ROB 101: Computational Linear Algebra

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Abstract

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Contents

Chapter 9

The Vector Space $\mathbb{R}^n$: Part 2

Lecture 18: Review and Approximating Nonlinear Equations

9.1 $\mathbb{R}^n$ as a Vector Space

14 Mar. 9:00

An n-tuple is essentially just an ordered list of n numbers:

$$(x_1, x_2, \ldots, x_n) \leftrightarrow \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}.$$

Further, we define $\mathbb{R}^n$ as the set of all n-column vectors with real entries:

$$\mathbb{R}^n \Leftrightarrow \left\{ \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} | x_i \in \mathbb{R}, 1 \leq i \leq n \right\}.$$

The choice of identifying n-tuples of numbers with column vectors rather than row vectors is arbitrary.

9.2 Subspaces of $\mathbb{R}^n$

Definition 9.2.1 (Subspace). Suppose that $V \subset \mathbb{R}^n$ is nonempty. V is a **subspace** of $\mathbb{R}^n$ if any linear combination consructed from elements of V and scalars in $\mathbb{R}$ is once again an element of V. Formally, $V \subset \mathbb{R}^n$ is a subspace of $\mathbb{R}^n$ if for all realy numbers $\alpha, \beta \in V$ and all $v_1, v_2 \in V$ we have

$$\alpha v_1 + \beta v_2 \in V$$

.

> **Remark.** Further, we say that V is **closed under linear combinations** if the above is true.

> **Remark.** Every subspace must contain the zero vector.

From the equivalence of being closed under linear combinations and closed under vector addition and scalar-vector multiplication, one can check that a subset is a subspace by checking individually that it is **closed under vector addition** and **closed under scalar times vector multiplication**.

Problem 9.2.1. Let $V \subset \mathbb{R}^2$ be the set of all points that lie on a line $y = mx + b$:

$$V := \left\{ \begin{bmatrix} x \\ mx + b \end{bmatrix} | x \in \mathbb{R} \right\}.$$

Is V a subspace?

Answer. V is a subspace if and only if it contains the zero vector. V contains the zero vector if and only if the y-intercept is zero, meaning $b = 0$. Now we confirm that V with $b = 0$ is **closed under vector addition**:

$$V := \left\{ \begin{bmatrix} x \\ mx \end{bmatrix} | x \in \mathbb{R} \right\}.$$

For arbitrary $v_1 = \begin{bmatrix} x_1 \\ mx_1 \end{bmatrix}, v_2 = \begin{bmatrix} x_2 \\ mx_2 \end{bmatrix}$, we can confirm:

$$v_1 + v_2 = \begin{bmatrix} x_1 + x_2 \\ mx_1 + mx_2 \end{bmatrix} = \begin{bmatrix} x_1 + x_2 \\ m(x_1 + x_2) \end{bmatrix} \in V$$

. To confirm that V with $b = 0$ is **closed under scalar-vector multiplication**, again for arbitrary $v_1 \in V$:

$$\alpha v_1 = \alpha \begin{bmatrix} x_1 \\ mx_1 \end{bmatrix} = \begin{bmatrix} \alpha x_1 \\ \alpha m x_1 \end{bmatrix} = \begin{bmatrix} \alpha x_1 \\ m(a x_1) \end{bmatrix} \in V.$$

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9.3 Null Space, Spans, and Column Spans

Definition 9.3.1 (Null Space)**.** For an $n \times m$ matrix A, its **null space** is defined as

$$\text{null}(A) := \{x \in \mathbb{R}^m | Ax = 0_{n\times 1}\},$$

or the set of all solutions (i.e. vectors) that result in Ax being the zero vector or the "null vector".

Remark. $Ax = 0$ has a unique solution if and only if $\text{null}(A) = \{0_{m\times 1}\}$, the zero vector in $\mathbb{R}^m$. If $Ax = b$ has a solution and $\text{null}(A) \neq \{0_{m\times 1}\}$, then the equation has an infinite number of solutions. We can find the solution with minimum norm.

Problem 9.3.1. Compute the null space of $A = \begin{bmatrix} 1 & 3 & 0 \\ 0 & 4 & 1 \end{bmatrix}$.

Answer. We note that A is a 2×3 matrix, so its null space is

$$\text{null}(A) := \{x \in \mathbb{R}^3 | Ax = 0_{2\times 1}\} \subset \mathbb{R}^3.$$

So we have

$$Ax = 0_{2\times 1} \Leftrightarrow \begin{bmatrix} 1 & 3 & 0 \\ 0 & 4 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 0_{2\times 1} \Leftrightarrow x_1 = -3x_2, x_2 = -4x_2.$$

Hence,

$$x \in \text{null}(A) \Leftrightarrow x = \begin{bmatrix} -3x_2 \\ x_2 \\ -4x_2 \end{bmatrix} = \left\{ \alpha \begin{bmatrix} -3 \\ 1 \\ -4 \end{bmatrix} | \alpha \in \mathbb{R}. \right\}.$$

⊛

Remark. Anticipating the next definition, we can express the above null space of A as

$$\text{null}(A) = \text{span}\{\begin{bmatrix} -3 \\ 1 \\ -4 \end{bmatrix}\} := \left\{ \alpha \begin{bmatrix} -3 \\ 1 \\ -4 \end{bmatrix} \mid \alpha \in \mathbb{R}. \right\}.$$

Definition 9.3.2 (Span)**.** Suppose that $S \subset \mathbb{R}^n$ is a set of vectors, the set of all possible linear combinations of elements of S is called the **span** of S:

$$\text{span}\{S\} := \{\text{all possible linear combinations of elements of } S\}$$

Remark. If S is a set, span $\{S\}$ is the smallest subspace that contains all of the elements of the set S.

Definition 9.3.3 (Column Span)**.** Let A be an $n \times m$ matrix. Then its columns are vectors in $\mathbb{R}^n$. Their span is called the **column span of A**:

$$\text{col span}\,\{A\} := \text{span}\left\{a_1^{\text{col}}, \ldots, a_m^{\text{col}}\right\}$$

Remark. $Ax = b$ has a solution if and only if $b \in \text{col span}\,\{A\}$.

Problem 9.3.2. Suppose $A = \begin{bmatrix} 3 & 2 \\ 1 & -2 \\ -1 & 1 \end{bmatrix}$ and $b = \begin{bmatrix} 0 \\ -8 \\ 5 \end{bmatrix}$ Does $Ax = b$ have a solution?

Answer. We first check that

$$b = -2a_1^{\text{col}} + 3a_2^{\text{col}} \in \text{span}\left\{a_1^{\text{col}}, a_2^{\text{col}}\right\},$$

and so b is in the column span of A, and the system of linear equations has a solution $x = \begin{bmatrix} -2 \\ 3 \end{bmatrix}$ ⊛

9.4 Dot Product and Orthonormal Vectors

Definition 9.4.1. For two column vectors $u, v \in \mathbb{R}^n$, the **dot product** of u and v is defined as

$$u \cdot v := \sum_{i=1}^{n} u_i v_i$$

The dot product is most commonly used for defining orthogonality between vectors. For example, two vectors w_1, w_2 are orthogonal, written $w_1 \perp w_2$ if and only if $w_1 \cdot w_2 = 0$.

Definition 9.4.2. A set of vectors $v_1, v_2, \ldots, v_n$ is **orthogonal** if for all $1 \leq i, j \leq n, i \neq j$

$$v_i \cdot v_j = 0$$

or equivalently, $v_i^T v_j = 0$ or $v_i \perp v_j$.

Definition 9.4.3. A set of vectors $v_1, v_2, \ldots, v_n$ is **orthonormal** if:

- they are orthognoal
- for all i, $\|v_i\| = 1$

Chapter 11

Solutions of Nonlinear Equations

Lecture 18: Review and Approximating Nonlinear Equations

14 Mar. 9:00

11.1 Bisection Algorithm

Theorem 11.1.1 (Intermediate Value Theorem). Suppose $f : \mathbb{R} \to \mathbb{R}$ is a continuous function and you know two real numbers, $a < b$, such that $f(a) \cdot f(b) < 0$. Then $\exists c \in \mathbb{R}$ such that:

$$a < c < b$$
$$f(c) = 0$$

Using the midpoint between two numbers to find the root may not give us the root right away. Further, the root isn't always exactly in between a and b. So, we can use the **bisection algorithm** to *approximate* roots:

Algorithm 11.1: Bisection Algorithm

```
Data: a < b ∈ ℝ such that f(a) · f(b) < 0
1 c = (a + b)/2
2 if f(c) = 0 then
3     return x* = c
4 else
5     if f(c) · f(a) < 0 then
6         b = c
7     else
8         a = c
9 Loop back to 1.
```

11.2 Derivatives and Approximation

Definition 11.2.1 (Derivative). A **derivative** is the slope of a function at a specific point.

There are 3 ways to represent the numerical approximation of a derivative:

1. **Forward Difference Approximation**: $\frac{df(x_0)}{dx} = \frac{f(x_0+h)-f(x_0)}{h}$
2. **Backward Difference Approximation**: $\frac{df(x_0)}{dx} = \frac{f(x_0)-f(x_0-h)}{h}$
3. **Symmetric Difference Approximation**: $\frac{df(x_0)}{dx} = \frac{f(x_0+h)-f(x_0-h)}{2h}$

Remark. If the 3 approximations above don't agree, then the limit does not exist and the function is not differentiable.

For a differentiable function, $f(x)$, $f(x) \approx f(x_0) + \frac{df(x_0)}{dx}(x - x_0)$ near point $(x_0, f(x_0)) \, \forall x_0$. We can use this idea to *find roots* using linear approximations to nonlinear functions.

11.3 Newton's Method

To find the roots using linear approximations to nonlinear functions we can use **Newton's Method**:

Definition 11.3.1 (Newton's Method)**.** Assume $f : \mathbb{R} \to \mathbb{R}$ is differentiable everywhere. Let x_k be our current estimate of a root, then:

$$f(x) \approx f(x_k) + \frac{df(x_k)}{dx}(x - x_k).$$

We want x_{k+1} such that $f(x_{k+1}) = 0$.

If we solve for x_{k+1} we get:

$$x_{k+1} = x_k - \frac{df(x_k)}{dx}^{-1} f(x_k).$$

This method takes very big "steps", so it may be more beneficial to take smaller "steps". This leads to the **damped Newton Method**,

$$x_{k+1} = x_k - \epsilon\Big(\frac{df(x_k)}{dx}\Big)^{-1} f(x_k),$$

where $0 < \epsilon < 1$ A typical value may be $\epsilon = 0.1$.

Lecture 19: Vectors and Approximating Nonlinear Equations

11.4 Vectors and Nonlinear Equations

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We can use vectors for linear approximations by understanding partial derivatives. Given nonlinear funcitons $f : \mathbb{R}^m \to \mathbb{R}^m$ we want the linear approximation at $x_0 \in \mathbb{R}^m$.

$$f(x) \approx f(x_0) + A(x - x_0)$$

where $A_{n\times m}, x, x_0 \in \mathbb{R}^m$, and $f(x_0), f(x) \in \mathbb{R}^n$. Here, A represents a matrix made up of partial derivatives.

Remark. Everything is the same as finding a linear approximation at a point. We are just replacing the slope with a matrix and the xs with vectors.

11.5 Partial Derivatives

Set $x = x_0 + he_i$ where he_i is some small outside adjustment to x_0 such that all x_0 remain the same except the i-th component.

$$x_0 + he_i = \begin{bmatrix} x_{01} \\ x_{02} \\ \vdots \\ x_{0m} \end{bmatrix} + h \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} x_{01} \\ x_{02} \\ \vdots \\ x_{0i} + h \\ \vdots \\ x_{0m} \end{bmatrix} \text{ where } h \text{ is small}$$

Equivalently, we have:

$$f(x_0 + he_i) \approx f(x_0) + A(x_0 + he_i - x_0) = f(x_0) + ha_i^{col}$$

where we can now solve for a_i^{col}, which represents the derivative of f with respect to x_i.

We can represent the numerical approximation of a partial derivative similar to how we represented the numerical approximation of a standard derivative. A partial derivative is represented with the mathematical symbol del: ∂.

11.6 Jacobian

Given the nonlinear functions $f : \mathbb{R}^m \to \mathbb{R}^m$, the **Jacobian** is

$$\frac{\partial f(x)}{\partial x} := \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \frac{\partial f(x)}{\partial x_2} \cdots \frac{\partial f(x)}{\partial x_m} \end{bmatrix}_{n \times m}.$$

- The partial derivatives are stacked to form a matrix
- For each $x \in \mathbb{R}^m$, $\frac{\partial f(x)}{\partial x}$ is an $n \times m$ matrix
- The **gradient** of $f : \mathbb{R}^m \to \mathbb{R}$ is a special Jacobian that for each $x \in \mathbb{R}^m$, $\nabla f(x)$ is a $1 \times m$ matrix

$f : \mathbb{R}^m \to \mathbb{R}^n$ looks like:

$$f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_n(x) \end{bmatrix}$$

$\frac{\partial f(x)}{\partial x}$ looks like:

$$\frac{\partial f(x)}{\partial x} = \begin{bmatrix} \frac{\partial f_1(x)}{\partial x_1} & \frac{\partial f_1(x)}{\partial x_2} & \cdots & \frac{\partial f_1(x)}{\partial x_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n(x)}{\partial x_1} & \frac{\partial f_n(x)}{\partial x_2} & \cdots & \frac{\partial f_n(x)}{\partial x_m} \end{bmatrix}$$

The linear approximation of nonlinear functions $f : \mathbb{R}^m \to \mathbb{R}^n$ at point $x_0 \in \mathbb{R}^m$ is

$$f(x) \approx f(x_0) + A(x - x_0) = f(x_0) + \frac{\partial f(x_0)}{\partial x}(x - x_0).$$

Problem 11.6.1. We have two functions:

$$f_1(x_1, x_2) = \log(x_1) + \sqrt{x_2}$$
$$f_2(x_1, x_2) = x_1 \cdot x_2$$

and let $x_0 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$.

Answer. $f : \mathbb{R}^2 \to \mathbb{R}^2$ so $\frac{\partial f(x)}{\partial x}$ is a 2×2 matrix. Using forward approximation we have $\frac{\partial f(x_0)}{\partial x} = \frac{f(x_0 + he_i) - f(x_0)}{h}$ with $h = 0.001$.

- f_1 w.r.t x_1:

$$\frac{\partial f_1(x_1, x_2)}{\partial x_1} = \frac{(\log(1 + 0.001) + \sqrt{2}) - (\log(1) + \sqrt{2})}{0.001} = 0.43408$$

- f_1 w.r.t. x_2:

$$\frac{\partial f_1(x_1, x_2)}{\partial x_2} = \frac{(\log(1) + \sqrt{2 + 0.0001}) - (\log(1) + \sqrt{2})}{0.001} = 0.35351$$

- f_2 w.r.t. x_1:

$$\frac{\partial f_1(x_1, x_2)}{\partial x_1} = \frac{(1.001)(2) - (1)(2)}{0.001} = 2$$

- f_2 w.r.t. x_2:

$$\frac{\partial f_1(x_1, x_2)}{\partial x_2} = \frac{(1)(2.001) - (1)(2)}{0.001} = 1$$

So, the linear approximation is $f(x) \approx f(x_0) + \frac{\partial f(x_0)}{\partial x}(x - x_0)$

$$\begin{aligned} f(x) &\approx f(x_0) + \frac{\partial f(x_0)}{\partial x}(x - x_0) \\ &= \begin{bmatrix} \log(1) + \sqrt{2} \\ (1)(2) \end{bmatrix} + \begin{bmatrix} 0.43408 & 0.35351 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} x_1 - 1 \\ x_2 - 2 \end{bmatrix} \end{aligned}$$

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11.7 Newton-Raphson Method

Just as Newton's Method was a useful tool for linear approximations, we can use the **Newton-Raphson Method** for *non-linear approximations.* Given $f : \mathbb{R}^n \to \mathbb{R}^n$, we want to find a root $f(x_0) = 0$. Using our approximation above, we can substitute in x_{k+1} and solve for it:

$$x_{k+1} = x_k - \frac{\partial f(x)}{\partial x}^{-1} f(x_k)$$

Remark. Similarly to when we were solving $Ax - b = 0$ we made sure $\det(A) \neq 0$, we want to make sure $\det\left(\frac{\partial f(x_k)}{\partial x} \neq 0\right)$.

We can find Δx_k to avoid the inverses in the equations above:

$$\Delta x_k = -\left(\frac{\partial f(x_k)}{\partial x}\right)^{-1} f(x_k)$$

Instead of the inverses or dividing matrices, we solve for Δx_k using LU or QR factorization. This can be done using the Newton-Raphson algorithm:

Algorithm 11.2: Newton-Raphson Algorithm

```
   Data: f
1  F ← LU(∂f(x_k)/∂x)                        // find Δx_k
2  y ← ForwardSub(F.L, F.P · −f(x_k))
3  Δx_k ← BackwardSub(F.U, y)
4  x_{k+1} ← x_k + Δx_k                      // use Δx_k to find x_{k+1}
5  if f(x_{k+1}) = 0 then
6      return x_{k+1} as the root
7  else
8      loop back to 1.
```

If we replace $x_{k+1} = x_k \Delta x_k$ with

$$x_{k+1} = x_k + \varepsilon \Delta x_k$$

we get the **Damped Newton-Raphson Method** for $\varepsilon > 0$ (usually $\varepsilon = 0.1$ is sufficient). This prevents Δx_k from being too big by decreasing the step size.

Chapter 12

Basic Ideas of Optimization

Lecture 20: Gradient Descent

21 Mar. 9:00

12.1 Gradient

Let $f : \mathbb{R}^m \to \mathbb{R}$, then the **gradient** of f is the partial derivatives of f with respect to x_i:

Definition 12.1.1 (Gradient (∇)).

$$\nabla f(x_0) = \begin{bmatrix} \frac{\partial f(x_0)}{\partial x_1} \frac{\partial f(x_0)}{\partial x_2} \dots \frac{\partial f(x_0)}{\partial x_m} \end{bmatrix}_{1\times m}.$$

For linear approximation about a point:

$$f(x) \approx f(x_0) + \nabla f(x_0)(x - x_0)$$

12.2 Building Towards Optimization

Optimization is finding a potential set of solutions to a problem in $\mathbb{R}^m$ The **cost function** $f : \mathbb{R}^m \to \mathbb{R}$ allows us to compare elements of $\mathbb{R}^m$ in order for us to decide which are more advantageous to us.

1. **REGRET** functions minimize. If $*$ is the minimum point of interest, as $x \in \mathbb{R}^m$ gets close to our x^*, it is small and as x get far from x^*, it is large. Mathematically:

$$x^* = \mathbf{argmin}_{x\in\mathbb{R}^m} f(x).$$

2. **REWARD** functions maximize. Here we will focus on minimization.

Suppose we start at $x_k \in \mathbb{R}$ and we want to find $x_{k+1} \in \mathbb{R}$ where $f(x_{k+1}) < f(x_k)$. We note that $f(x_{k+1}) - f(x_k) < 0$ if and only if $\frac{\partial f(x_k)}{\partial x}(x_{k+1} - x_k) < 0$.

Remark. Make sure that you do not begin with $\frac{\partial f(x_k)}{\partial x} = 0$, as this would indicate x_k is already an extremum.

So, we let $\Delta x_k = -s\frac{\partial f(x_k)}{\partial x}$ for $s > 0$ (**step size**). If s is too big then we may overshoot our estimate. We typically use $s \approx 0.1$. Solving for x_{k+1} (i.e. our *next best guess* closer to the local extremum):

$$x_{k+1} = x_k - s\frac{\partial f(x_k)}{\partial x}$$

12.3 Gradient Descent

Note that the gradient vanishes at local minima: $\nabla f(x^*) = 0$. In order to find an extremum (in our case: a minimum) we can start at some arbitrary x_k and calculate (for a satisfactory k), $x_{k+1} = x_k - s(\nabla f(x_k))^T$.

Remark. We transpose $\nabla f(x_k)$ because the gradient is a row vector, so we must transpose it into a column.

Finding the Minimum: Gradient Descent Algorithm

Note that our *key condition* is

$$\nabla f(x_k)\Delta x_k < 0.$$

Using the above, we can find a minimum starting with the linear approximation of $f : \mathbb{R}^m \to \mathbb{R}$ near x_k:

$$f(x) \approx f(x_k) + \nabla f(x_k)(x - x_k)$$

We want x_{k+1} such that $f(x_{k+1}) < f(x_k)$. We find that if $\Delta x_k = -s(\nabla f(x_k))^T$ then we have:

$$\nabla f(x_k)\Delta x_k = -s\|(\nabla f(x_k))^T\|^2 < 0, \ \forall s > 0$$

We can construct an algorithm from this:

Algorithm 12.1: Gradient Descent Algorithm

Data: $f, x_i \leftarrow 0, s \leftarrow 0.1$

while $\|\nabla f(x_i)\| < tol$ & $i < i_{\max}$ **do**
- $\Delta x_i \leftarrow -s \cdot \nabla f(x_i)$
- $x_i \leftarrow x_i + \Delta x_i$
- $i \mathrel{+}= 1$

return x_i

Lecture 21: Root Finding With the Second Derivative

12.4 Hessian

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Definition 12.4.1. The **Hessian** of a function $f : \mathbb{R}^m \to \mathbb{R}$ is the Jacobian of the *gradient transpose* of f:

$$\nabla^2 f(x) := \frac{\partial(\nabla f(x))^T}{\partial x}$$

where $x \in \mathbb{R}^m$ and $f(x) \in \mathbb{R}$.

Definition 12.4.2 (Gradient Transpose)**.** The **gradient transpose** is defined as:

$$(\nabla f(x))^T := \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \vdots \\ \frac{\partial f(x)}{\partial x_m} \end{bmatrix}_{m \times 1}$$

$$\nabla^2 f(x) = \begin{bmatrix} \frac{\partial^2 f(x)}{\partial x_1^2} & \cdots & \frac{\partial^2 f(x)}{\partial x_1 \partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f(x)}{\partial x_m \partial x_1} & \cdots & \frac{\partial^2 f(x)}{\partial x_m^2} \end{bmatrix}$$

Figure 12.1: The Hessian in terms of individual entries.

The **Jacobian** for $g : \mathbb{R}^m \to \mathbb{R}^m$ is

$$\frac{\partial g(x)}{\partial x} := \left[\frac{\partial g(x)}{\partial x_1} \dots \frac{\partial g(x)}{\partial x_m}\right]_{m \times m}.$$

To summarize the above, the two methods for finding a minimum that we have seen include:

Definition 12.4.3 (*Scalar* Optimization (Newton's Method)). For $f : \mathbb{R} \to \mathbb{R}$:

$$x_{k+1} = x_k - \left(\frac{\partial^2 f(x_k)}{\partial x^2}\right)^{-1} \frac{\partial f(x_k)}{\partial x}$$

and its *damped* version where $0 < s < 1$:

$$x_{k+1} = x_k - s(\left(\frac{\partial^2 f(x_k)}{\partial x^2}\right)^{-1} \frac{\partial f(x_k)}{\partial x}).$$

Definition 12.4.4 (*Vector* Optimization (Newton-Raphson)). For $f : \mathbb{R}^m \to \mathbb{R}$:

$$\nabla^2 f(x_k) \Delta x_k = -(\nabla f(x_k))^T$$

and its *damped* version where $0 < s < 1$:

$$x_{k+1} = x_k s \Delta x_k.$$

Remark. Use LU or QR factorization (i.e. $Ax = b$) to solve for Δx_k.

The Hessian used in the Newton-Raphson algorithm gives us the root of the gradient function. For us, our goal was to find the local minimum. In some problems, Newton-Raphson with the Hessian has a faster

Lecture 22: Root Finding With the Second Derivative

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Appendix

Appendix A

Eigenvalues and Eigenvectors

Consider the **scalar linear difference equation**

$$z_{k+1} = az_k$$

where $a, z_0 \in \mathbb{C}$. We compute some steps of the equation:

$$\begin{aligned} z_1 &= az_0 \\ z_2 &= a_{z1} = a^2 z_0 \\ z_3 &= a_{z2} = a^3 z_0 \\ &\vdots \\ z_k &= a^k z_0 \end{aligned}$$

A.1 Iterating with Matrices: A Case for Eigenvalues

We now analyze the matrix versions of the above equations:

$$x_{k+1} = Ax_k,$$

where A is a $n \times n$ real matrix. If we allow entries of A to be complex and $x_0 \in \mathbb{C}$ we have:

$$z_k = A^k z_0.$$

Now we shift our attention towards finding conditions on A such that $\|z_k\|$ contracts, blows up, or stays bounded as k tends to infinity. Further, upon being given z_0 we will detail the evolution of z_k for $k > 0$. finish eigenstuff