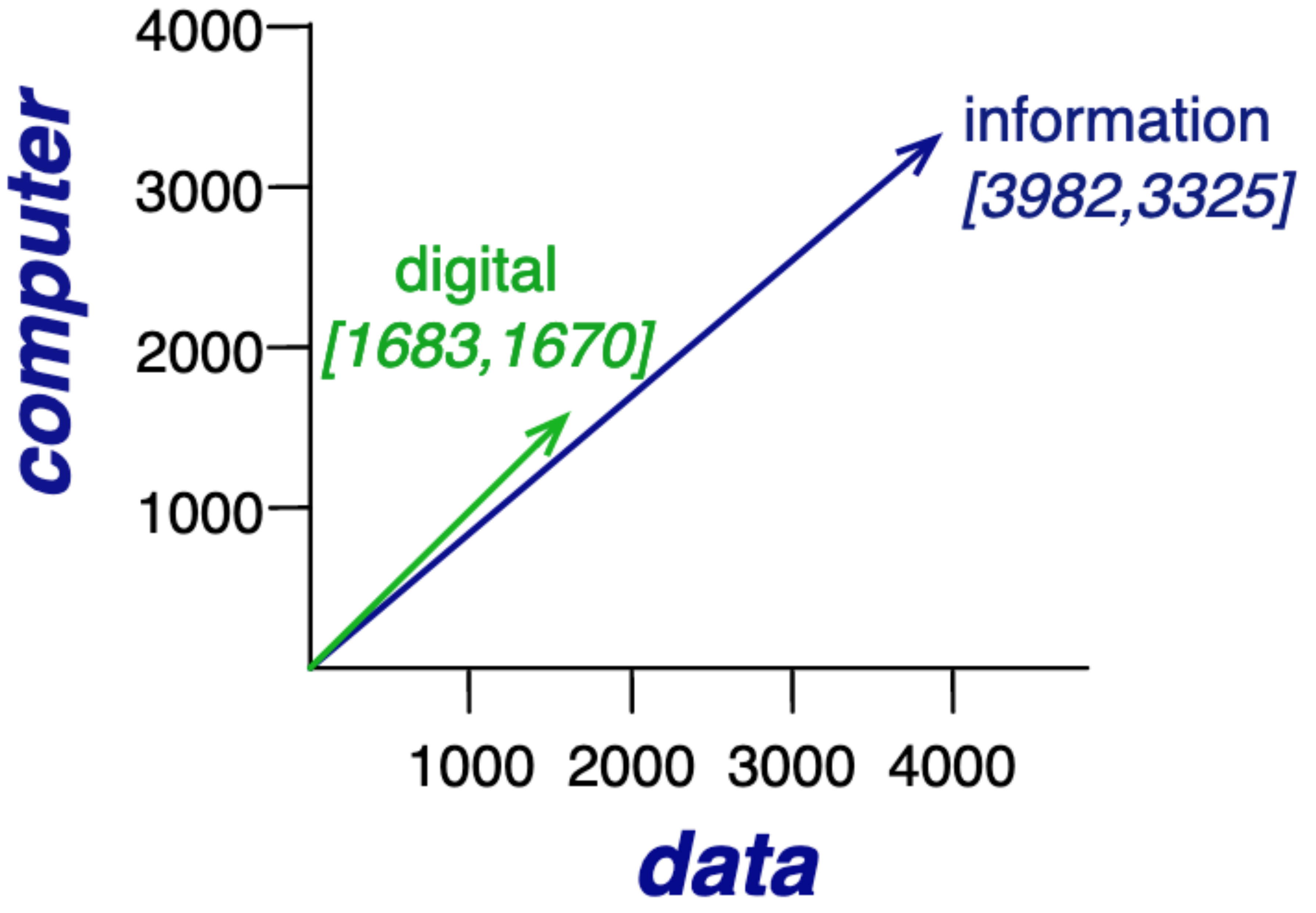
	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...



Bag of Words Vectors

- Usually re-weighted, with e.g. tf-idf, ppmi
- Still sparse
- Very high-dimensional: |V|

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...



Homework 1

Next Time

- Skip-Gram with Negative Sampling
  - How optimization framework applies to this problem
- Introduction of two tasks that we will use throughout the class
  - Language modeling
  - Text classification [sentiment analysis]