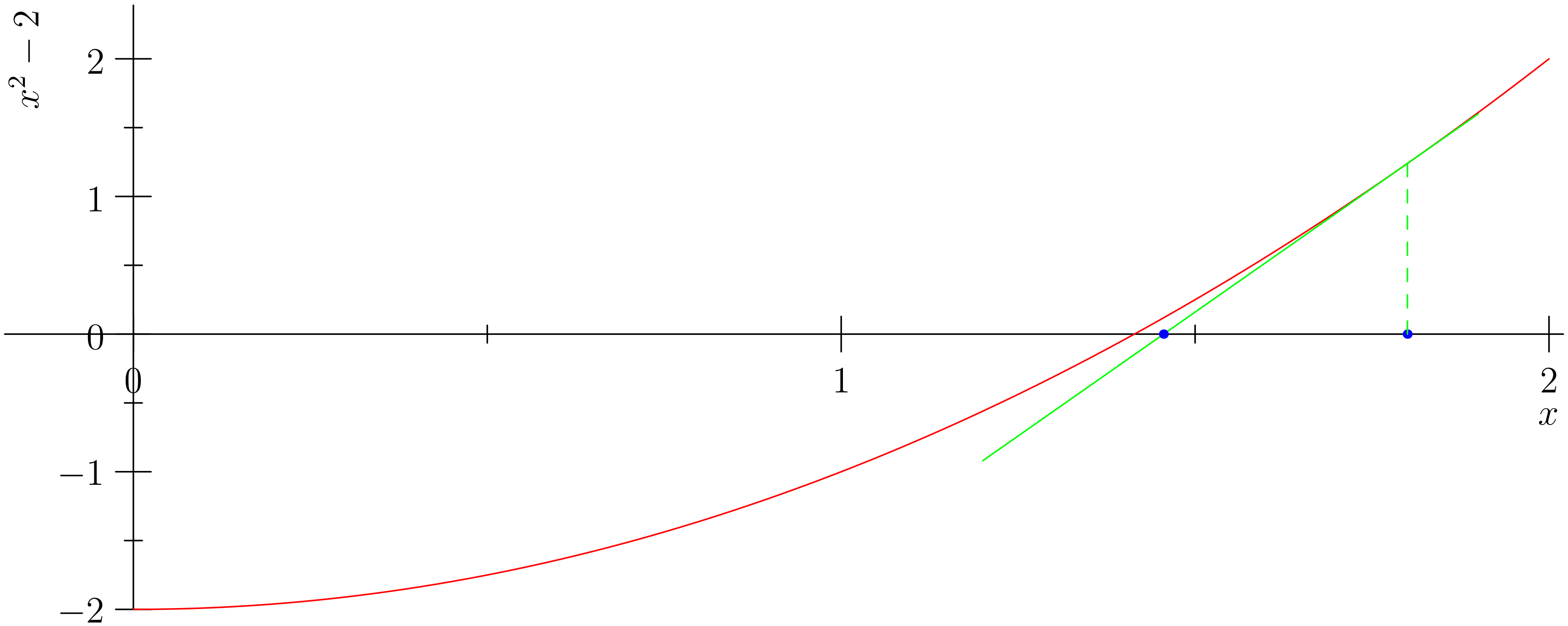
Algorithms and Analysis

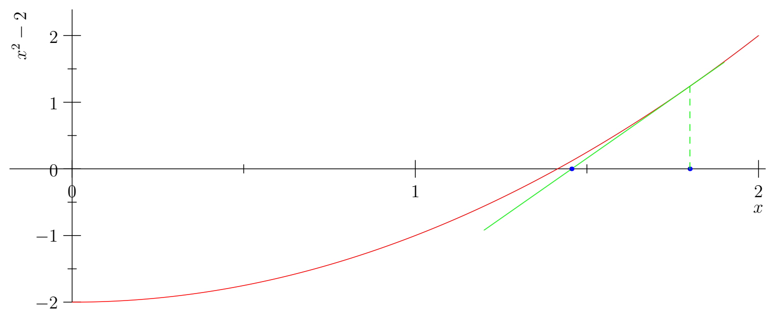
Lesson 30: *Understand Numerics*



Representing reals, rounding error, convergence, stability, conditioning

Outline

1. **Numerical Approximations**
2. Iterating to a Solution
3. Linear Algebra



Numerical Analysis

- Numerical algorithms are usually taught separately from the "discrete algorithms" we have predominantly looked at
- The main difference stems from the fact that numerical algorithms model continuous variables
- Computers can only approximate continuous variables
- Numerical algorithms have to take into account this approximation

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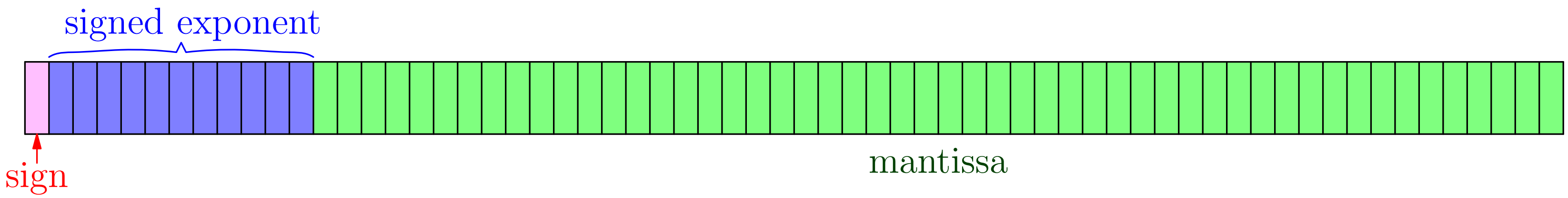
Representing Reals

- All real numbers are approximated by a binary encoding



- $x = m \times 2^{e-t}$
- t is precision so that if $e = t$, then $0.5 \leq x < 1$
- For IEEE double $t = 1023$, $expon_{\min} = -1021$, $expon_{\max} = 1024$
- Typical rounding error is $u = 1 \times 10^{-16}$

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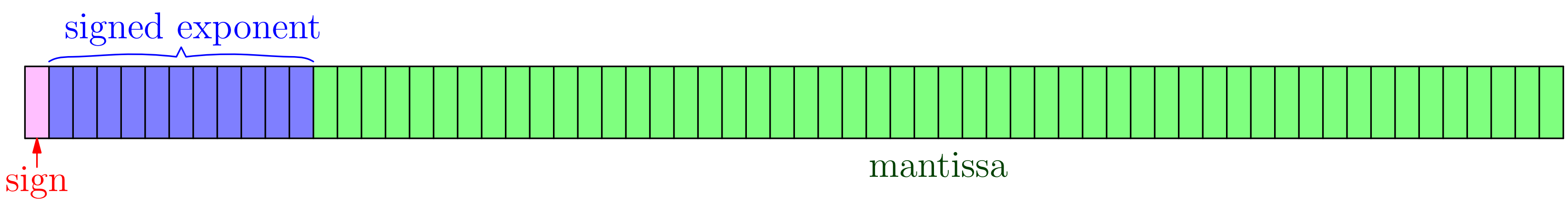

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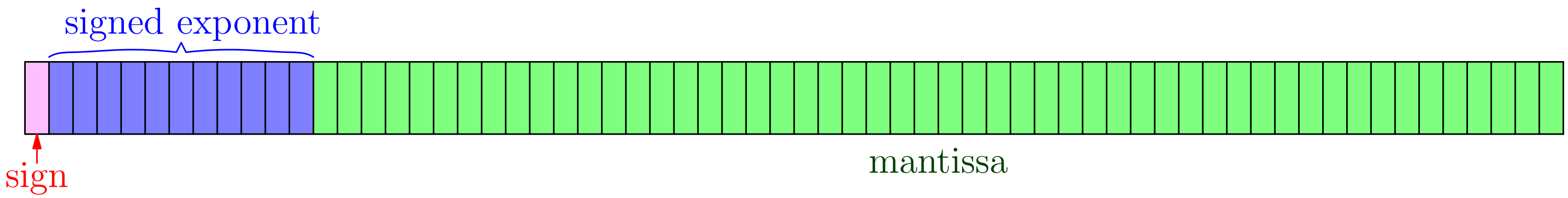

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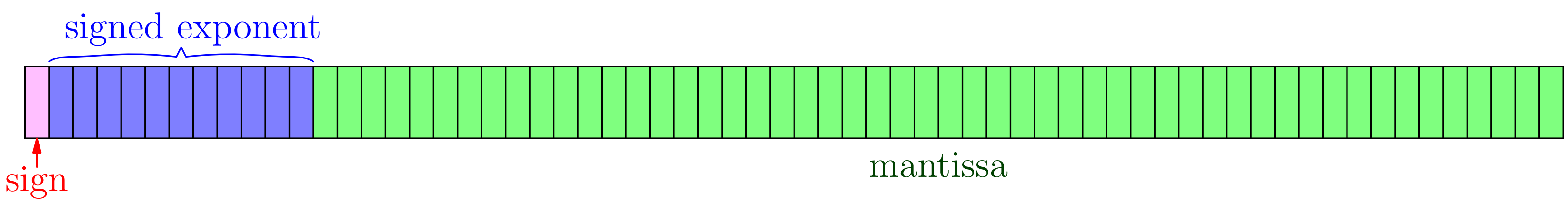

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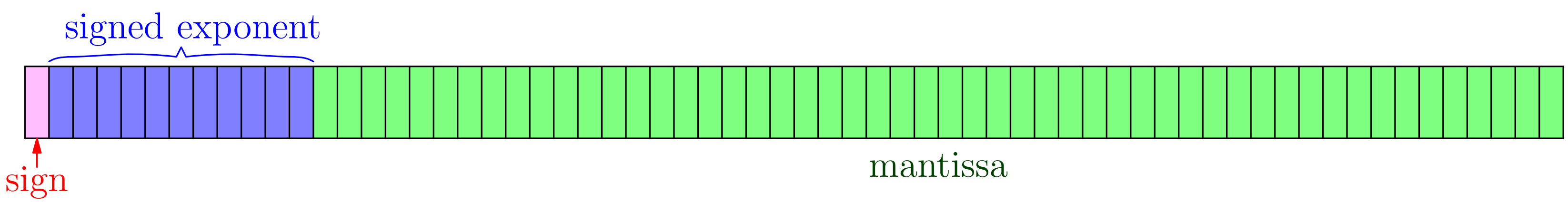

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The Number Line

- We approximate the continuous number line by a set of discrete values

- Imagine using a mantissa of 3 bits and an exponent of 2 bits (and a sign)

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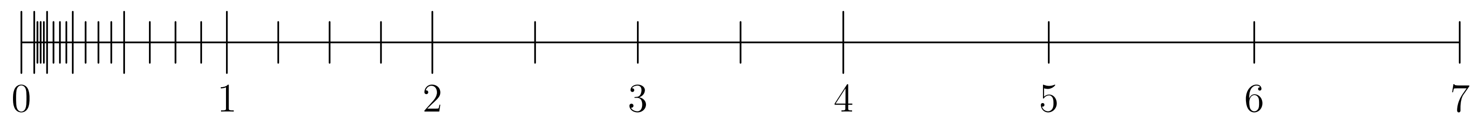

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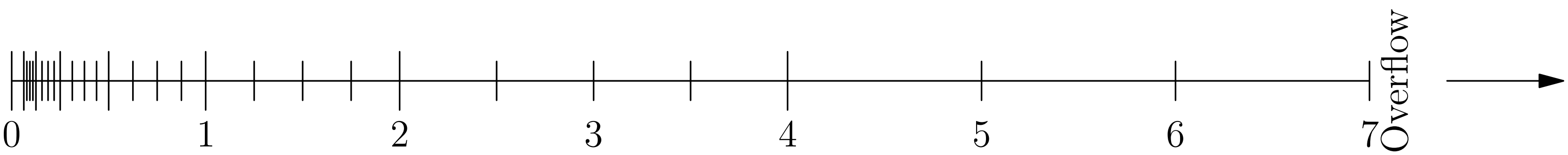

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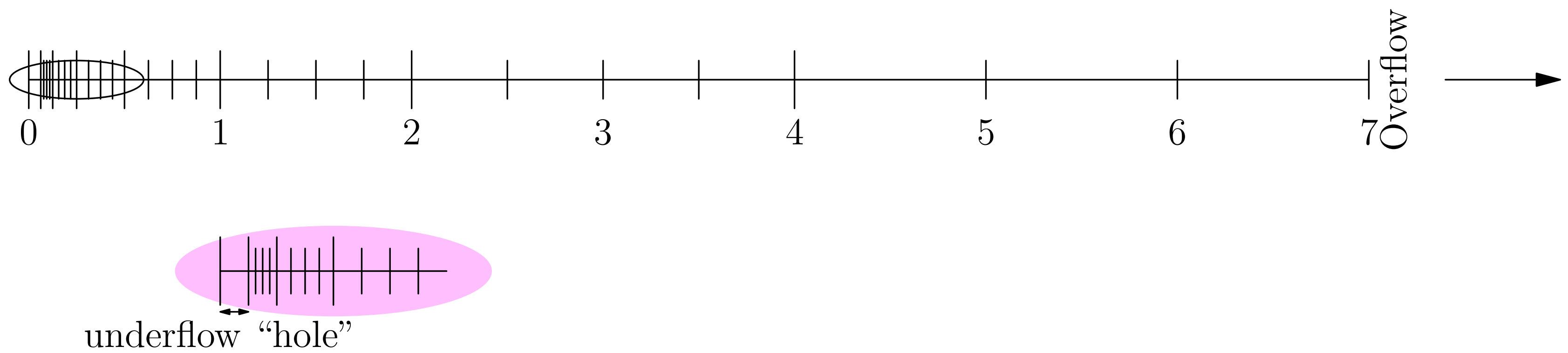

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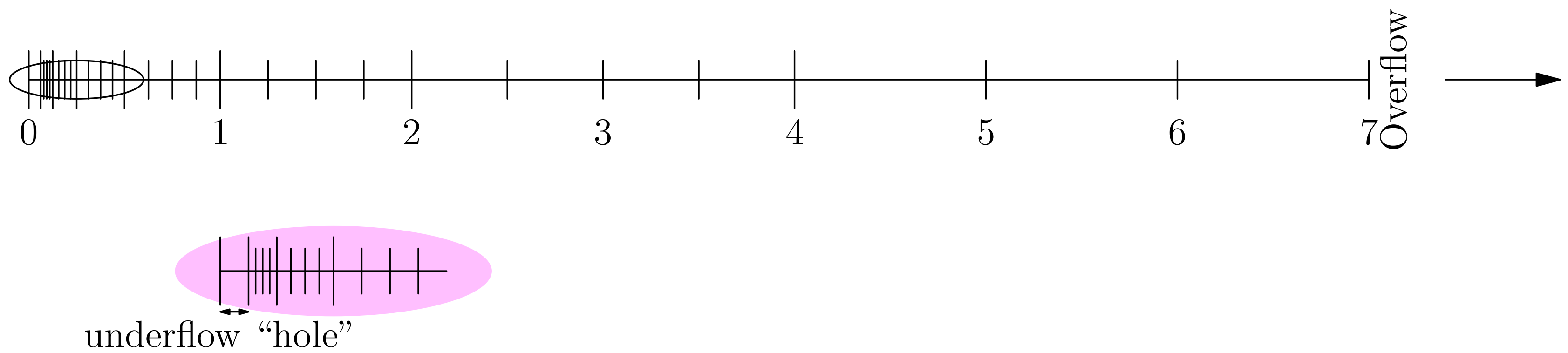

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Overflow and Underflow

- An overflow will cause a program to fall over at run time
- An underflow is ignored
- This is usually innocuous, but can lead to trouble
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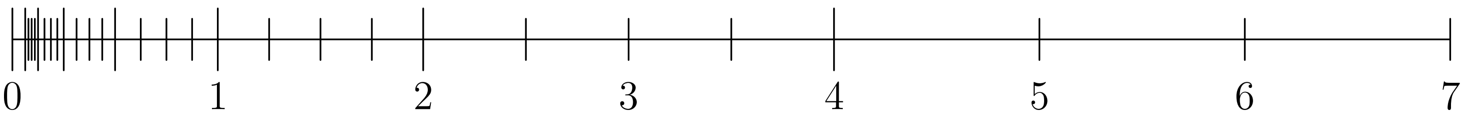

- The distance between two real numbers Δx grows with the number such that $\Delta x / x \leq u$ where $u \approx 10^{-16}$ for doubles

- Measure relative error

$$\text{Relative error} = \left| \frac{\text{Approx} - \text{Exact}}{\text{Exact}} \right|$$

- Thus almost every operation is only accurate up to this small (relative) rounding error

- Most operations are carefully designed that these rounding errors are unbiased so that the sum of random errors grows sub-linearly

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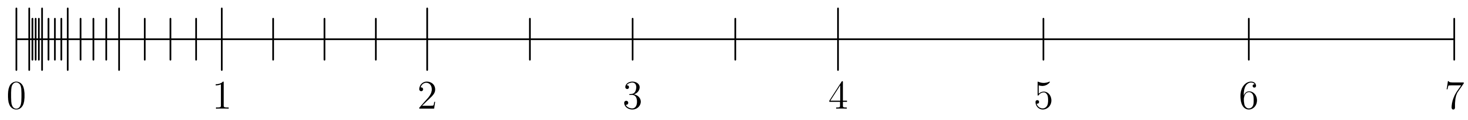

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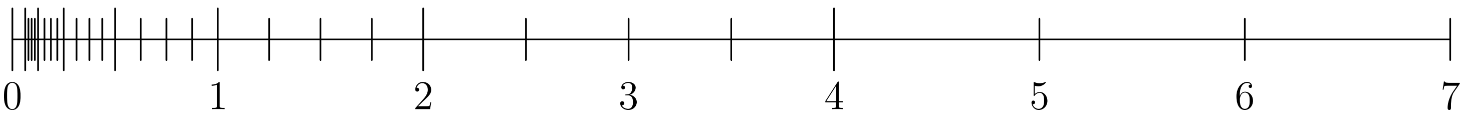

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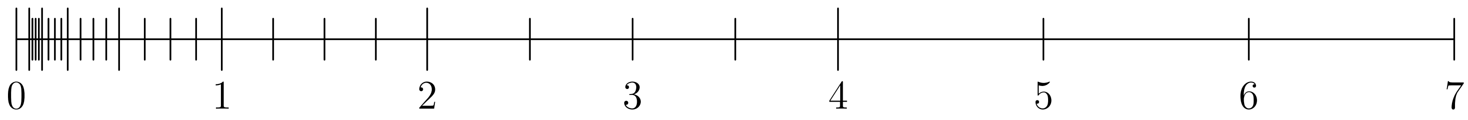

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Losing Precision

- There seems to be plenty of precision, so what's the problem?
- One issue is that its easy to lose precision
- Consider estimating derivatives by finite differencing

$$f'(x) \approx \frac{f(x+\epsilon) - f(x-\epsilon)}{2\,\epsilon}$$

- The problem is $f(x+\epsilon)$ and $f(x-\epsilon)$ are very close so in taking their difference we lose precision
- $f(x) = \sin(x)$, $f'(x) = \cos(x)$ at $x = 1.0$

ϵ	10^{-6}	10^{-8}	10^{-10}	10^{-12}	10^{-14}
relative error	5×10^{-11}	5×10^{-9}	1×10^{-7}	2×10^{-5}	6×10^{-3}

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Solving Quadratic Equations

- A classic example where you can lose precision is in solving a quadratic equation $a\,x^2 + b\,x + c = 0$

$$x = \frac{-b \pm \sqrt{b^2 - 4\,a\,c}}{2\,a}$$

- If $b^2 \gg |4\,a\,x|$ then for one solution we end up subtracting numbers very close

- We rather use this equation to compute one solution

$$x_1 = \frac{-b - \mathrm{sgn}(b)\sqrt{b^2 - 4\,a\,c}}{2\,a}$$

- Use the identity $x_1\,x_2 = c/a$ to find x_2

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Accumulation of Rounding Error

- With many significant figures surely we can afford to lose some accuracy?

- This is sometimes true, but we often use “for loops” where we might be losing accuracy all the time

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x = 1.6;
for (i=0; i<50; i++)
   x = sqrt(x);
for (i=0; i<50; i++)
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- Gave the answer 1.2840 (if I run the for loop 60 times it gives the answer 1 for almost any input)

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Coping With Truncation Errors

- Nothing is exact so to check that $x = y$ we use

  `Math.abs(x-y) < 1.0e-10` $// \; a \; small \; constant$

- Sometimes sums that add up to 1 don't quite so we have not to rely on anything being exact

- Avoid operations that are likely to lose accuracy (e.g. by taking the difference of similar numbers) where possible

- Sometimes it pays to do some operations using higher precision **`long double`**

- Make sure that errors are unbiased

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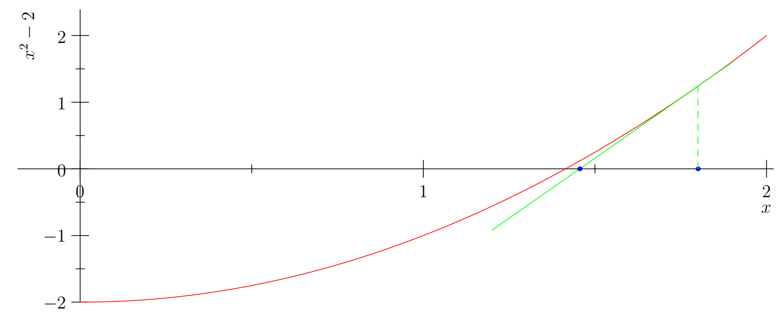

Iterative Algorithms

- We solve many numerical tasks by obtaining successively better solutions

$$x^{(0)},\ x^{(1)},\ x^{(2)},\ x^{(3)},\ x^{(4)},\ \ldots$$

- We often stop when the change in solution is below some threshold, e.g. $|x^{(i+1)} - x^{(i)}| \leq \epsilon \approx u$

- The time complexity depends on the speed of convergence

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Bisection

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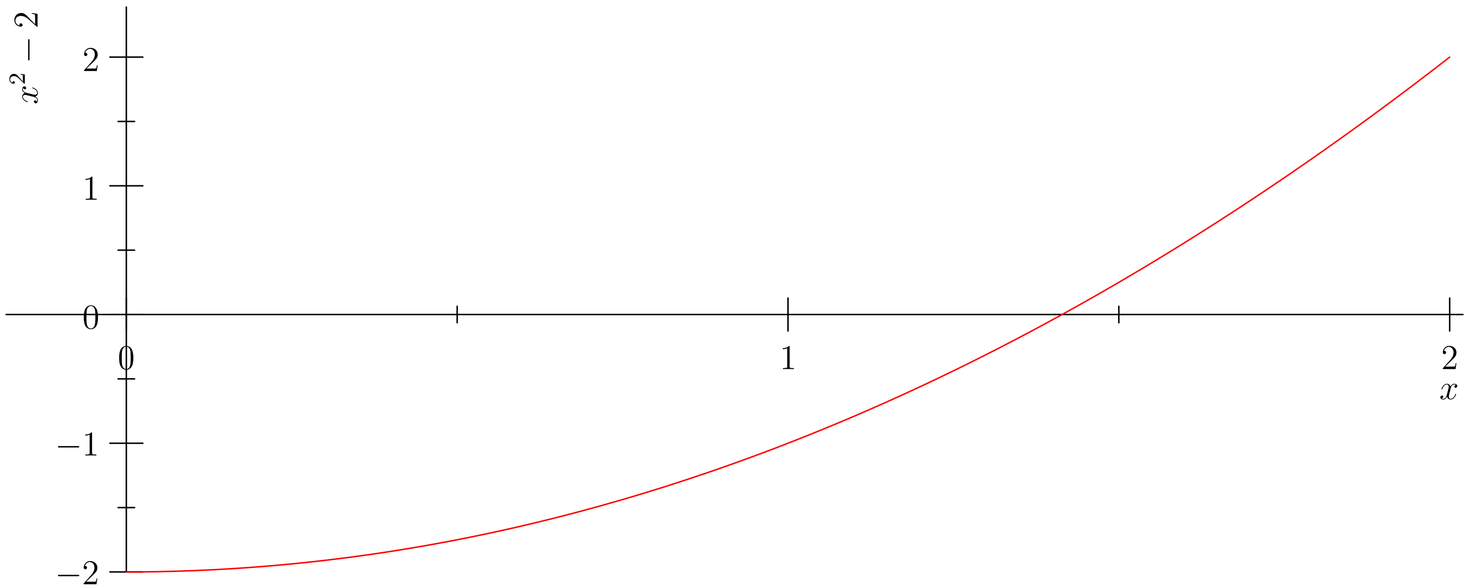
$$f(x) = x^2 - 2 = 0$$

- One of the classic methods of solving $f(x) = 0$ is **bisection**



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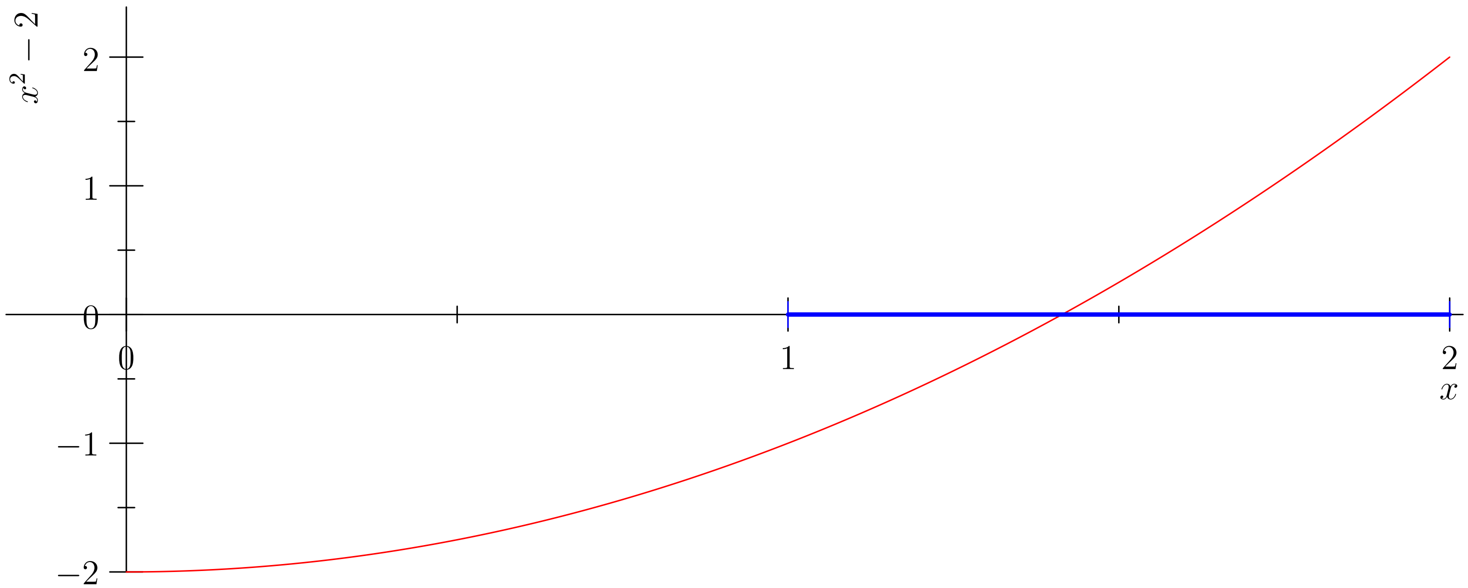

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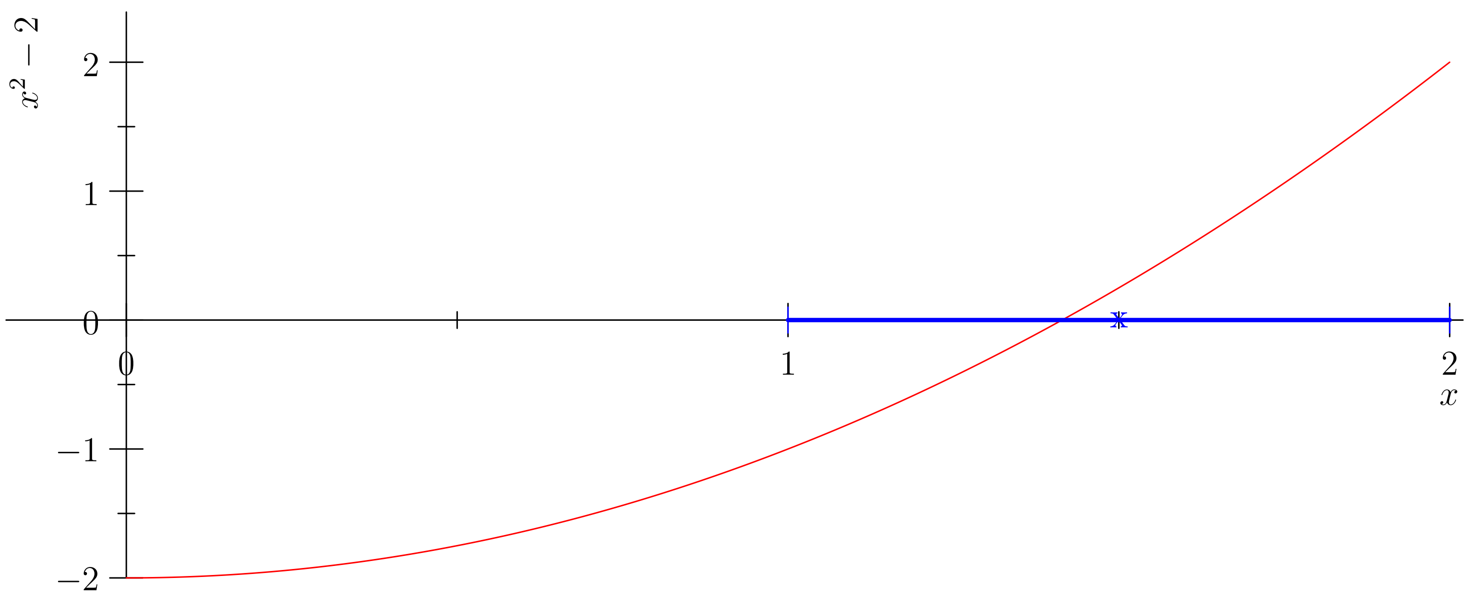

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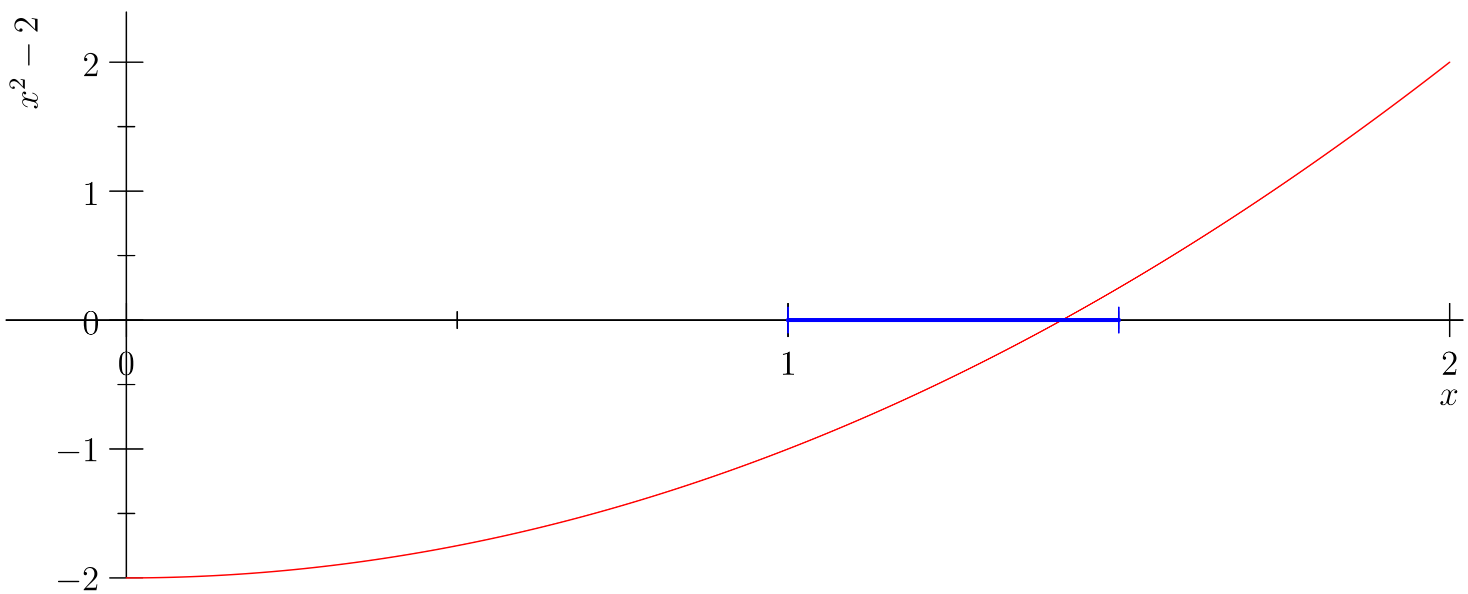

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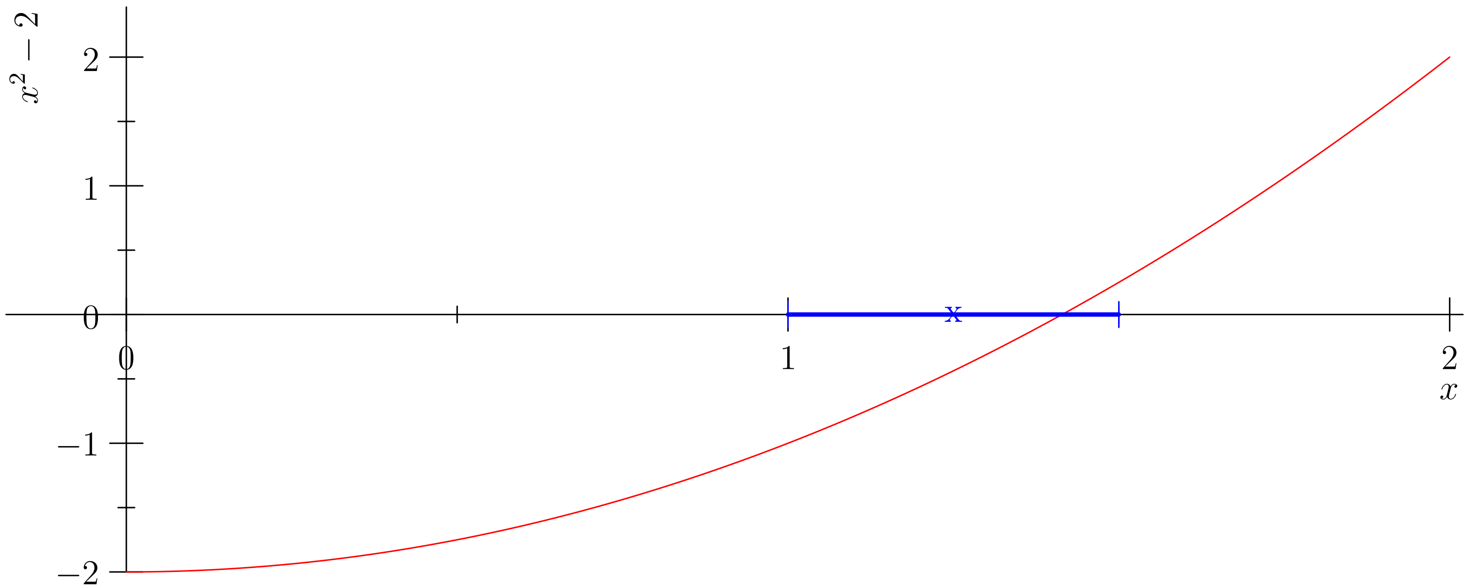

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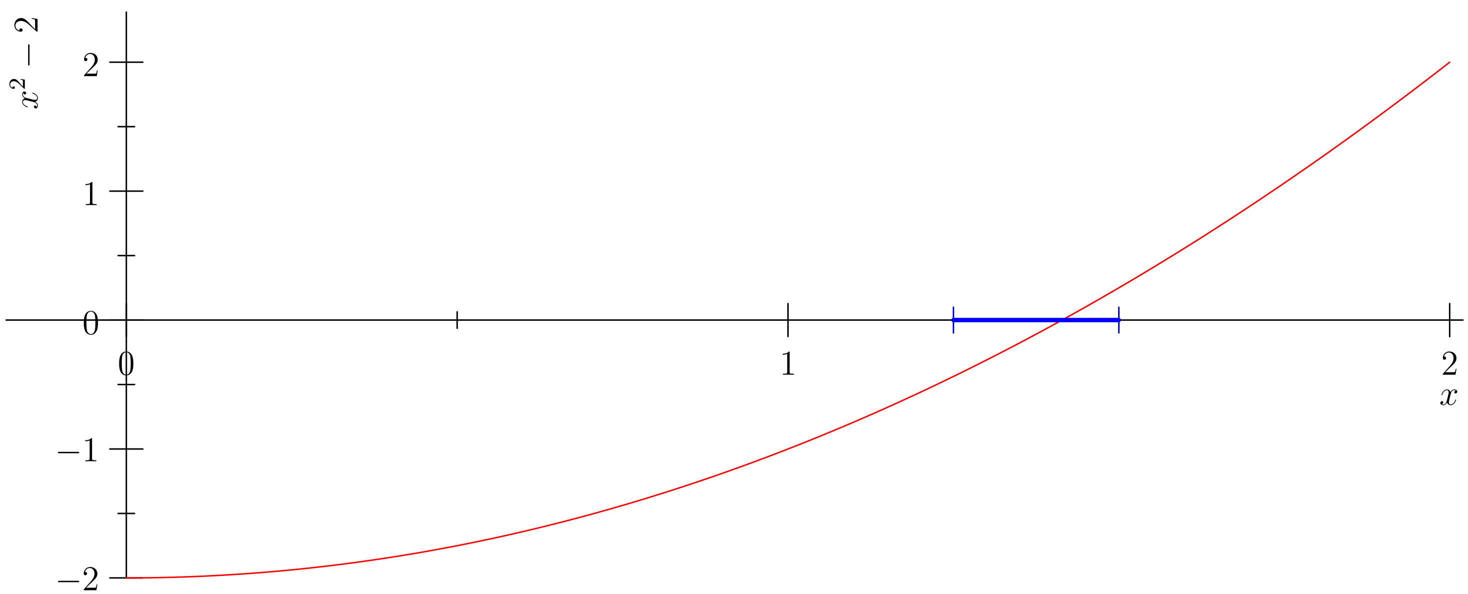

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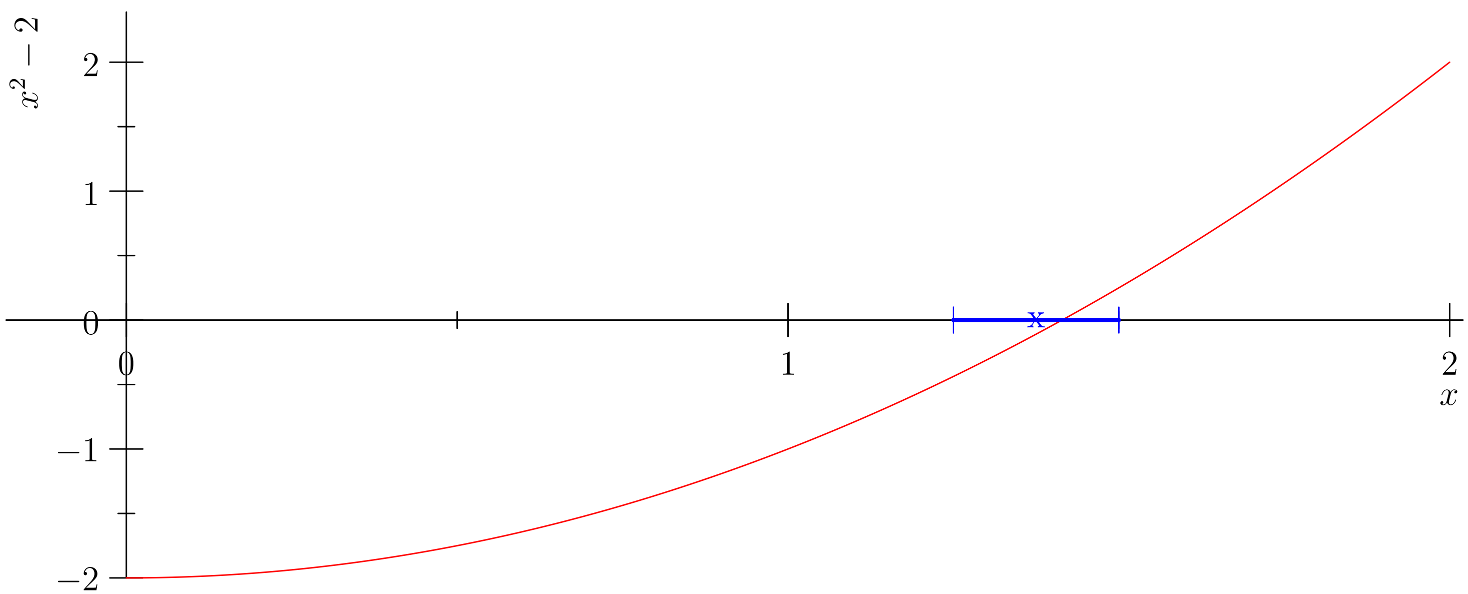

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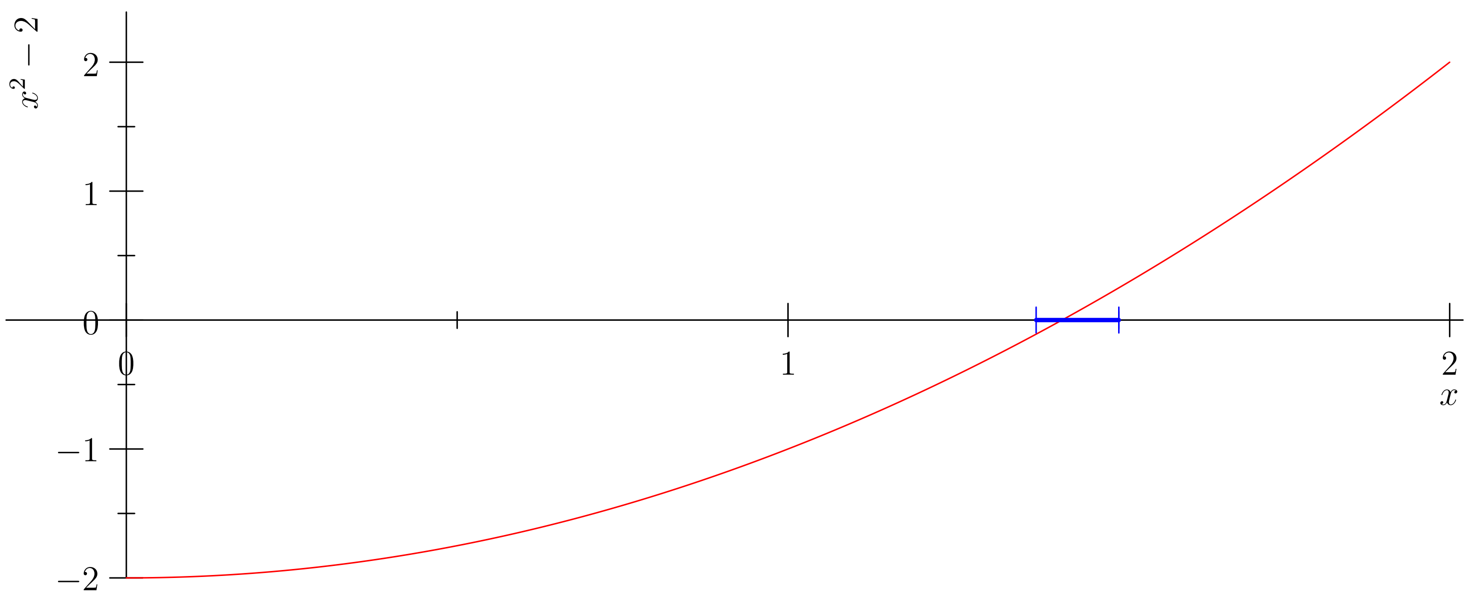

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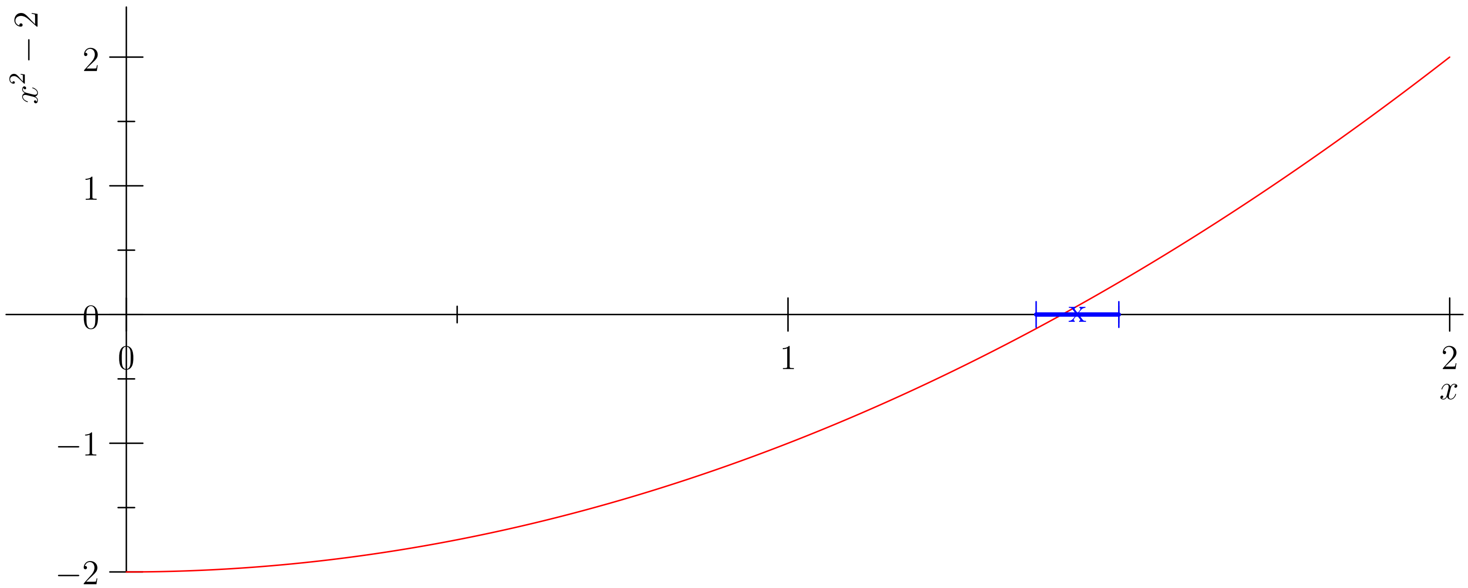

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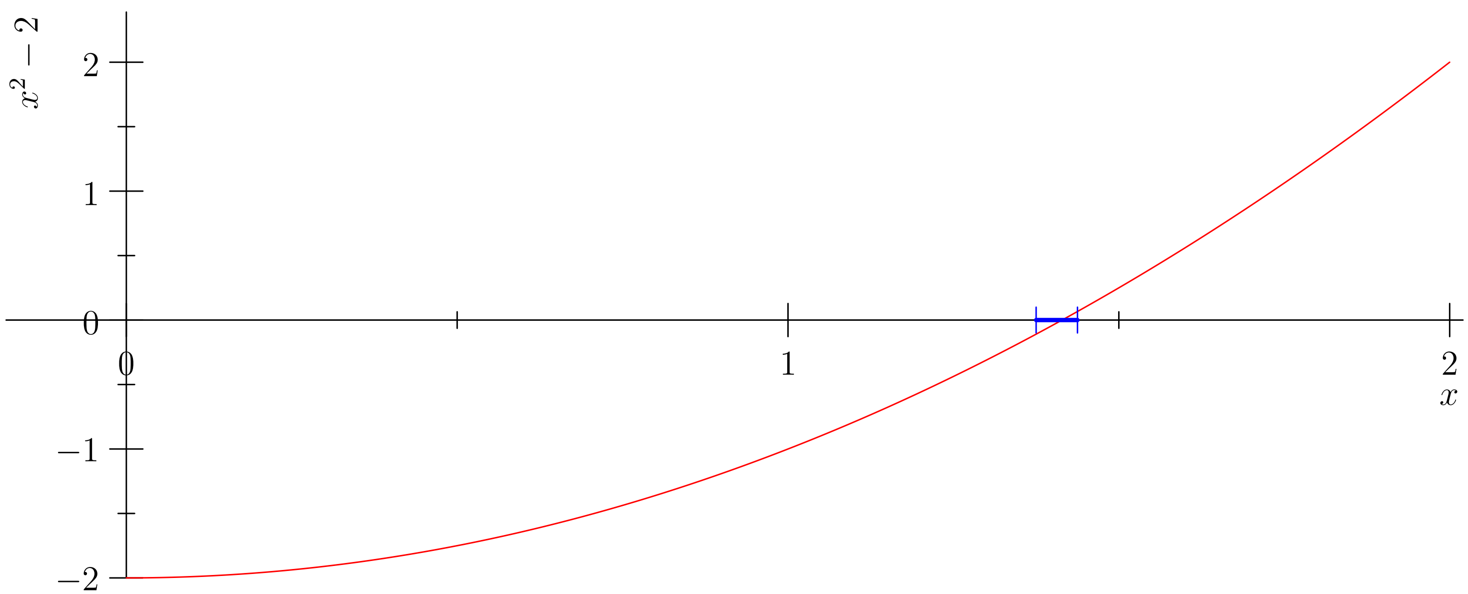

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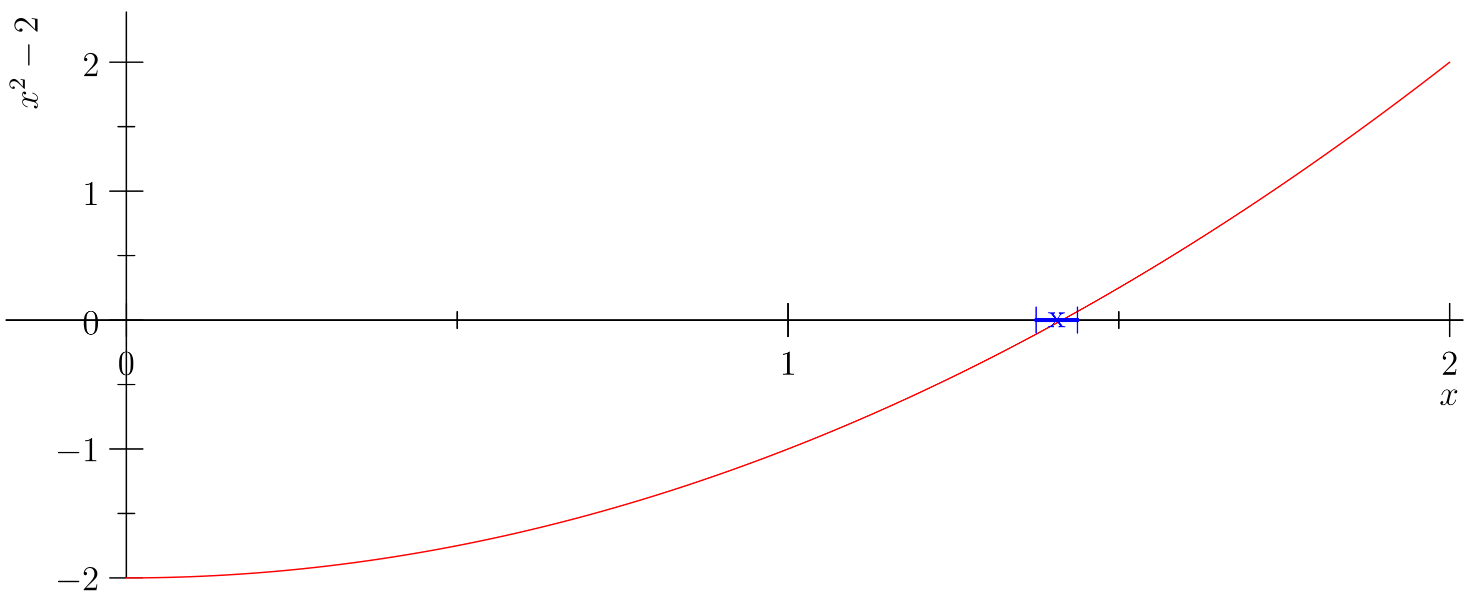

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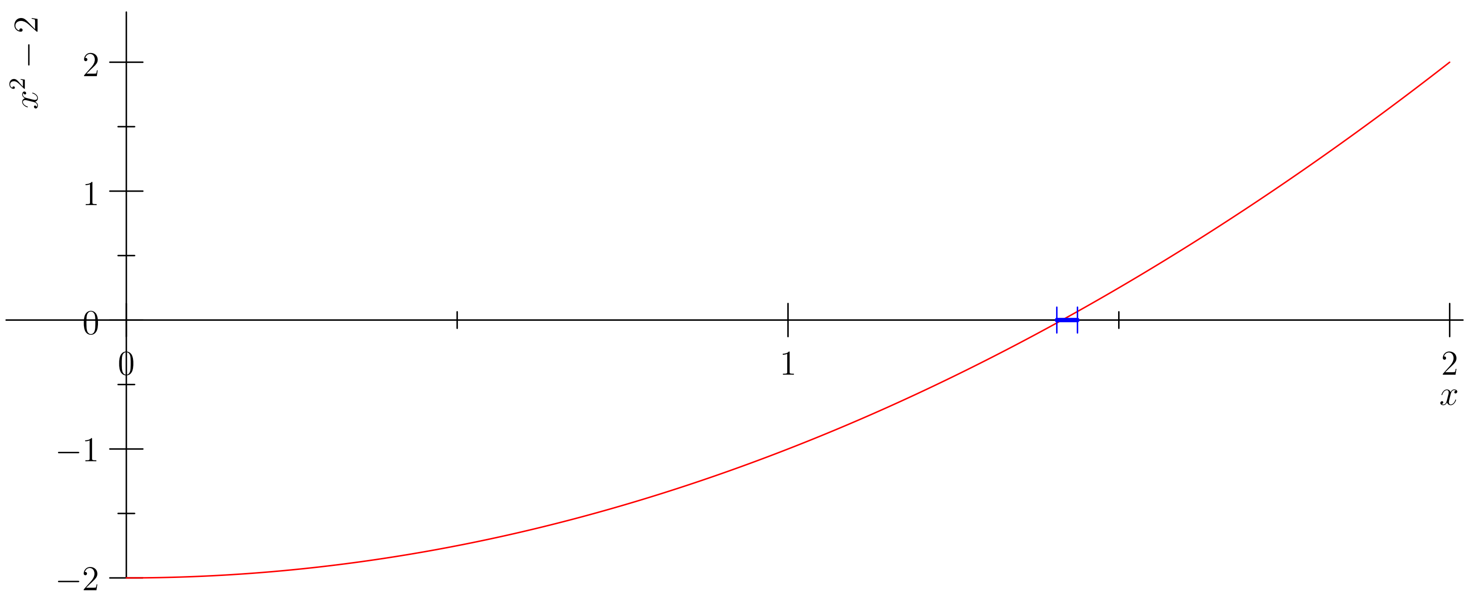

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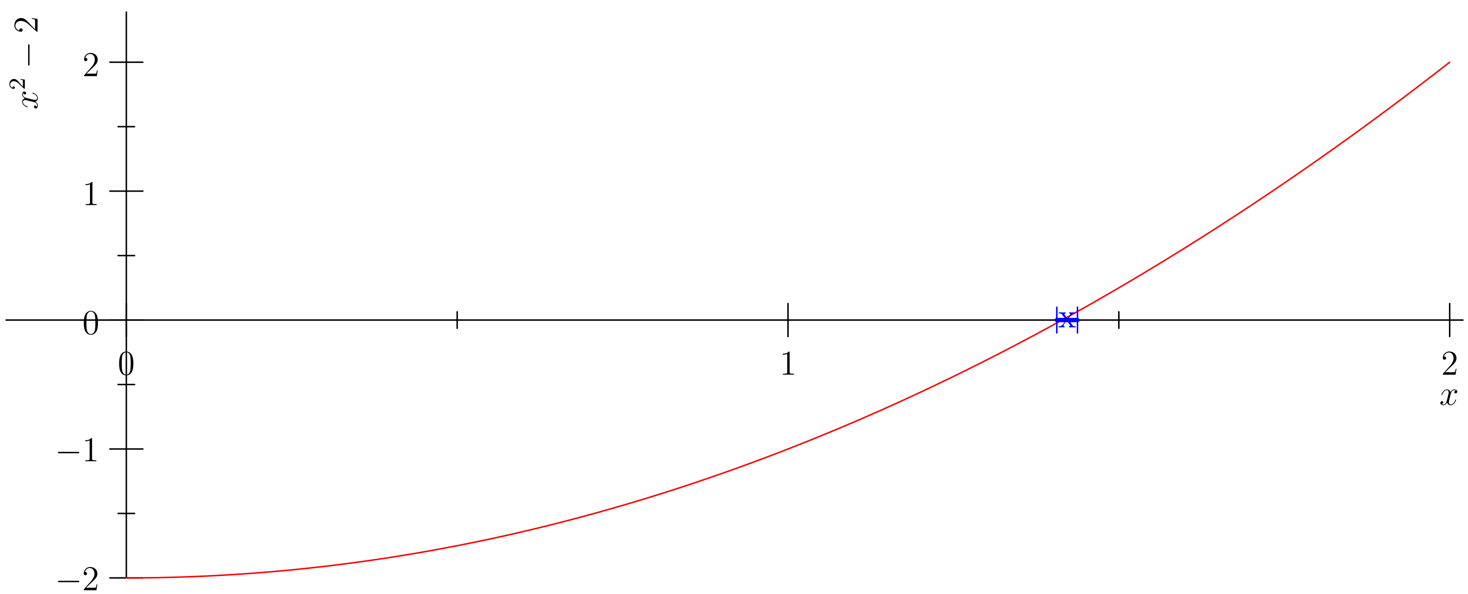

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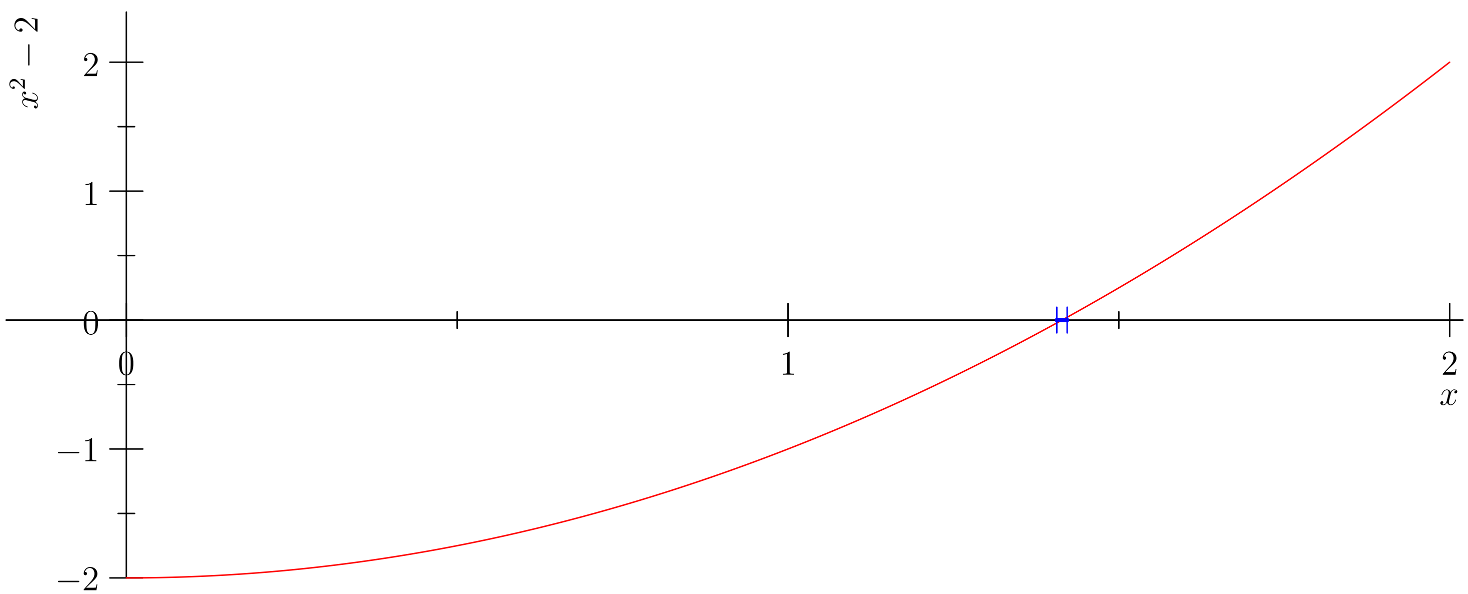

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$$x^{(i+1)} = x^{(i)} - \frac{f(x^{(i)})}{f'(x^{(i)})}$$

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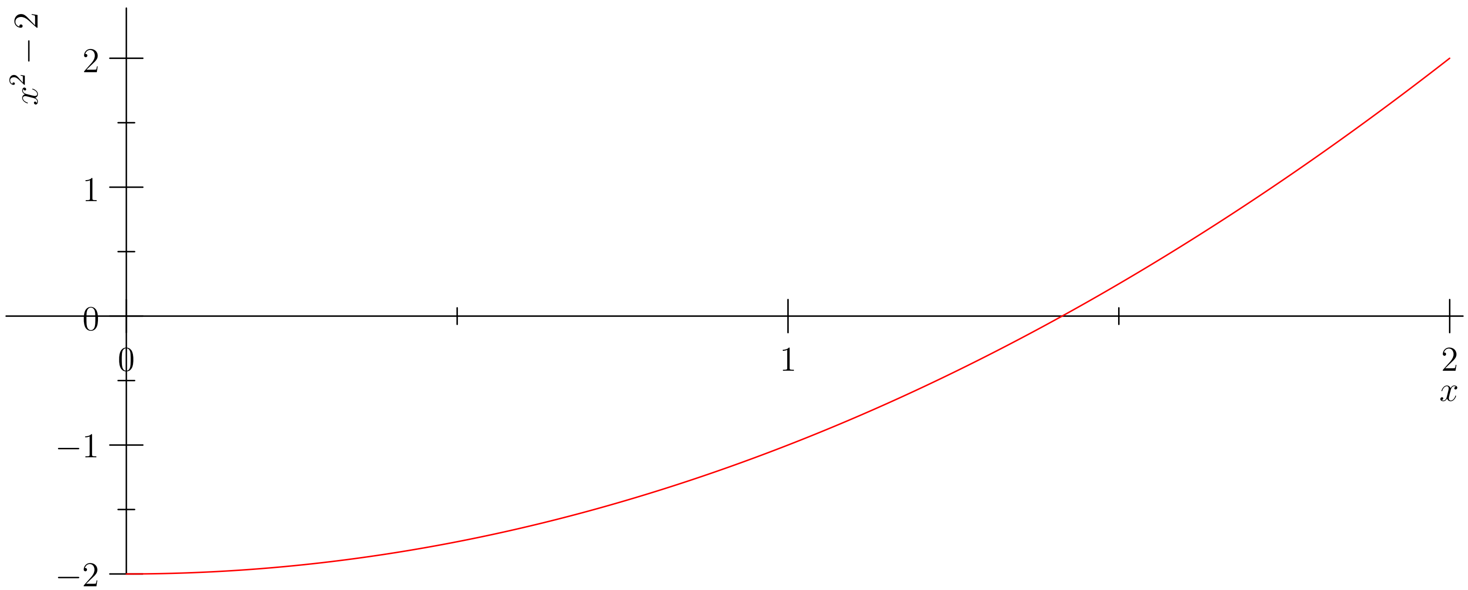

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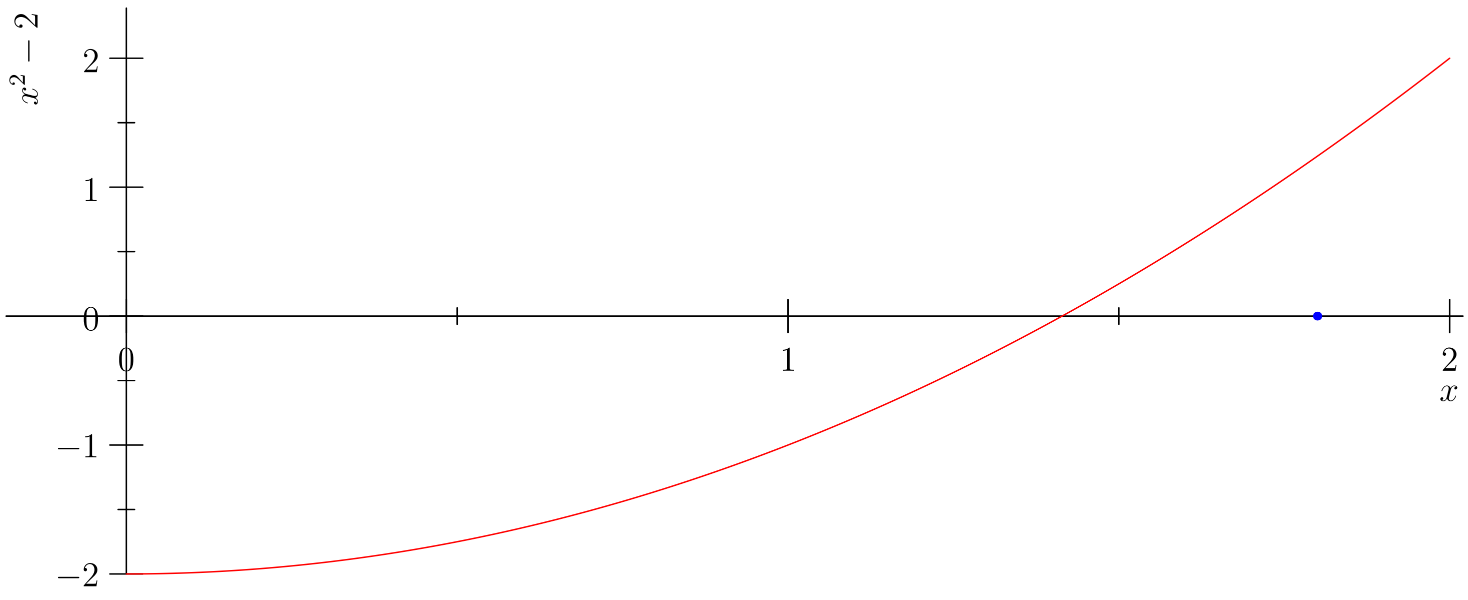

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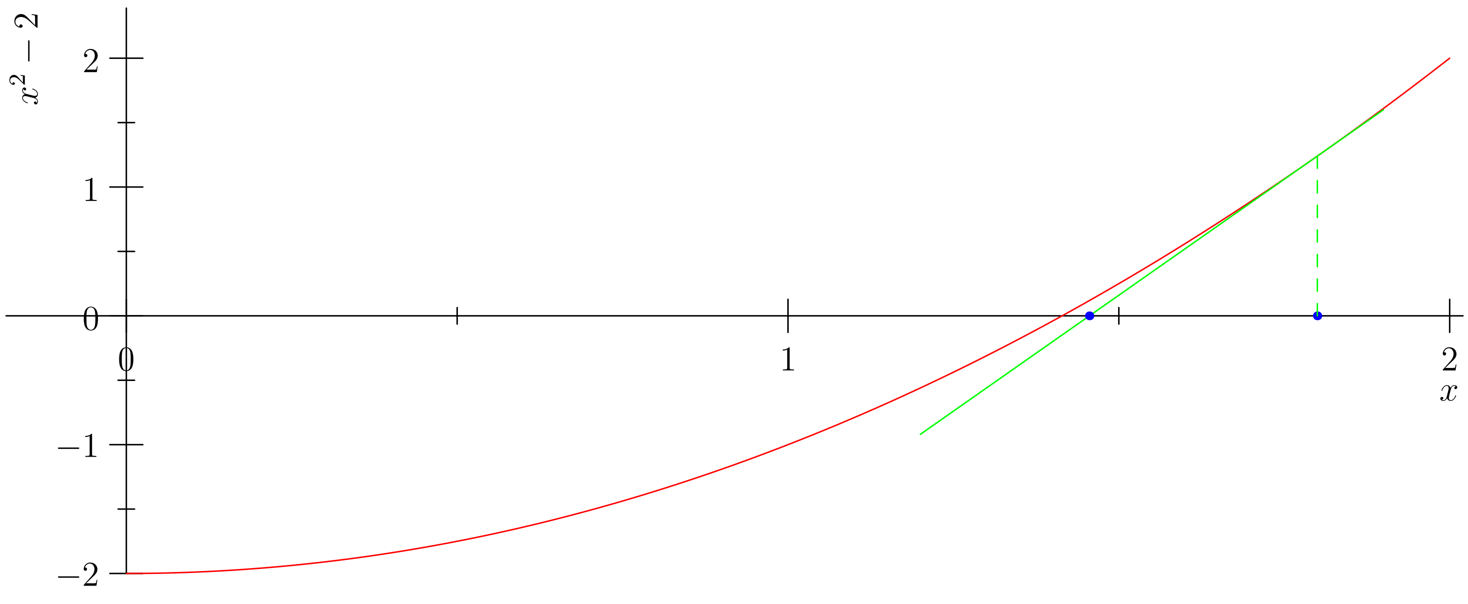

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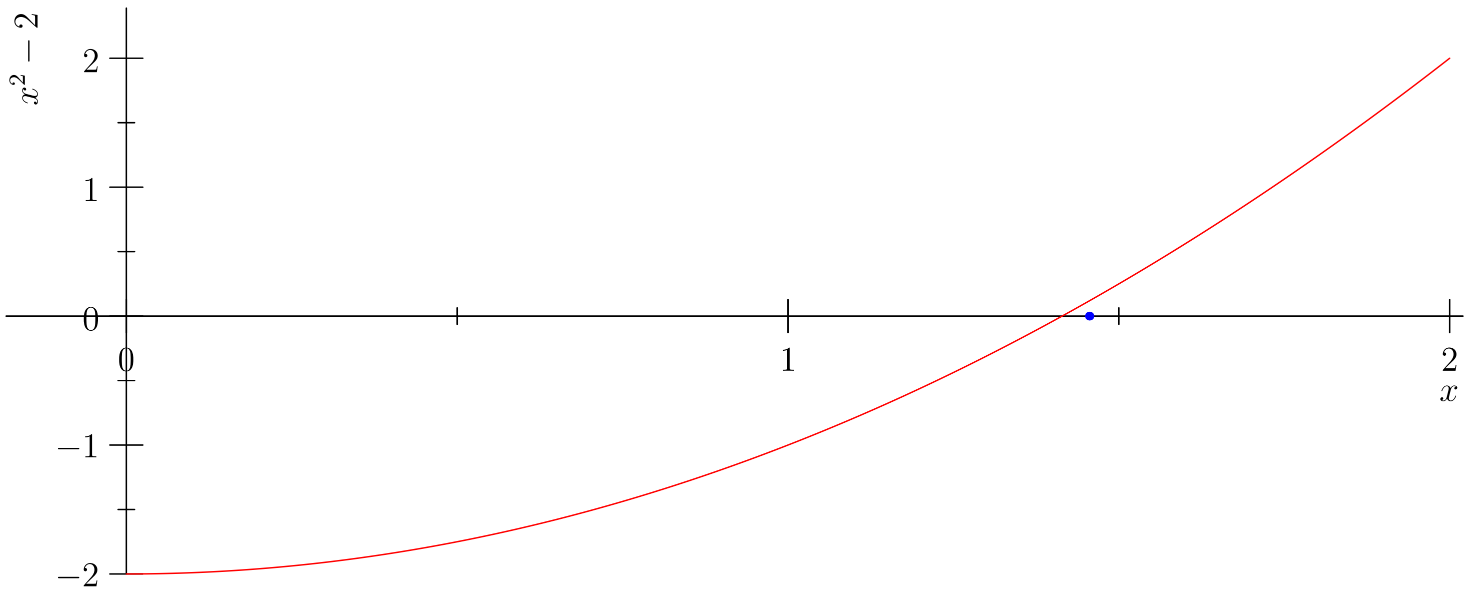

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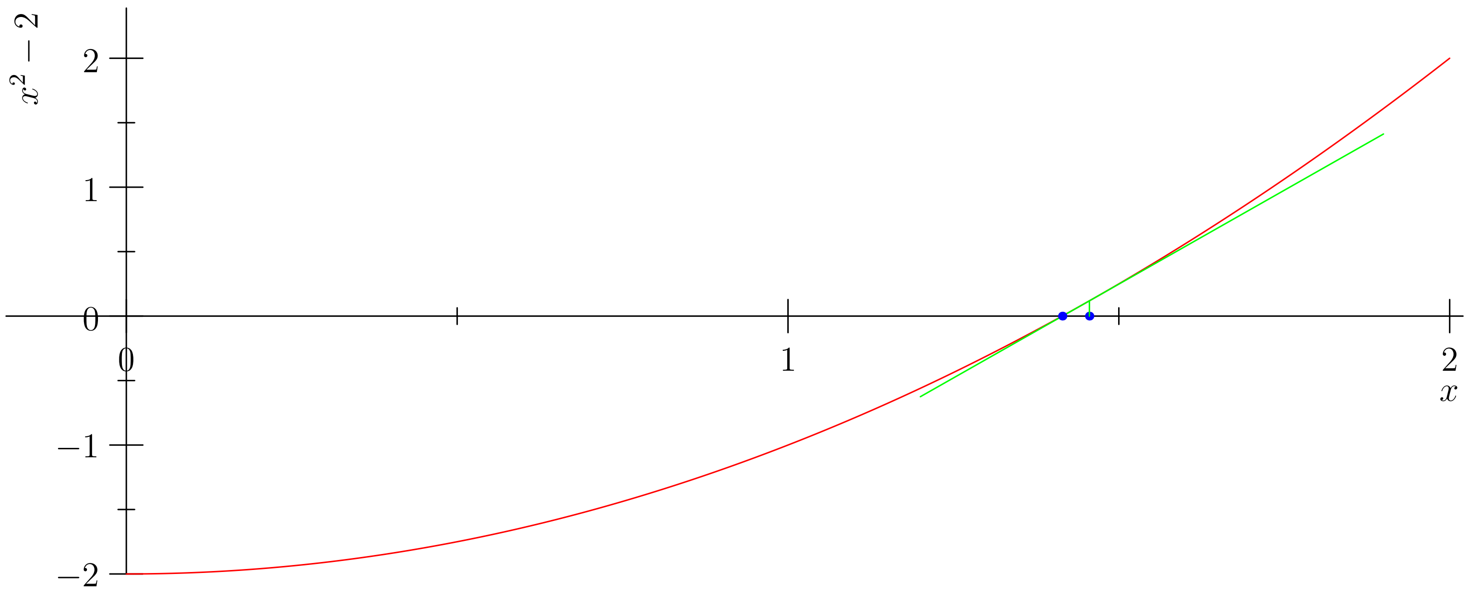

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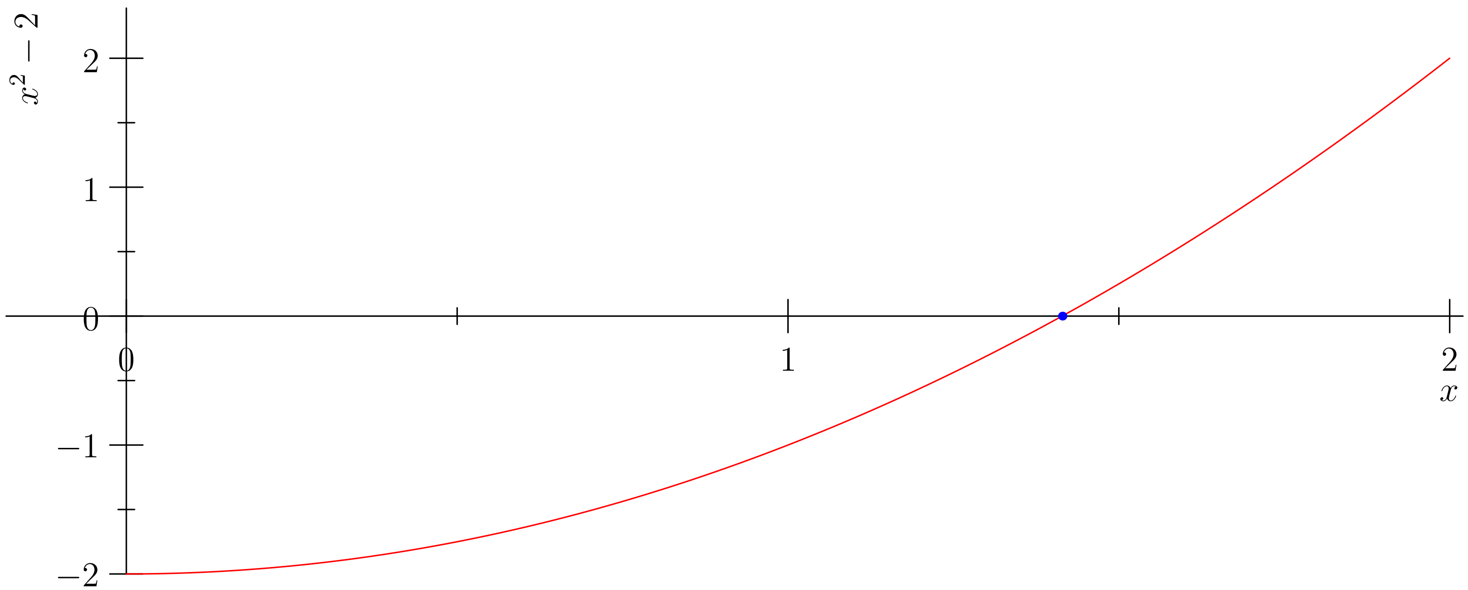

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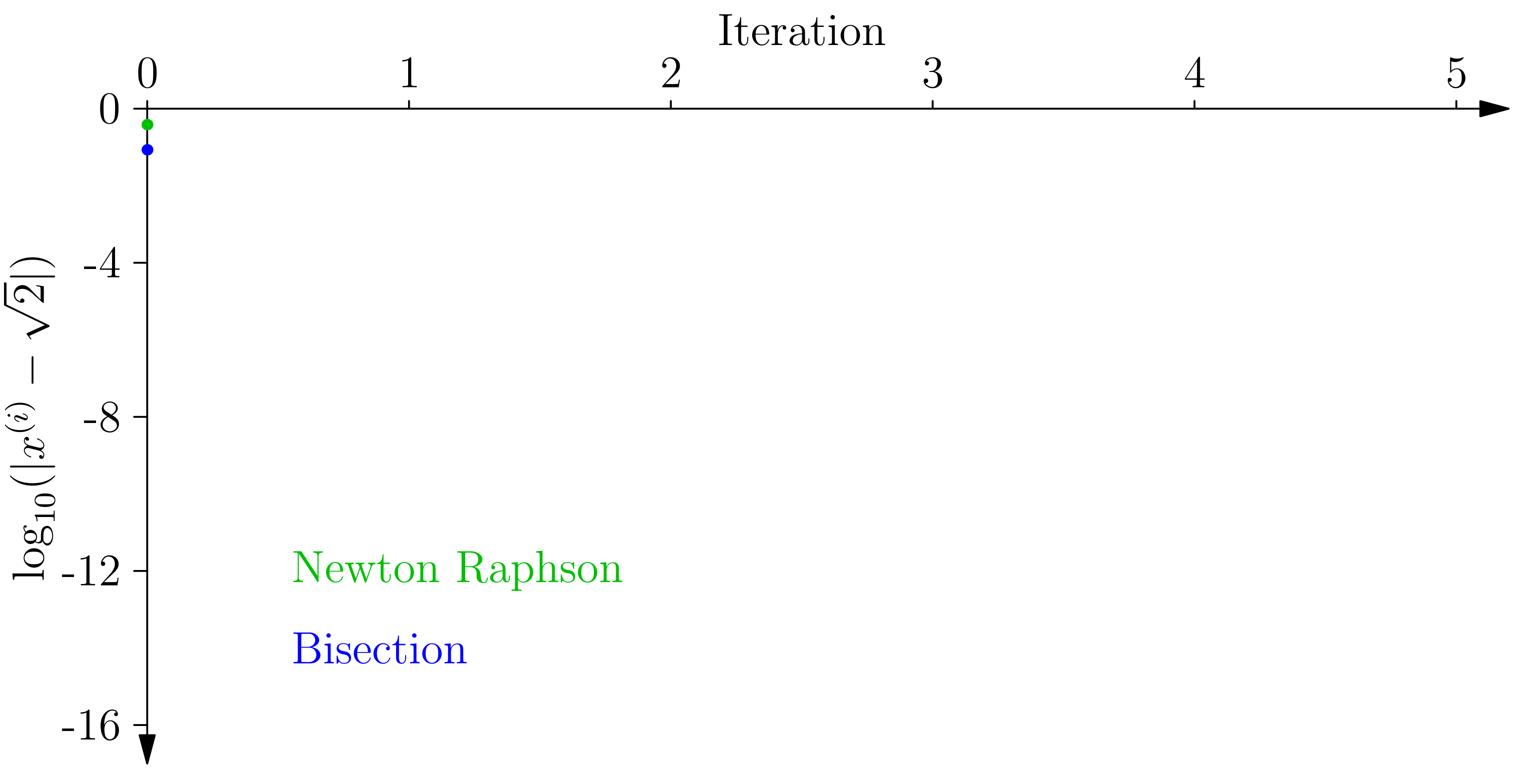

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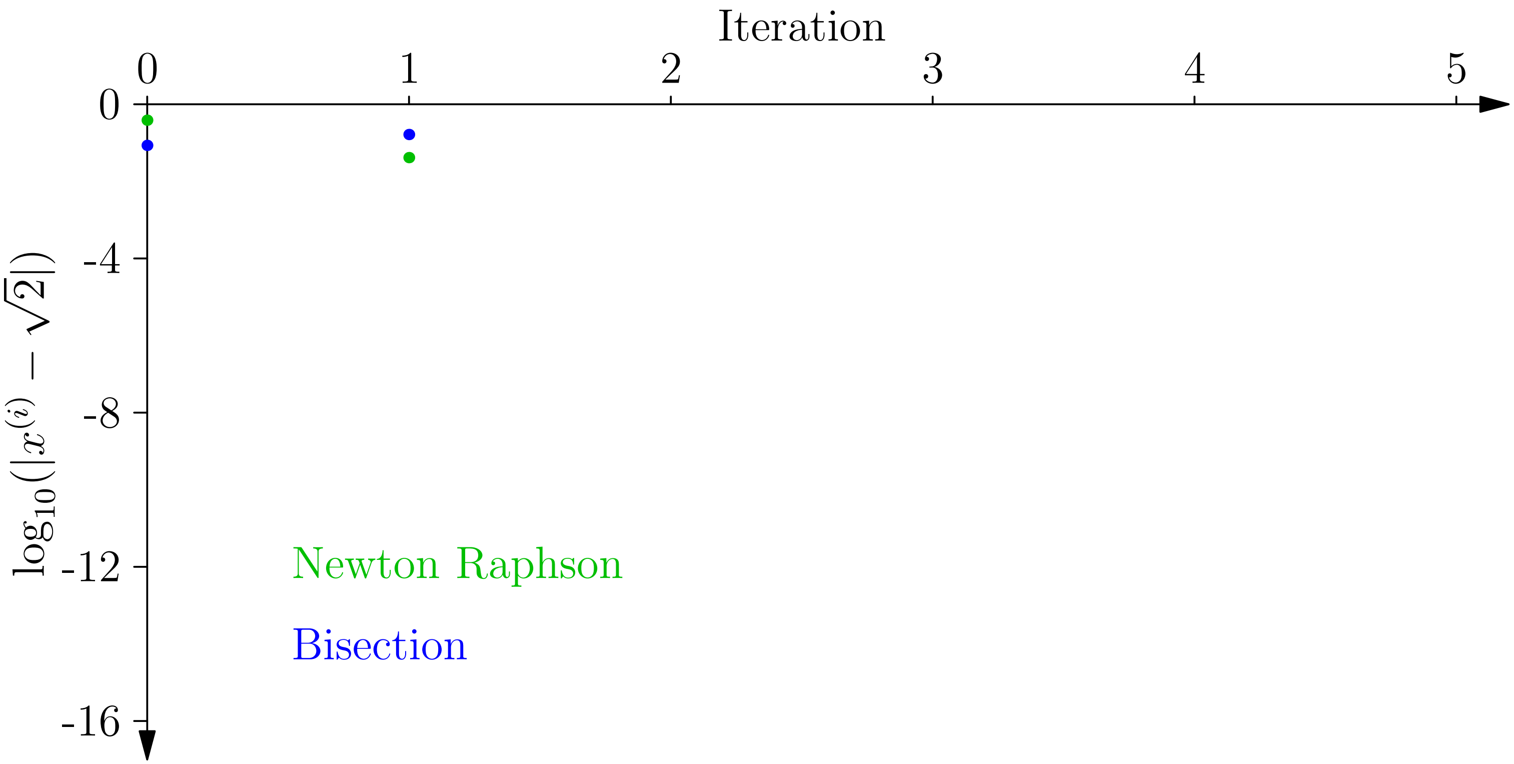

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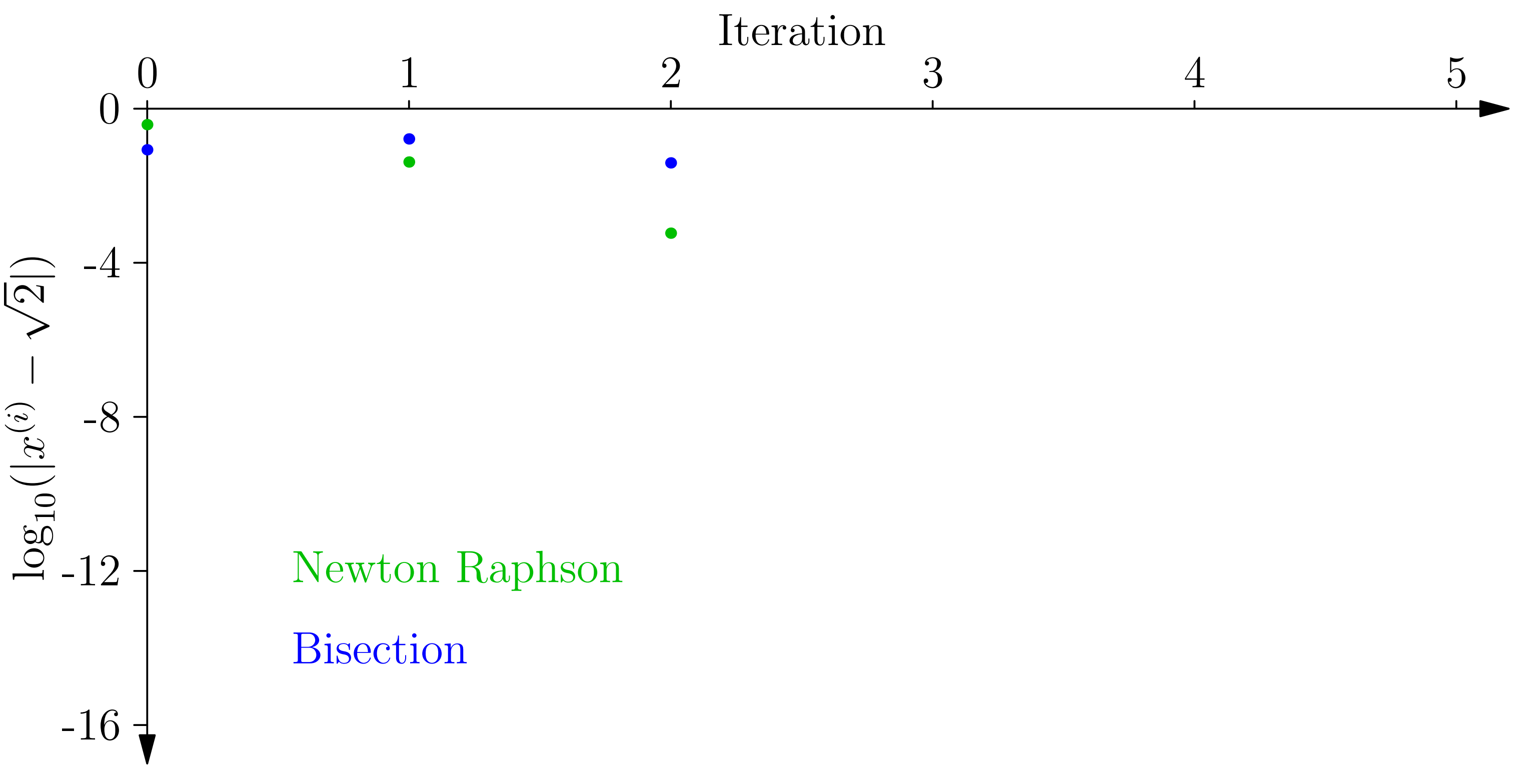

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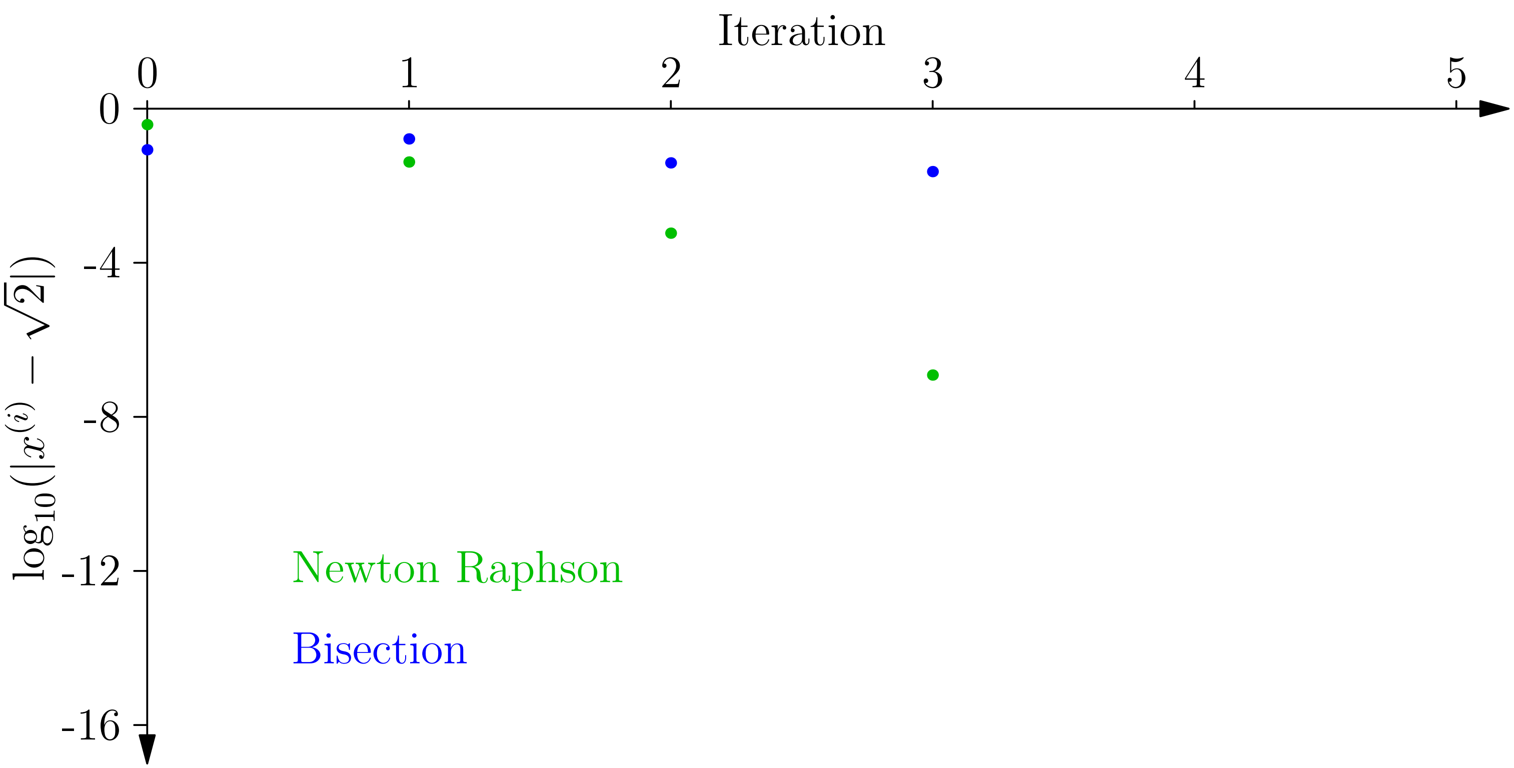

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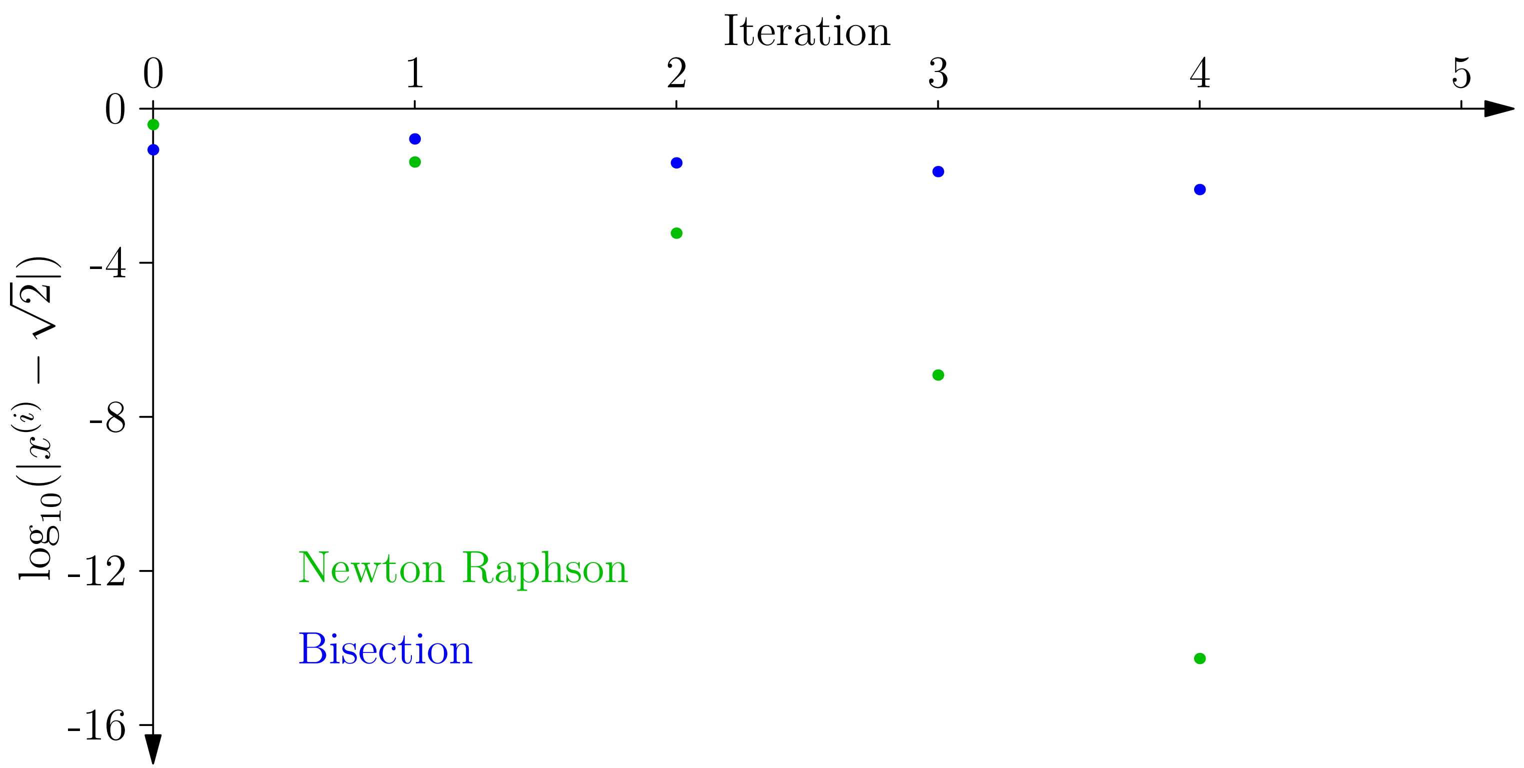

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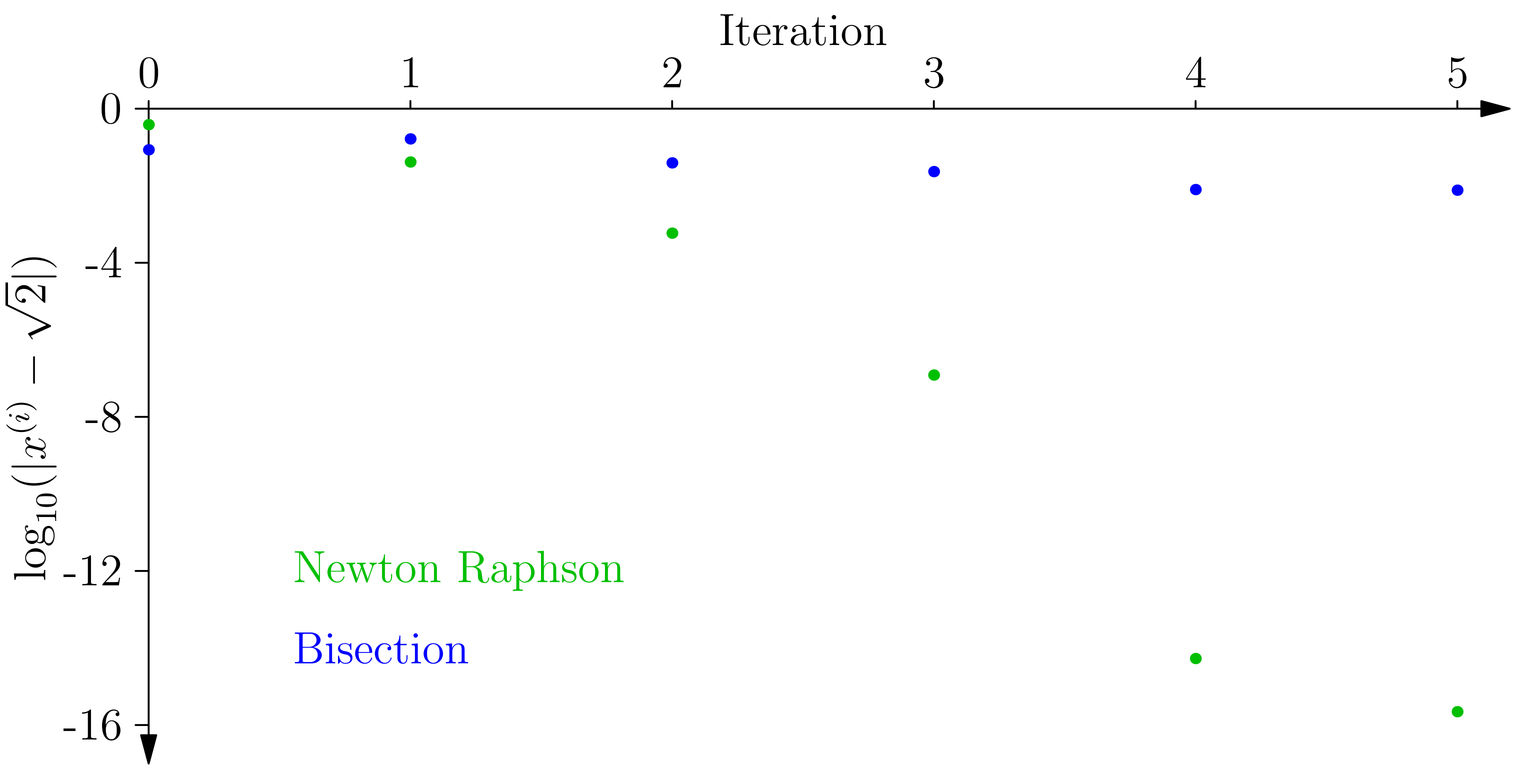

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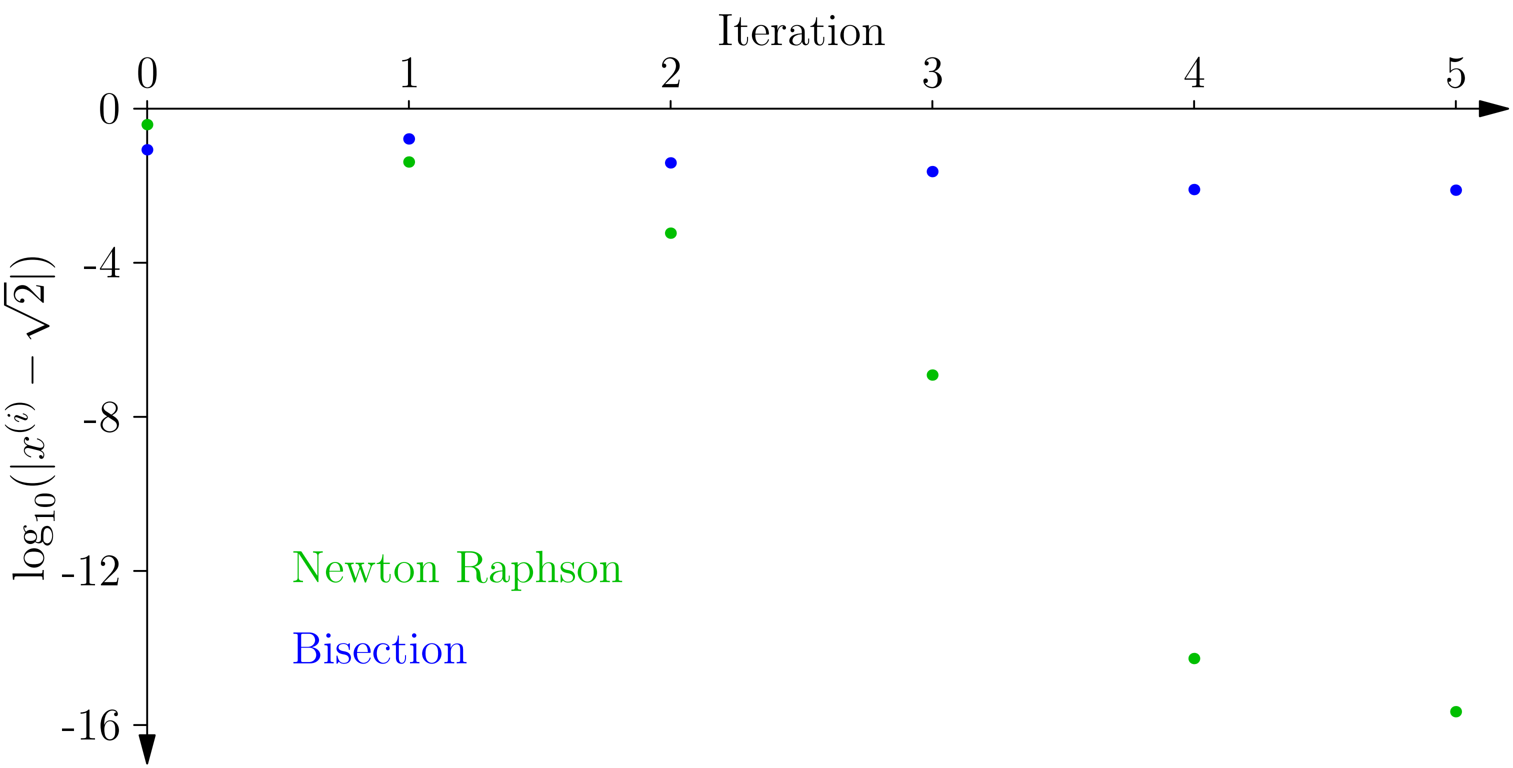

- Bisection shows linear convergence (exponential increase in accuracy)

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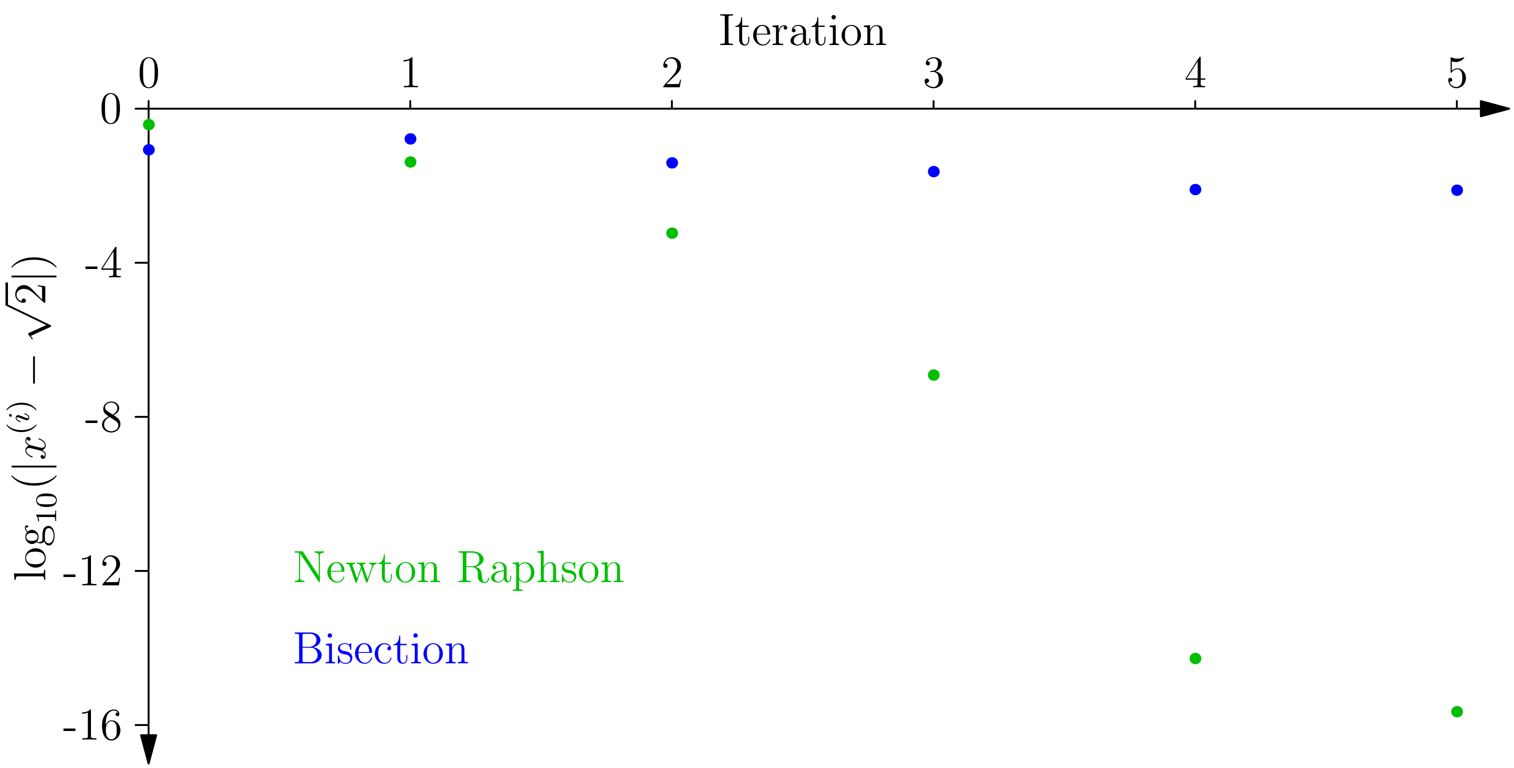

- Bisection shows linear convergence (exponential increase in accuracy)
- Newton Raphson shows quadratic convergence

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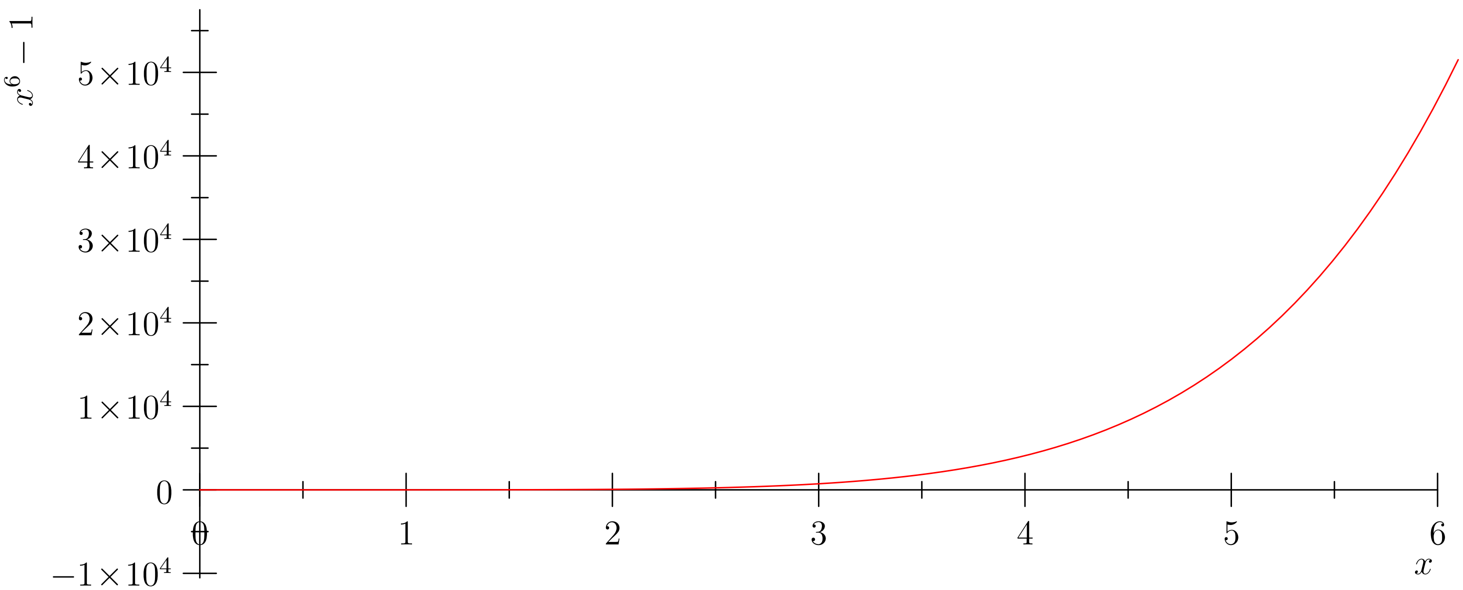
- Newton Raphson only converges quadratically if you start close enough to the solution

- Consider solving $x^6 - 1 = 0$ starting with $x^{(0)} = 0.5$



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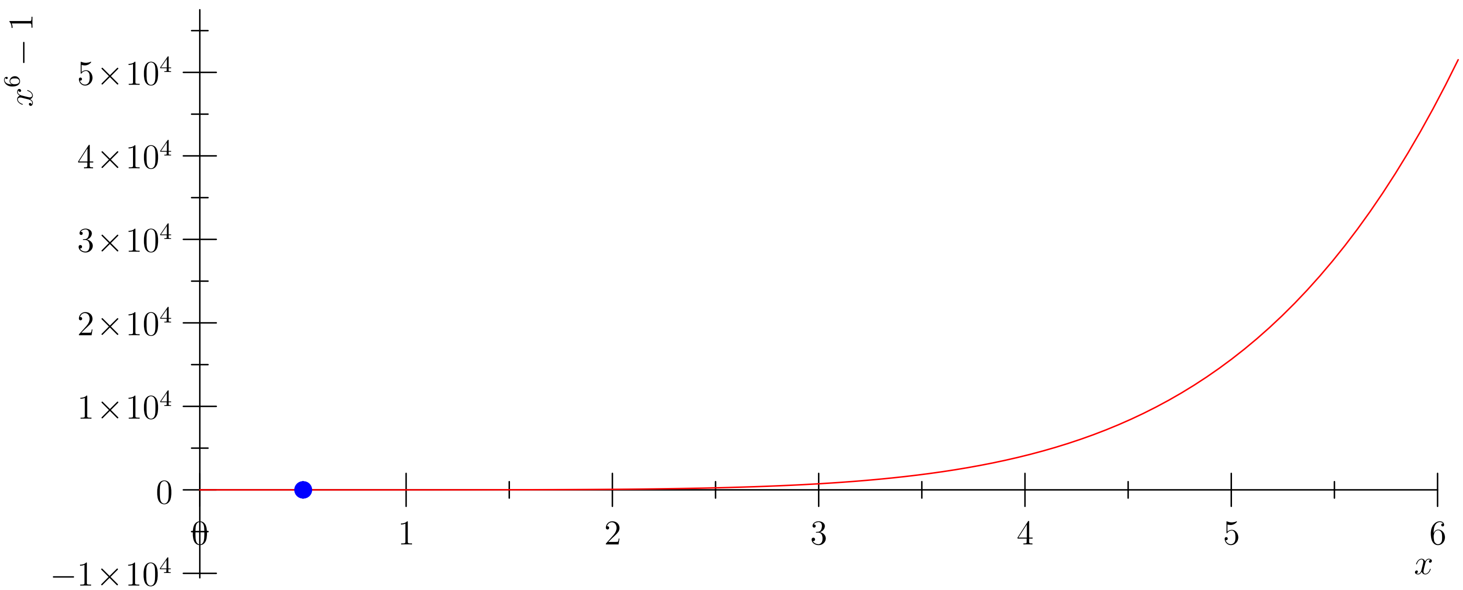

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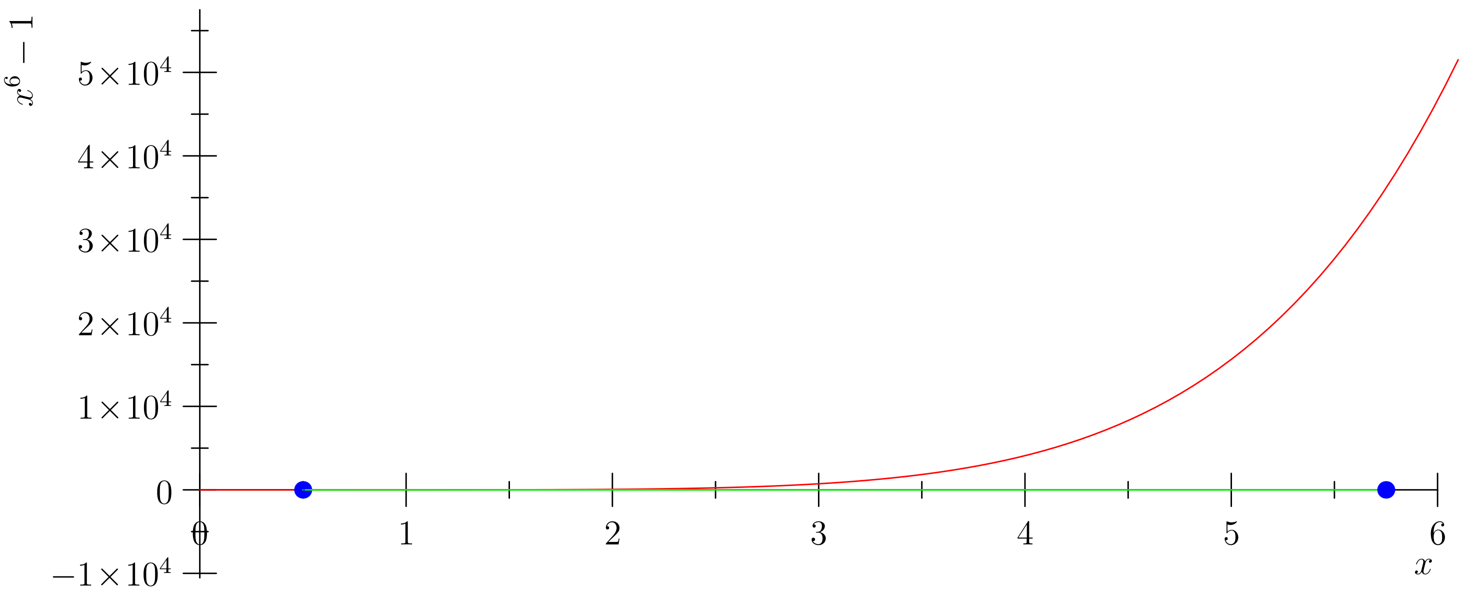

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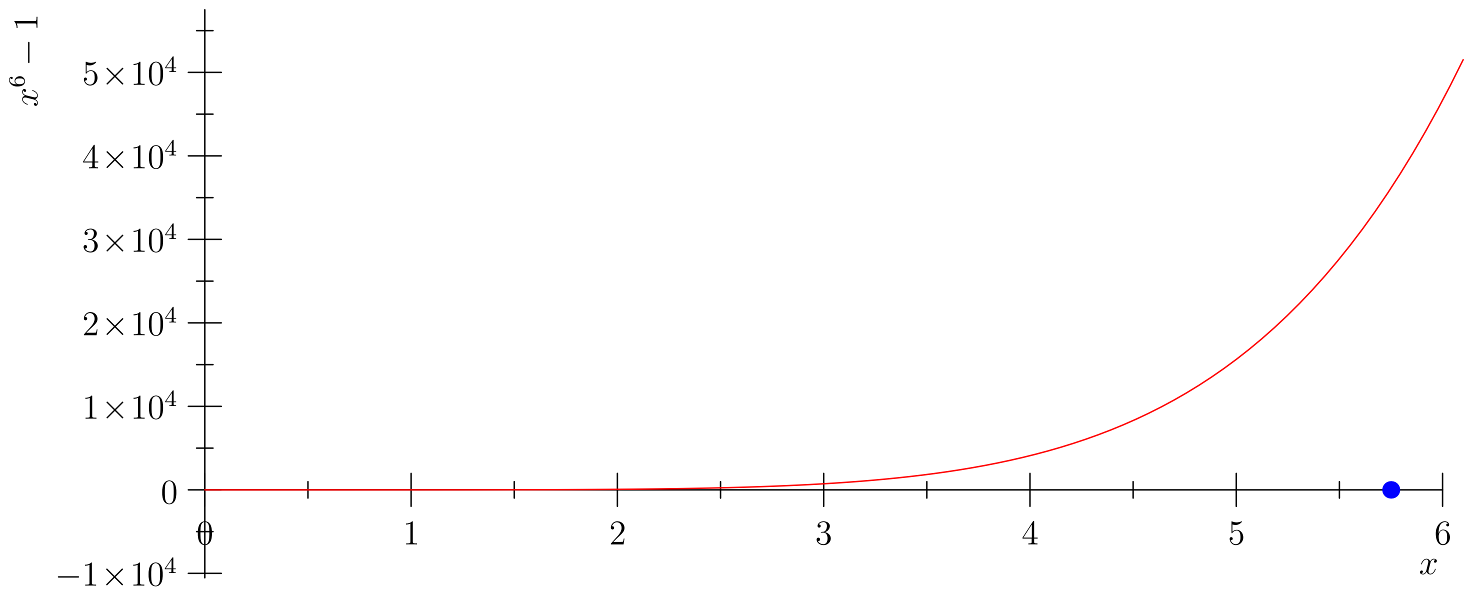

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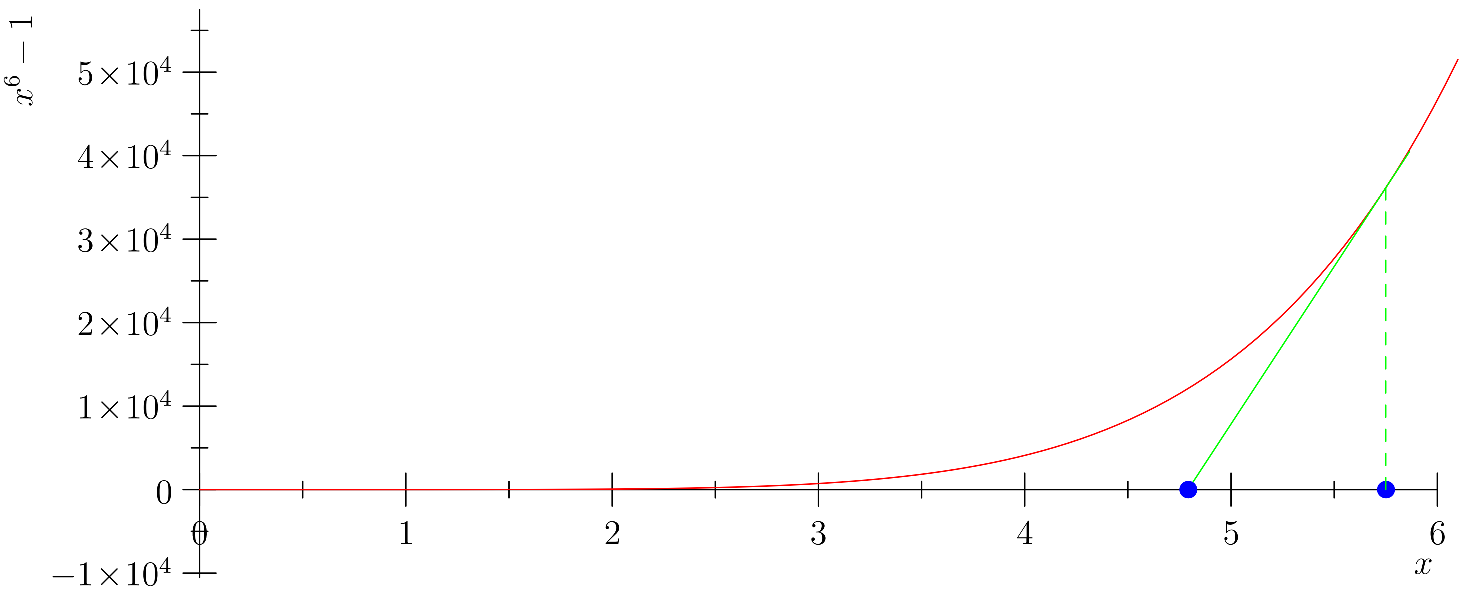

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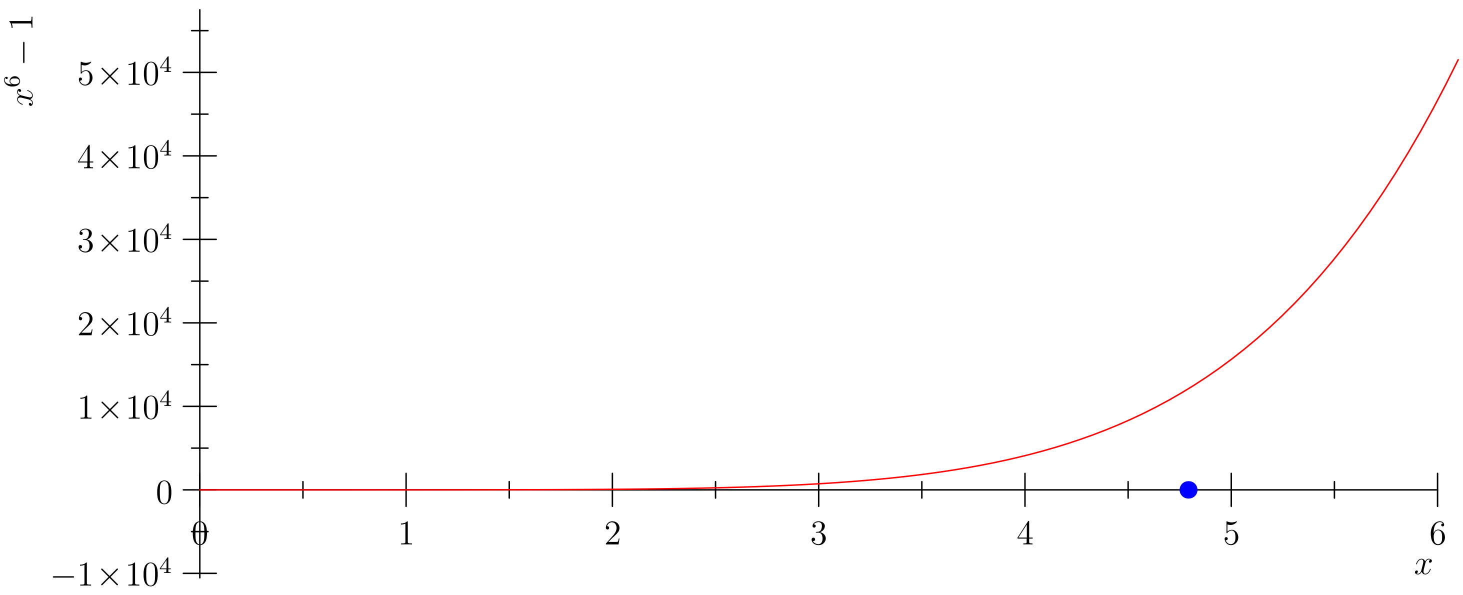

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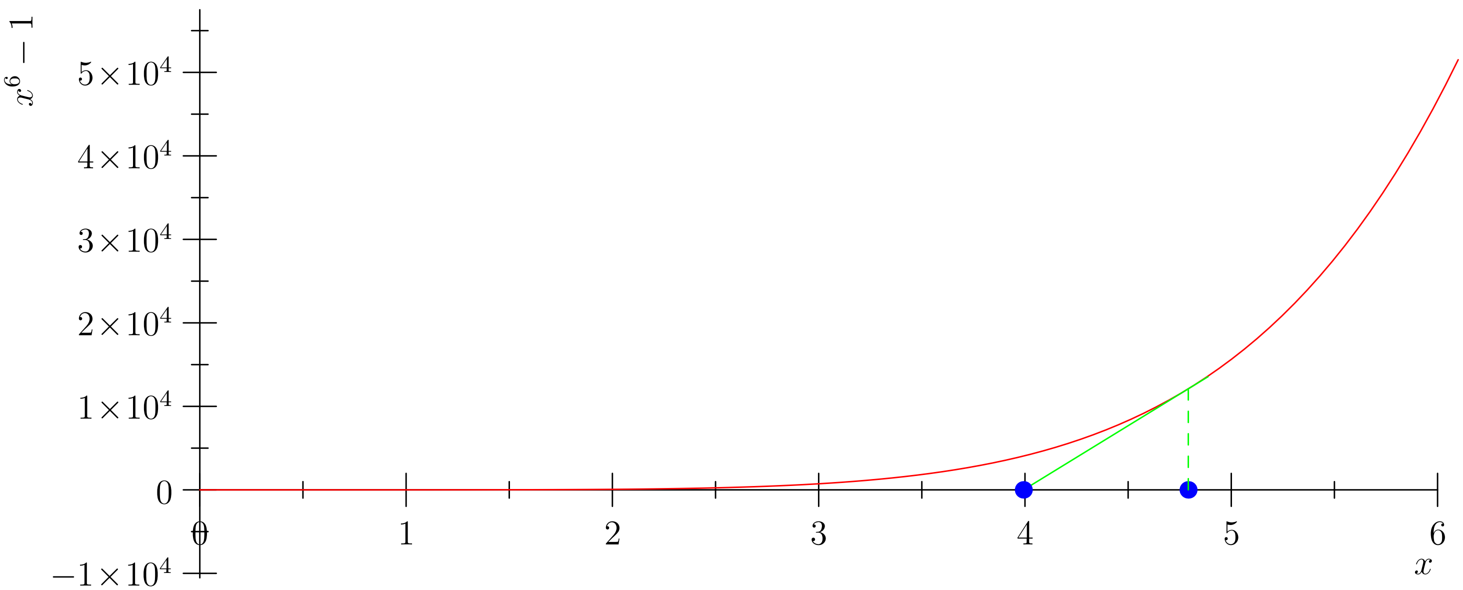

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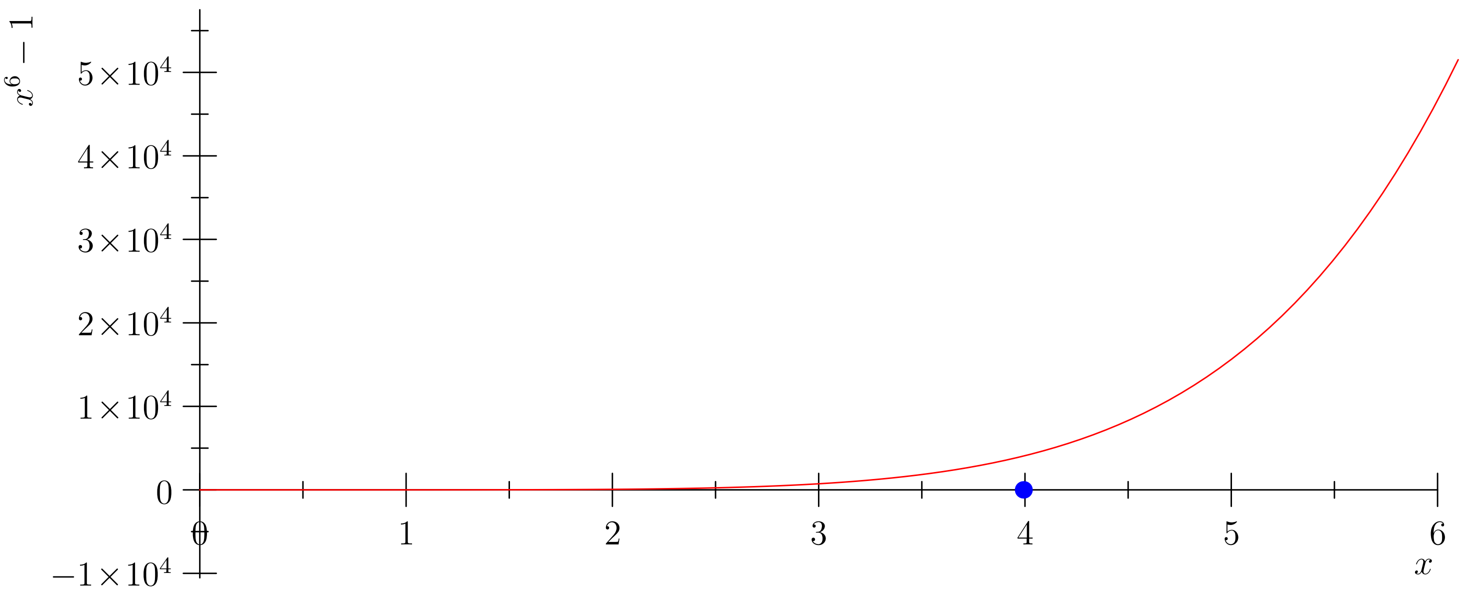

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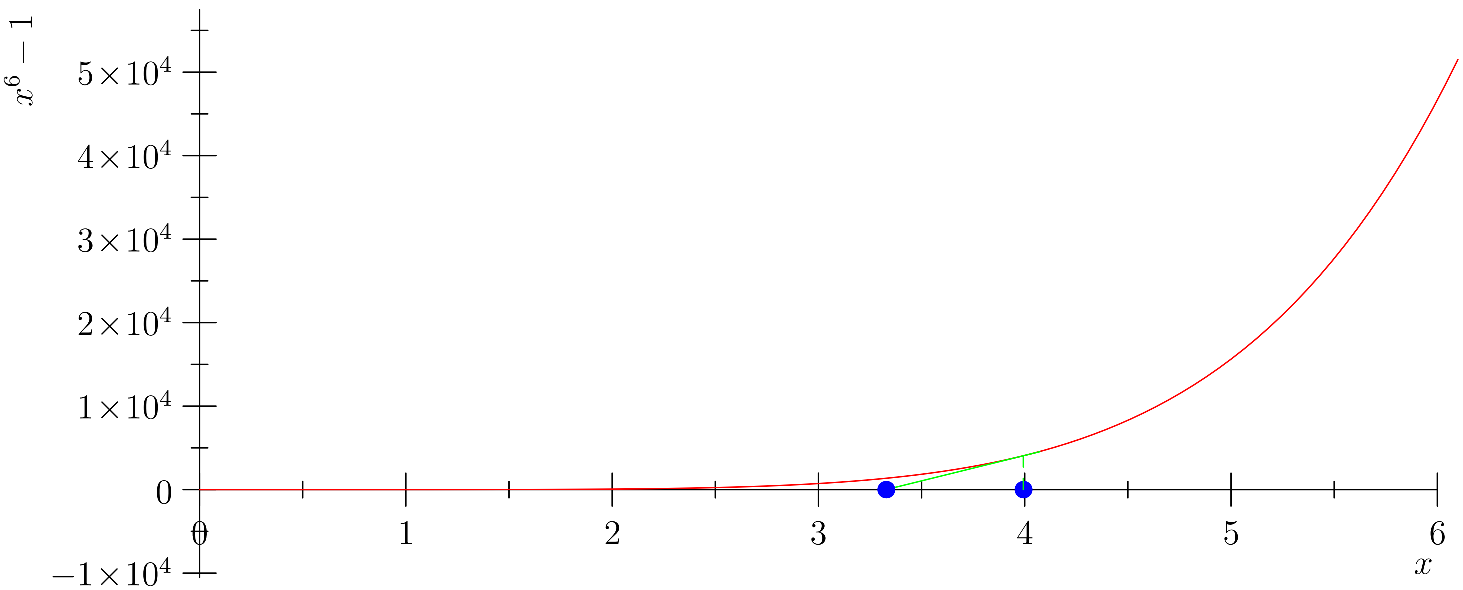

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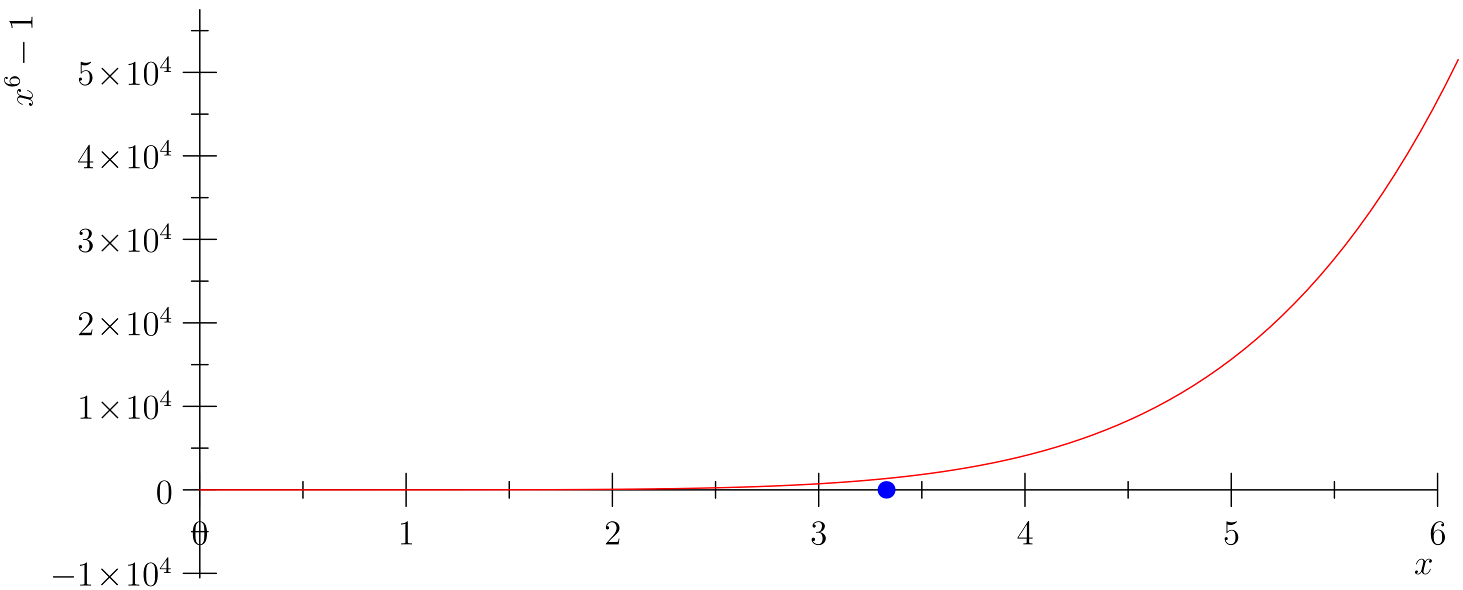

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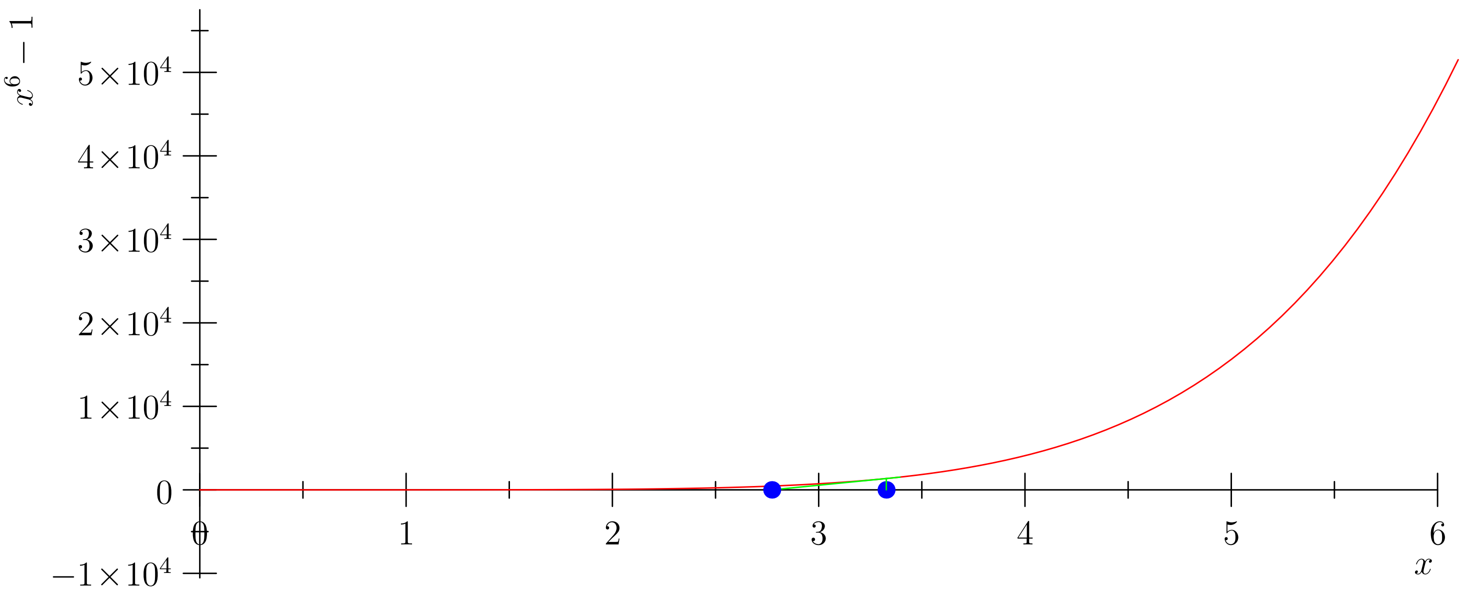

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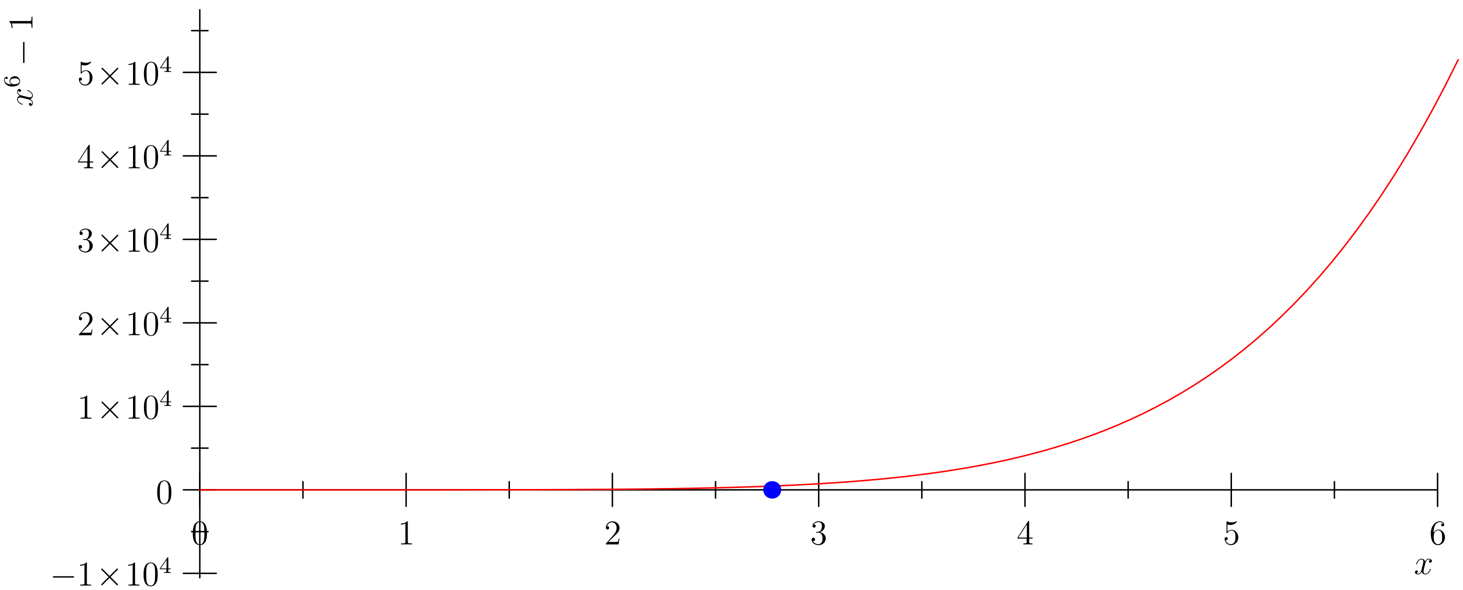

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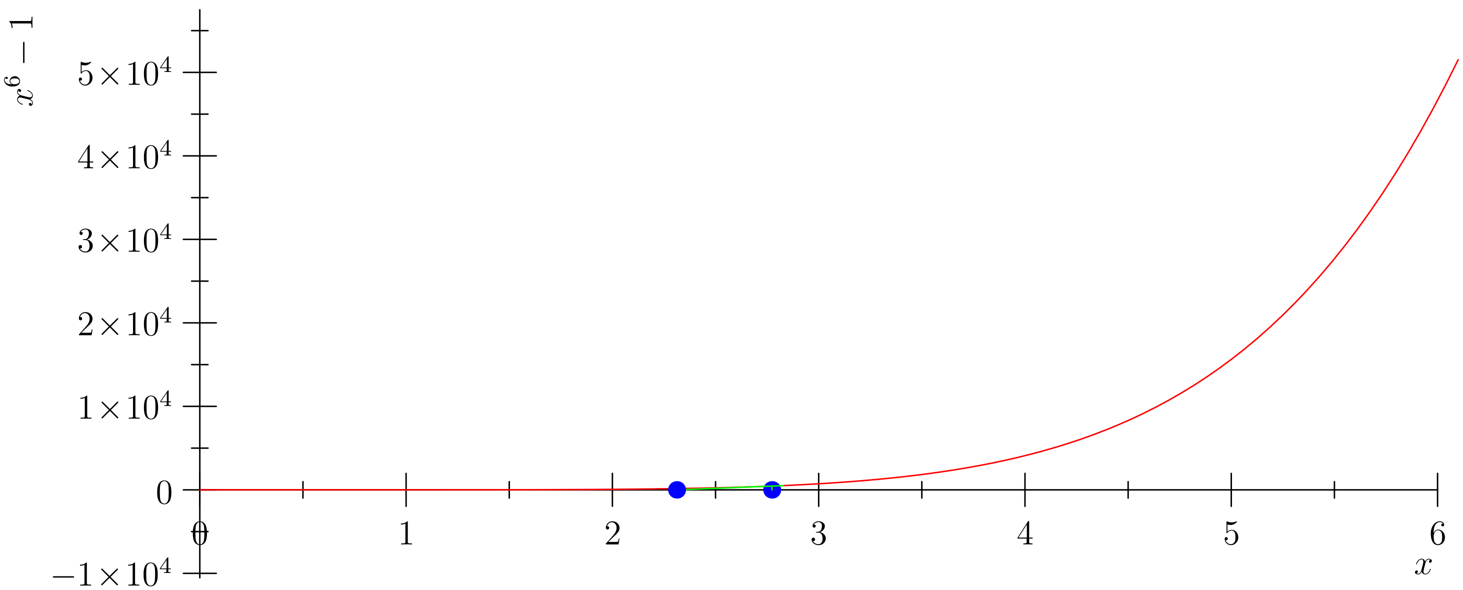

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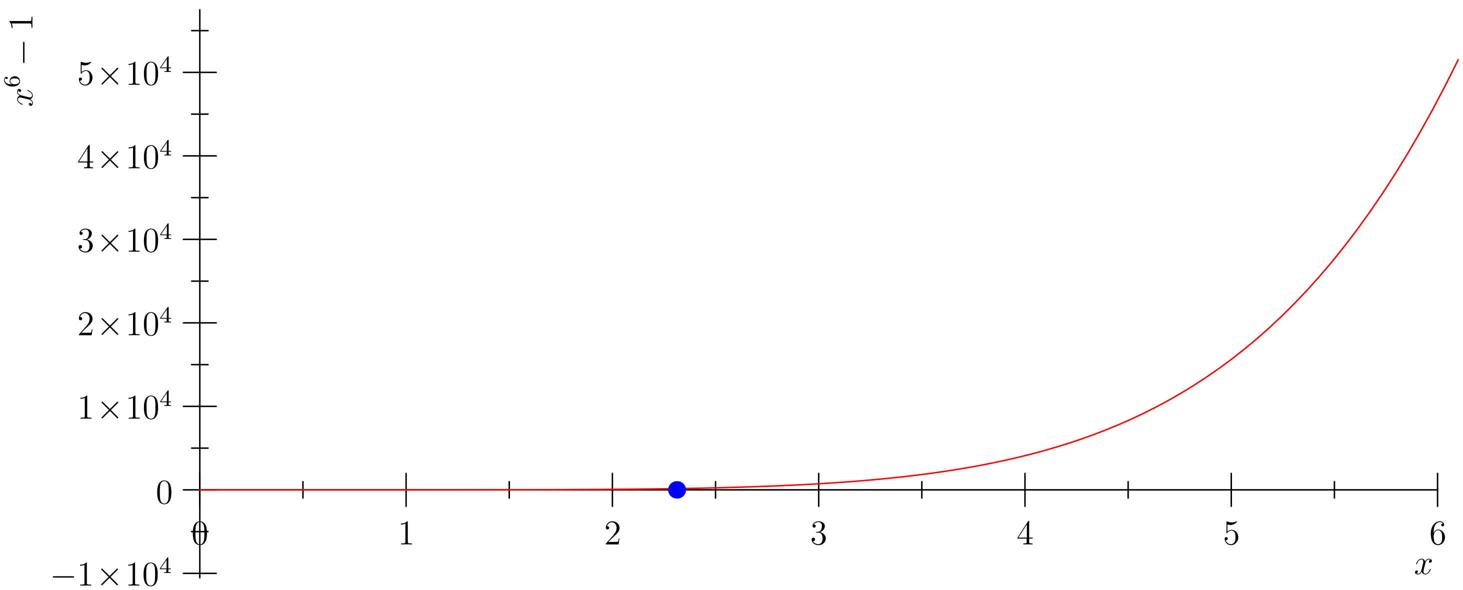

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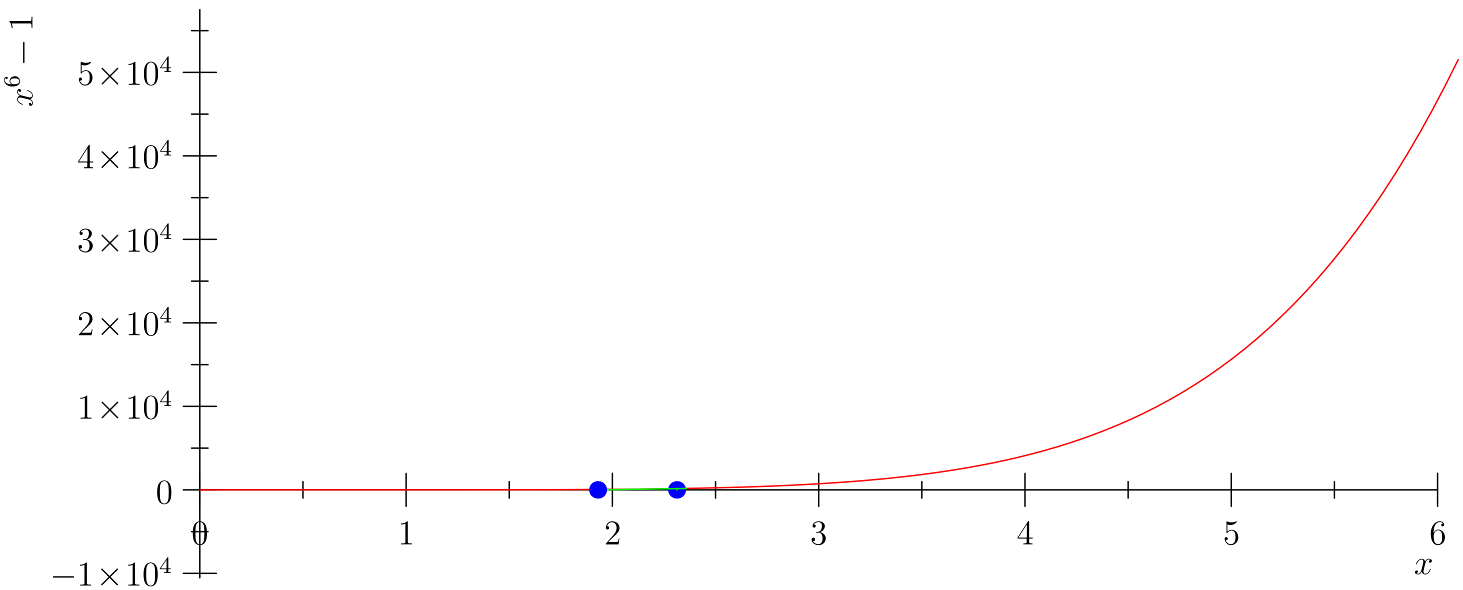

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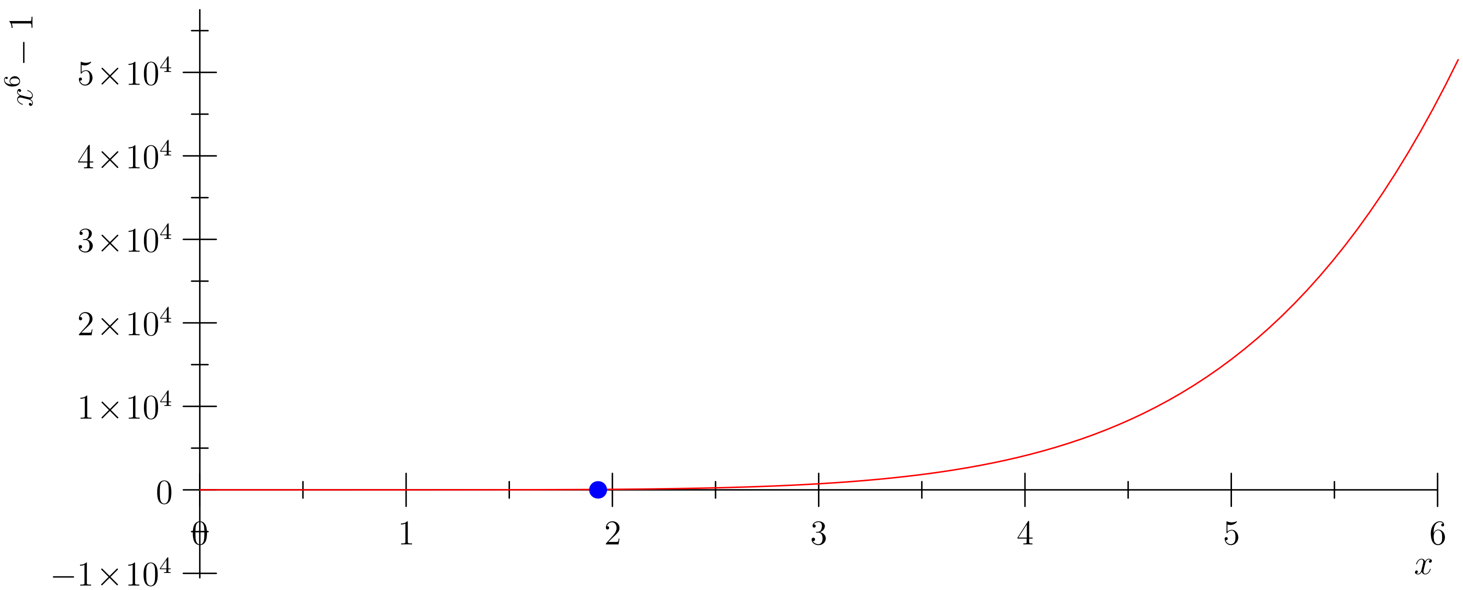

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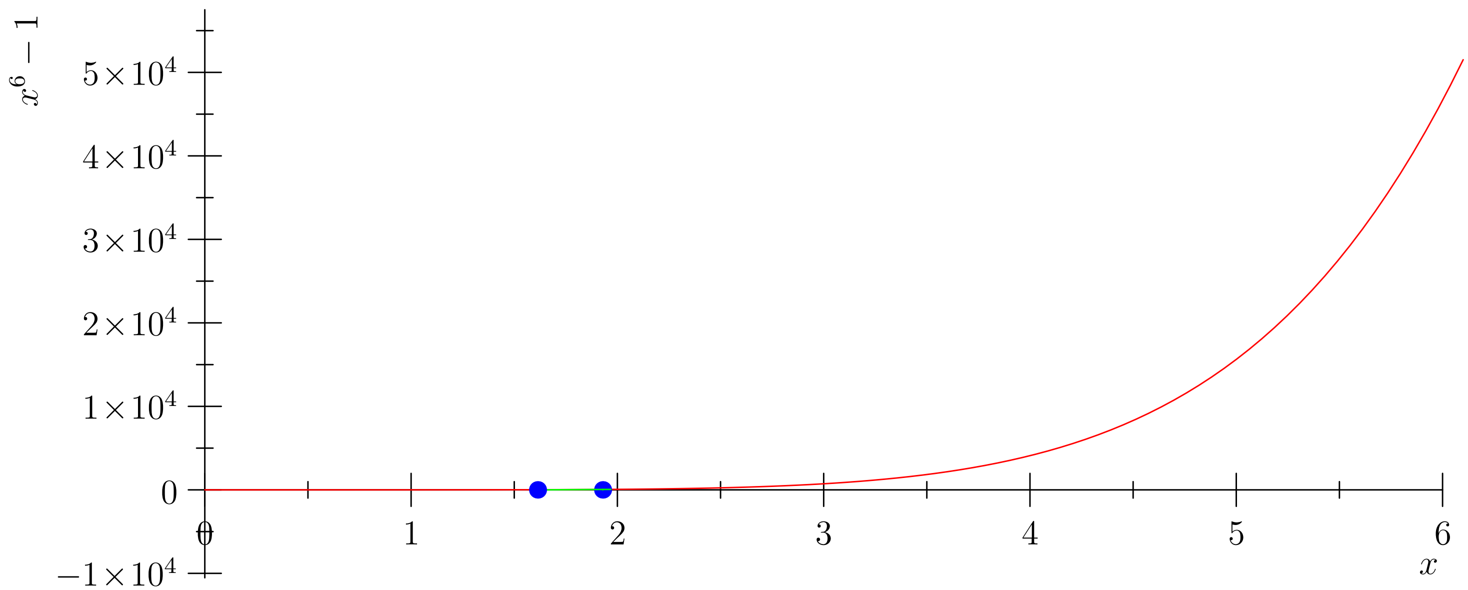

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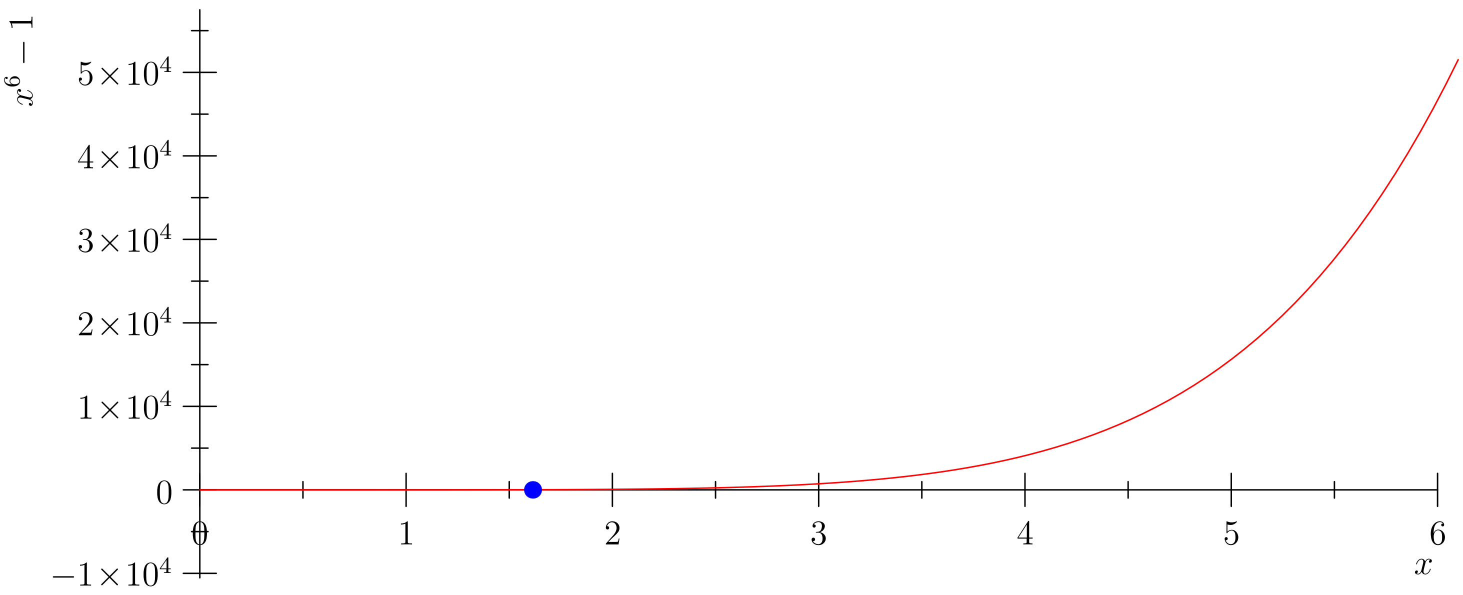

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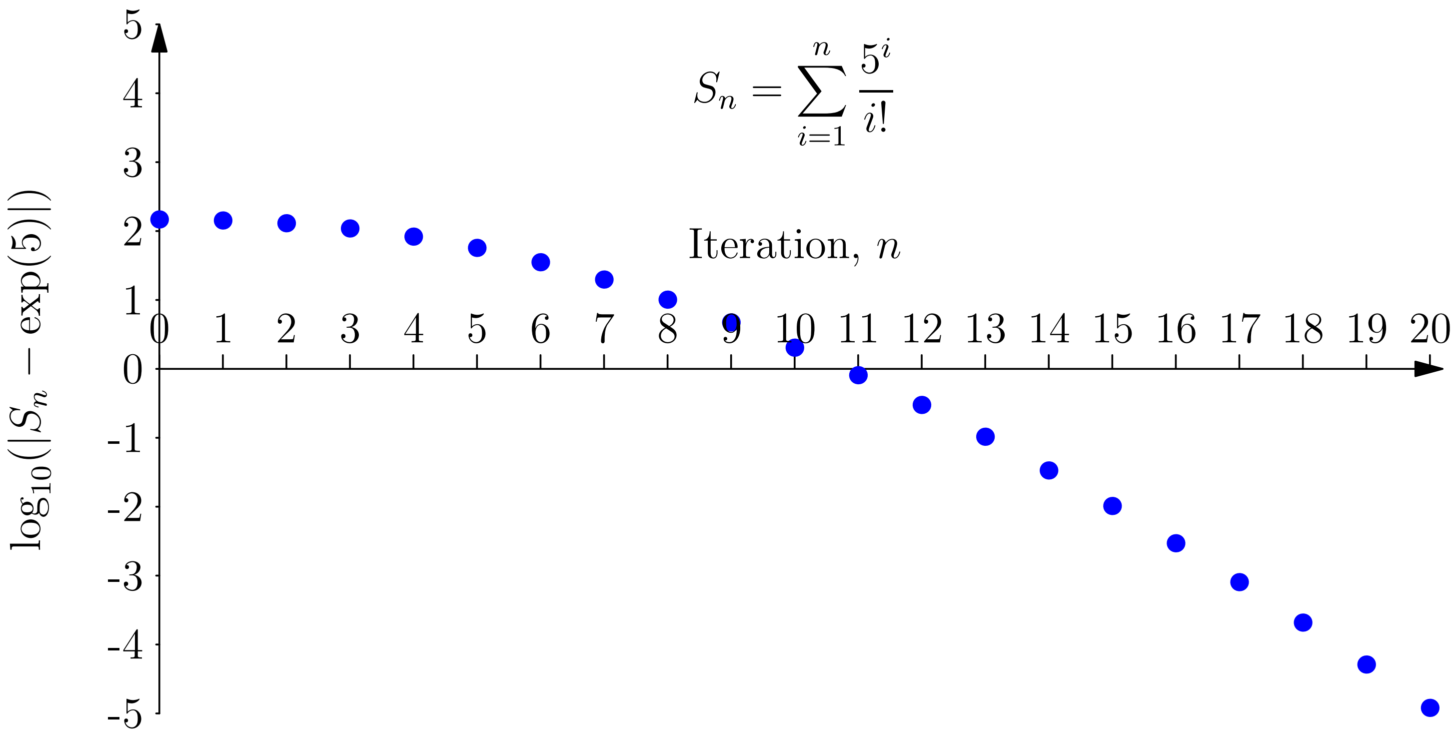

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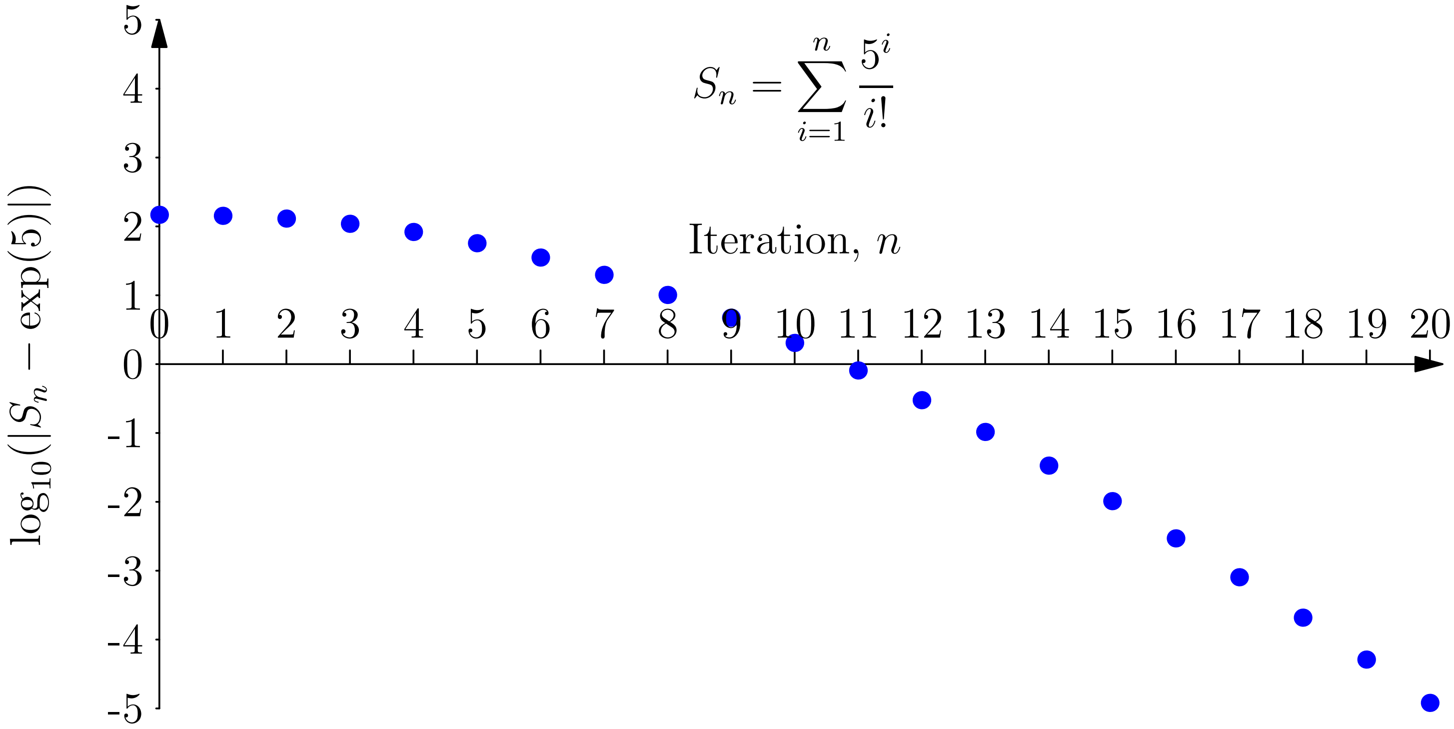

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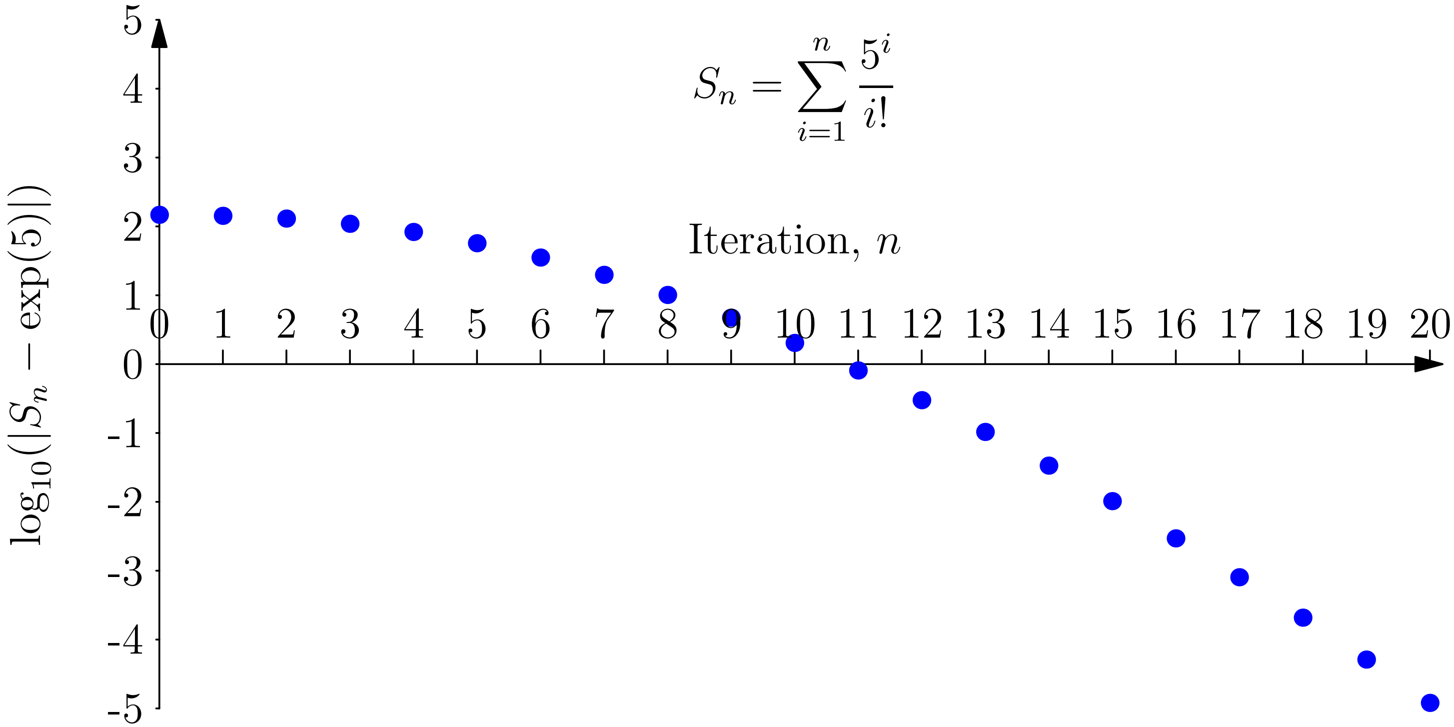

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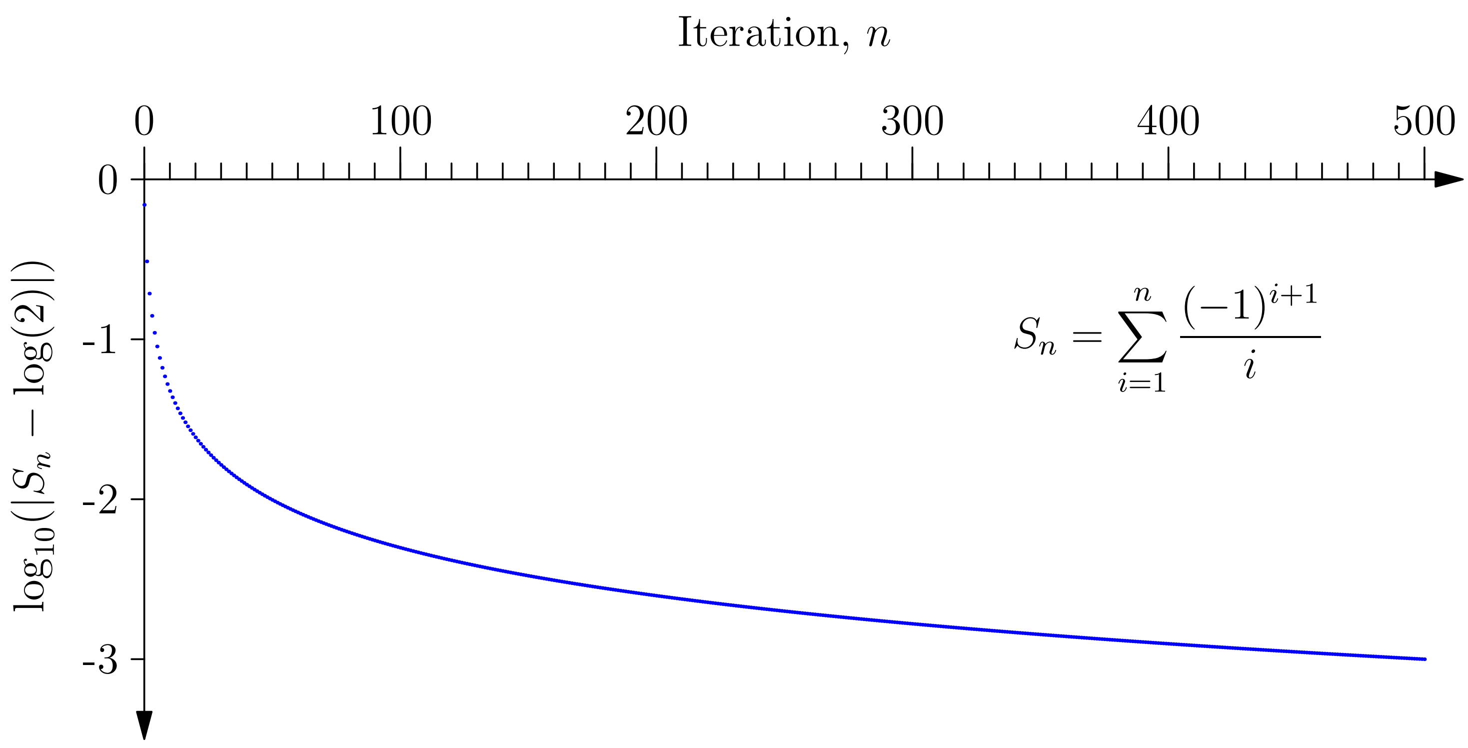
- Converges for $-1 < x \leq 1$, but converges slowly for $x = 1$



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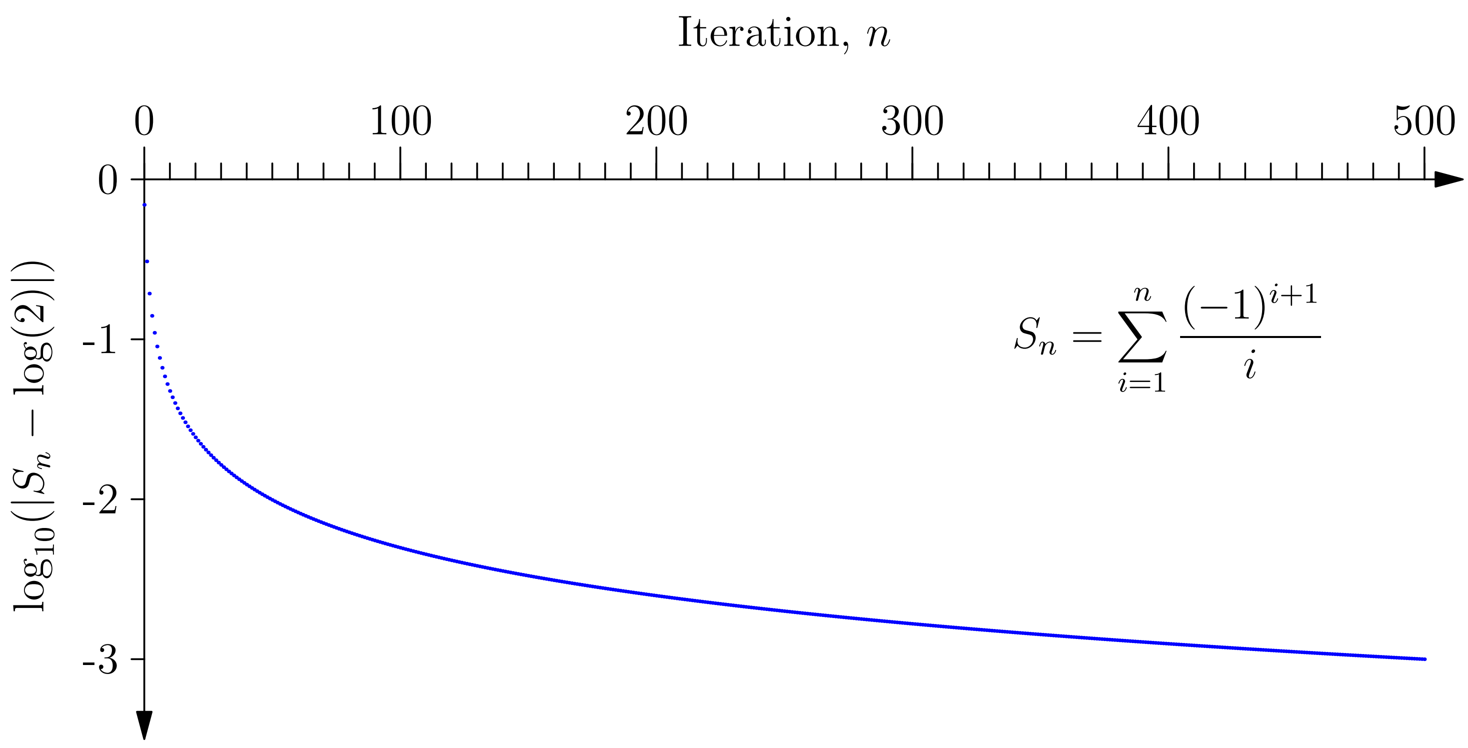

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- We want the truncation error to be around machine accuracy
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- Many functions can be approximated by a sum
- We get a truncation error by taking only a finite number of elements
- We want the truncation error to be around machine accuracy
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Differential Equations

- Differential equations are used in many applications, for example in modelling the motion of object
- A typical equation of motion might be

$$\frac{\mathrm{d}^2 x(t)}{\mathrm{d}t^2} = 2\,\frac{\mathrm{d}x(t)}{\mathrm{d}t} + 3\,x(t)$$

- Which has a general solution $x(t) = c_1 \mathrm{e}^{-t} + c_2 \mathrm{e}^{3\,t}$
- The constants are determined by initial conditions, for example, if $x(0) = 1$ and $\dot{x}(0) = -1$ then $x(t) = \mathrm{e}^{-t}$

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Euler's Method

- To solve a differential equation we use an approximate update equation

$$x(t + \epsilon) \approx x(t) + \epsilon \dot{x}(t)$$
$$\dot{x}(t + \epsilon) \approx \dot{x}(t) + \epsilon \ddot{x}(t)$$

- This becomes more exact as $\epsilon \to 0$

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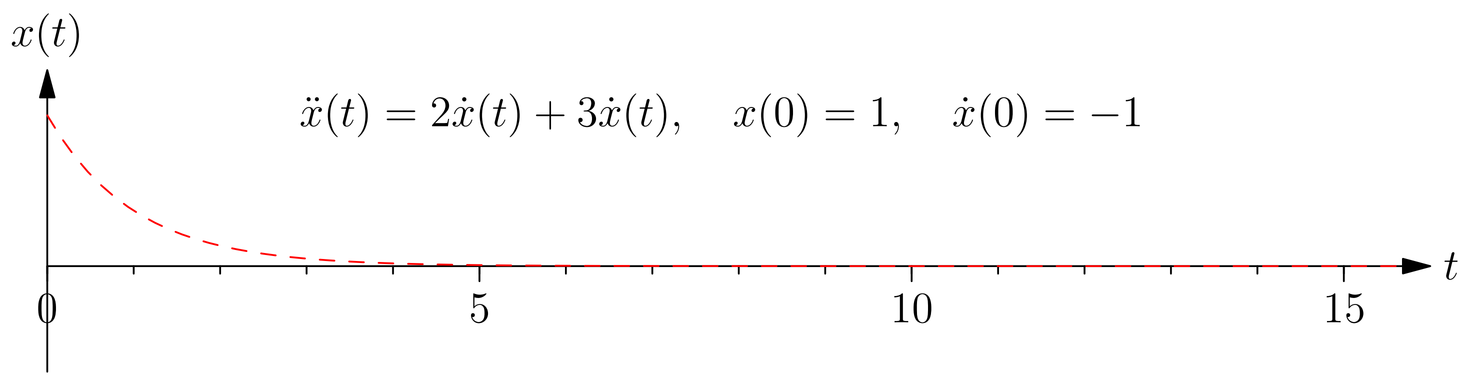

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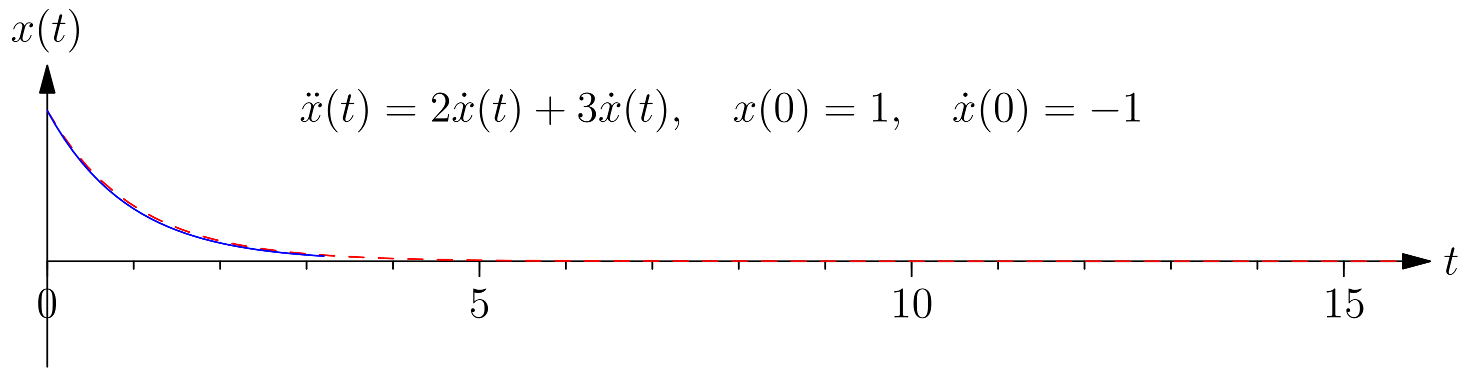

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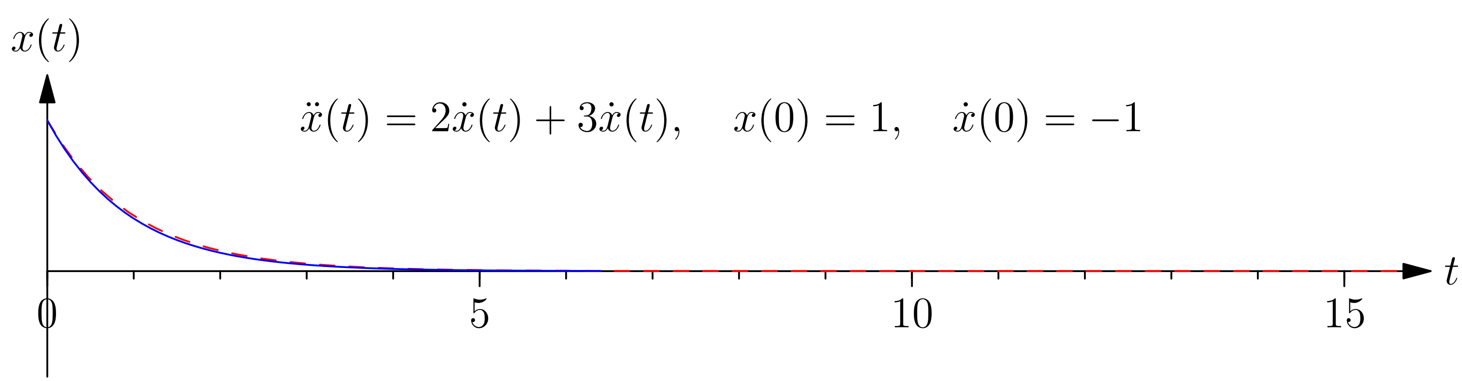

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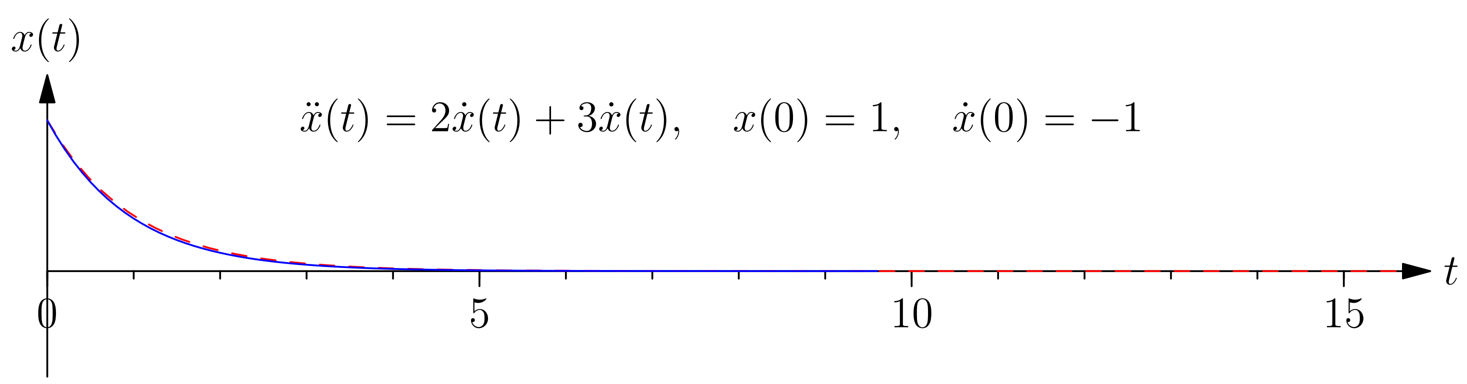

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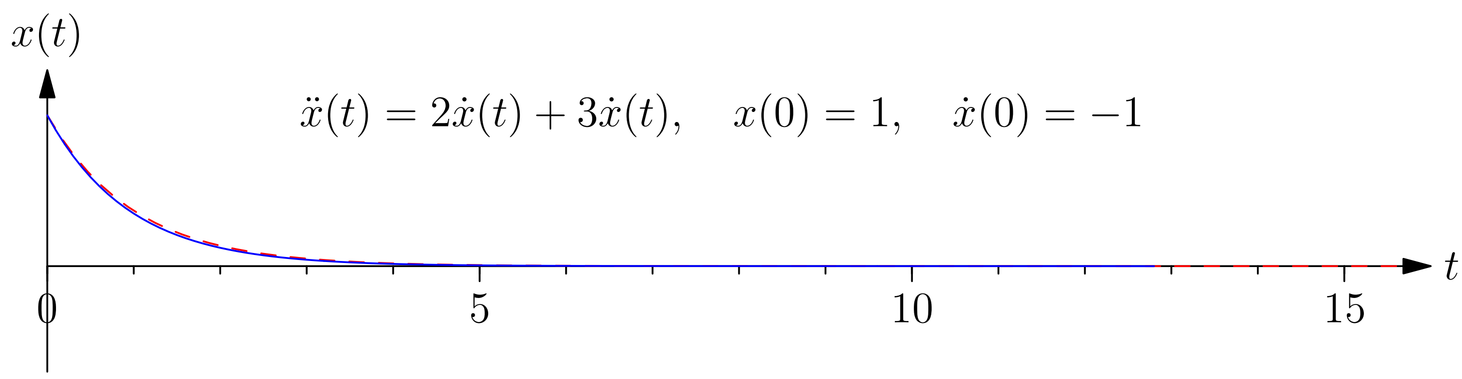

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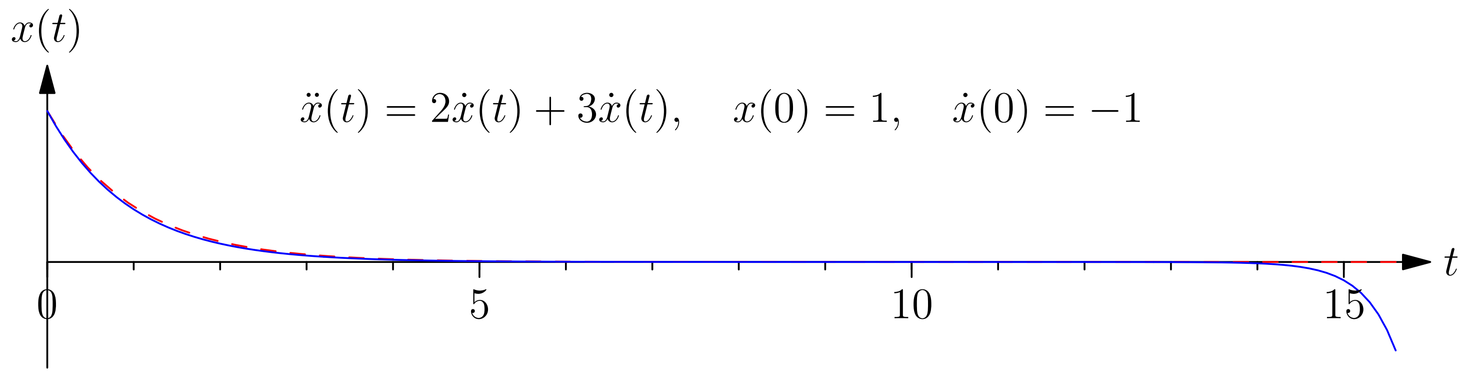

Stability

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- Finding stable algorithms and avoiding unstable algorithms can be key to getting accurate predictions

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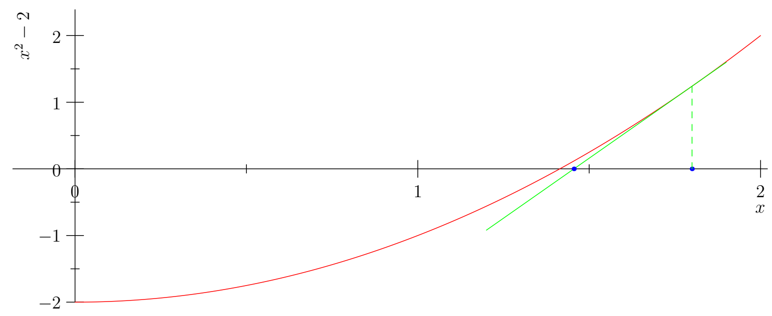
Outline

1. Numerical Approximations
2. Iterating to a Solution
3. **Linear Algebra**



Solving Simultaneous Equations

- When problems involve many variables it is convenient to use matrices and vectors to store the numbers

$$3x + 2y = 5 \qquad\qquad \begin{pmatrix} 3 & 2 \\ 7 & -8 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 5 \\ -11 \end{pmatrix}$$
$$7x - 8y = -11$$

- Or $\mathbf{A}\boldsymbol{x} = \boldsymbol{b}$ with solution $\boldsymbol{x} = \mathbf{A}^{-1}\mathbf{b}$

- Linear algebra is an abstraction allowing mathematicians, scientists and engineers to write solutions at a higher level

- The job of the numerical analyst is to write the code that does this

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Linear Algebra

- There are a large number of problems with matrices that people care about
- The solution often depends on the problem
- These include
  - ⋆ Multiply matrices together
  - ⋆ Solving linear equations $\mathbf{A}\boldsymbol{x} = \boldsymbol{b}$
  - ⋆ Finding eigenvalues of symmetric and non-symmetric matrices
  - ⋆ Performing singular valued decomposition
- These are important tasks that need to be done efficiently and reliably

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- We consider the classic problem of solving $\mathbf{A}\boldsymbol{x} = \boldsymbol{b}$
- Although we can solve this by computing $\mathbf{A}^{-1}\boldsymbol{b}$, finding the inverse of a matrix is typically a $\Theta(n^3)$ operation
- It is preferable to decompose $\mathbf{A}$ into a product of a lower triangular matrix $\mathbf{L}$ and an upper triangular matrix $\mathbf{U}$ which takes $\Theta(n^2)$ operations

$$\mathbf{A} = \begin{pmatrix} 4 & 2 & 6 \\ 3 & 5 & 9 \\ 1 & 2 & 3 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0.75 & 1 & 0 \\ 0.25 & 0.428 & 1 \end{pmatrix} \begin{pmatrix} 4 & 2 & 6 \\ 0 & 3.5 & 4.5 \\ 0 & 0 & -4.28 \end{pmatrix} = \mathbf{LU}$$

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LU-Decomposition

- LU-decomposition is achieved by Gaussian-elimination
- This is a straightforward procedure, but if done carelessly can lead to large rounding errors
- The standard solution is to permute the rows of the matrix (aka pivoting) to prevent loss of accuracy
- In addition we can "polish" solutions

$$\mathbf{A}(\boldsymbol{x} + \delta\boldsymbol{x}) - \boldsymbol{b} = \boldsymbol{\epsilon}$$

- Thus $\delta\boldsymbol{x} = \mathbf{A}^{-1}\boldsymbol{\epsilon}$ which we can use to get an improved estimate of $\boldsymbol{x}$

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Norms

- With some work we can get a good approximation to $\boldsymbol{x}$ such that $\mathbf{A}\boldsymbol{x} = \boldsymbol{b}$

- But what if we have some error in $\boldsymbol{b}$, this induces an error $\delta\boldsymbol{x} = \mathbf{A}^{-1}\,\delta\boldsymbol{b}$

- How big is $\delta\boldsymbol{x}$?

- To measure the size of a vector we use a norm $\|\delta\boldsymbol{x}\|$, which is a number encoding the size of $\delta\boldsymbol{x}$

- There are a number of different norms, e.g.

$$\|\delta\boldsymbol{x}\|_2 = \sqrt{\delta x_1^2 + \cdots + \delta x_n^2}, \qquad \|\delta\boldsymbol{x}\|_1 = |\delta x_1| + \cdots + |\delta x_n|$$

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Conditioning

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$$\|\delta\boldsymbol{x}\| = \|\mathsf{A}^{-1}\delta\boldsymbol{b}\| \leq \|\mathsf{A}^{-1}\|\,\|\delta\boldsymbol{b}\|$$

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- The size of the error in $\boldsymbol{x}$: $\mathbf{A}\,\boldsymbol{x} = \boldsymbol{b}$ when $\boldsymbol{b}$ has error $\delta\boldsymbol{b}$ is

$$\|\delta\boldsymbol{x}\| = \|\mathbf{A}^{-1}\delta\boldsymbol{b}\| \leq \|\mathbf{A}^{-1}\|\,\|\delta\boldsymbol{b}\|$$

- Where $\|\mathbf{A}^{-1}\|$ provides a measure of the size of the error in the worst case
- For large matrices $\|\mathbf{A}^{-1}\|$ can be large meaning that any error in $\boldsymbol{b}$ is potentially magnified significantly
- Such matrices are said to be ill-conditions
- Ill-conditioning is not to due with rounding errors but the structure of the matrix

Linear Algebra

- Linear algebra packages provide an important set of tools used for solving linear equations
- Care has to be taken to ensure that needless operations (such as inverting a matrix) are not done
- Algorithms must ensure that as little accuracy as possible is lost (e.g. by permuting rows in LU-decomposition)
- Even when the algorithms are precise, small errors can get amplified in some operations, which requires care in formulating the problem
- The idea of poor conditioning (errors being amplified) is useful in understanding many numerical tasks

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Lessons

- Be wary of numerical algorithms, because computers approximate real numbers you don't always get what you expect
- Don't avoid numerical algorithms, they are hugely important with vast areas of applications
- This is a well studied area with large libraries of reliable algorithms that work most of the time
- There are some good books such as "Numerical Recipes" by Press, *et al.*, which describes the issues and provides code

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