

Hochschule Bonn-Rhein-Sieg University of Applied Sciences





Calculus

Speaker Sven Ludwig

Authors Divin, Santosh, Michal, Musharraf, Kishan, Sven

Course Calculus Refresher

Program Autonomous Systems (MSc)

Introduction

What is Calculus?

A branch of mathematics which deals with "study of continuous change" of functions or sequences









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Major Branches

- Differential Calculus
- Integral Calculus





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General Applications

- Optimisation
- To Solve Differential Equations
- Function Approximations
- Length, Area, Volume, Center of Mass, Moment of Inertia Calculations







Kinematics

- Modelling mobile robot (eg: differential drive) and environment
- Transform between different spaces







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 - Euler-Lagrange equations







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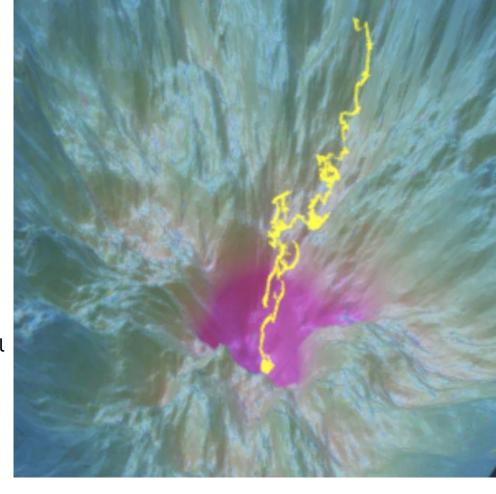




Calculus in Deep Learning

Prominent application of computing the gradient, i.e. first derivatives, when minimizing loss function

- Loss landscape is all loss values over all combinations of parameter values.
- Computing gradient, i.e. partial first derivatives, requires some form of differentiation of the loss function.
- Gradient indicates how to update the model parameters θ to minimize loss.
- With stochastic gradient descent, model parameters are updated iteratively with respect to subsets (batches) of the training dataset.



Calculating first derivatives in batches on the GPU with PyTorch

```
# given x values
x = torch.tensor([-3., -2., -1., 0., 1., 2., 3.], dtype=torch.float32, device=device, requires_grad=True)
\# f(x) = x^2
two_dot_zero = torch.tensor(2.0, dtype=torch.float32, device=device)
y = x.pow(two_dot_zero)
# f'(x) via autograd
ones = torch.ones_like(y, dtype=torch.float32, device=device)
y.backward(ones)
gradients = x.grad
print(f''x = \{x\}'')
print(f''f(x) = \{y\}'')
print(f"f'(x) = {gradients}")
```

Adam Paszke et al. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library https://pytorch.org/

Calculating first derivatives in batches on the GPU with JAX

```
print(jax.devices())
def f(x):
    return x**2.0
x = \text{jnp.array}([-3., -2., -1., 0., 1., 2., 3.])
f_prime = jax.grad(f)
gradients = []
for i in range(0, len(x)):
  y_prime = f_prime(x[i])
  gradients.append(float(y prime))
print(f"x = {x.tolist()}")
print(f''f(x) = \{f(x).tolist()\}'')
print(f"f'(x) = {gradients}")
[cuda(id=0)]
x = [-3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0]
f(x) = [9.0, 4.0, 1.0, 0.0, 1.0, 4.0, 9.0]
f'(x) = [-6.0, -4.0, -2.0, 0.0, 2.0, 4.0, 6.0]
```

James Bradbury et al. (2018). JAX: Composable transformations of Python+NumPy programs https://jax.readthedocs.io

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- **➤** Logic
 - Situational calculus







Functions vs Relations

- Functions

Eg:
$$y = x^2 + 4x$$

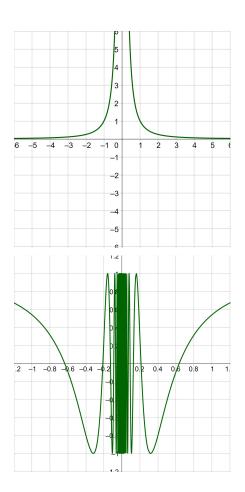
- Relations

Eg:
$$x^2+y^2 = 25$$









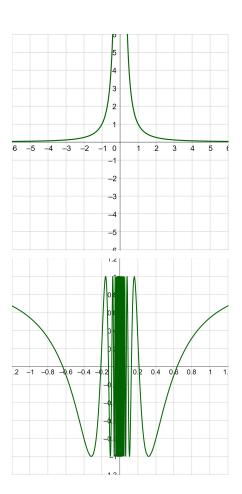
Functions vs Relations

- Functions have one unique output for a given input Eg: $y = x^2+4x$
- Relations can have more than one output Eg: $x^2+y^2 = 25$









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Limit

 Unique value of a function when its input approaches a particular number from both sides

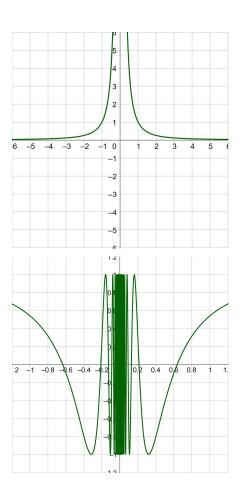
$$\lim_{x o c}f(x)=L$$

Eg:
$$f(x) = \frac{x^2-1}{x-1}$$
.









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$$\lim_{x o c}f(x)=L$$

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Continuity

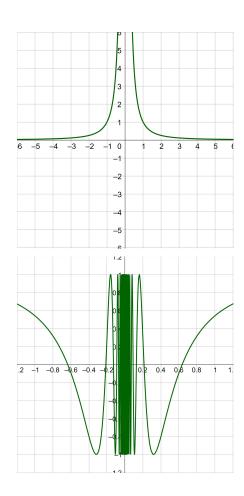
- For all values of input to a function, it must satisfy,

$$\lim_{x \to c} f(x) = f(c)$$









Characteristics of Data

Analog

continuous



Digital

discrete

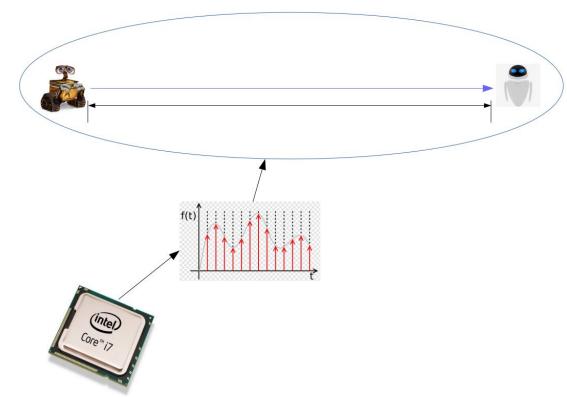
















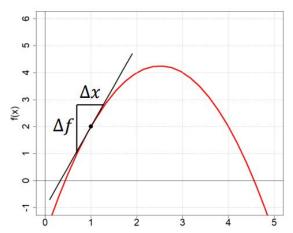




Derivative of a Function

- Rate of change
- In a 2D system, derivatives = slope = $tan(\theta)$

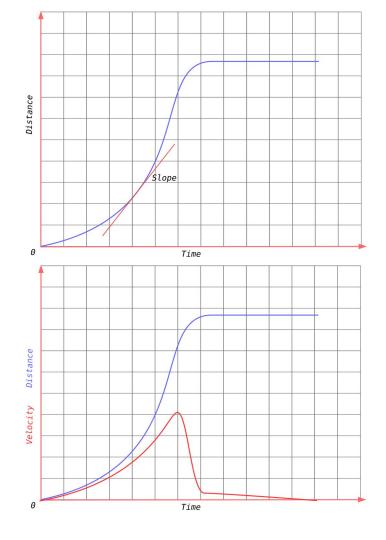
Leibniz notation: $y = x^2$; $\frac{dy}{dx} = 2x$









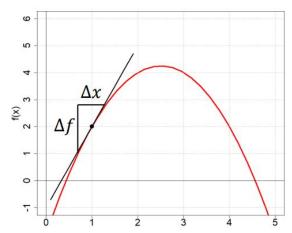


Derivative of a Function

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- Another view:

The line itself is the best <u>linear approximation</u>

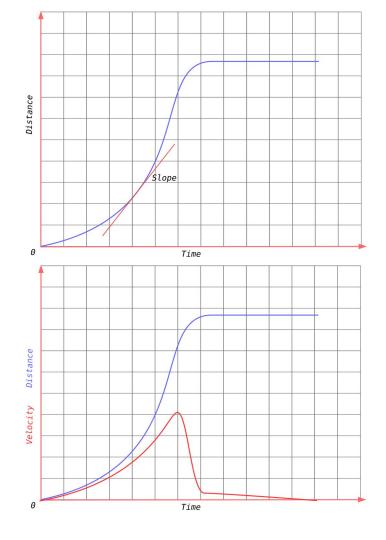
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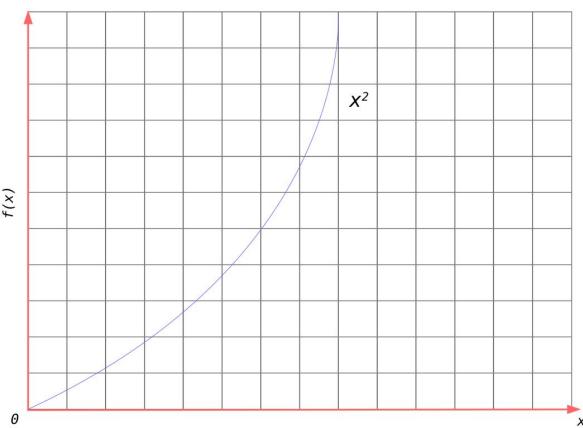












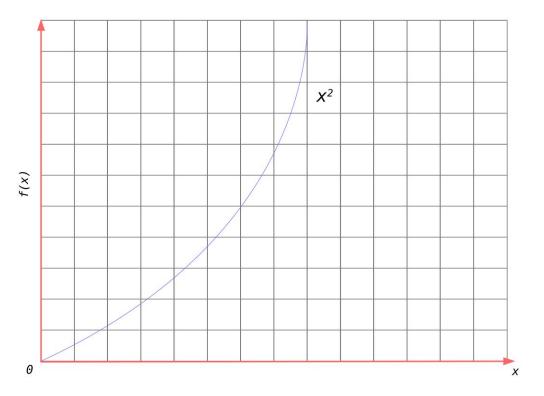








How to handle discrete functions?









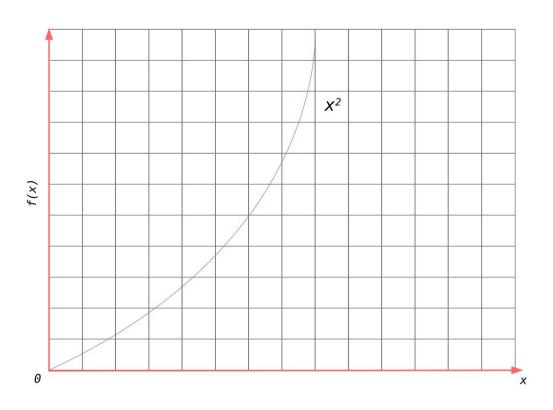
How to handle discrete functions?

Approximate!

$$f'(x) = \lim_{\epsilon \to 0} \frac{f(x+\epsilon) - f(x)}{\epsilon}$$

$$f'(x) \approx \frac{f(x+h) - f(x)}{h}$$

h - small, positive, fixed epsilon









Differential Calculus - Rules (single variable)

Addition Rule
$$\frac{d}{dx}[f(x)+g(x)]=\frac{d}{dx}f(x)+\frac{d}{dx}g(x)$$

Product Rule
$$\longrightarrow$$
 $\frac{d}{dx}[f(x)\cdot g(x)] = f(x)\cdot \frac{d}{dx}g(x) + g(x)\cdot \frac{d}{dx}f(x)$

Power Rule
$$\longrightarrow \frac{d}{dx}[x^n] = n \cdot x^{n-1}$$

Quotient Rule
$$\qquad \qquad \frac{d}{dx} \left[\frac{f(x)}{g(x)} \right] = \frac{g(x) \cdot \frac{d}{dx} f(x) - f(x) \cdot \frac{d}{dx} g(x)}{(g(x))^2}$$

Derivative of Constant
$$\Longrightarrow \frac{d}{dx}[c] = 0$$

Chain Rule
$$\frac{dy}{dx} = \frac{dy}{du} \cdot \frac{du}{dx}$$

Other Rules: For logarithmic and exponential functions



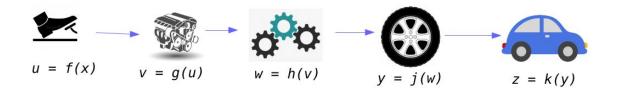






Differential Calculus - Chain Rule

Dependent Systems



$$\frac{dz}{dx} = \frac{dz}{dy} * \frac{dy}{dw} * \frac{dw}{dv} * \frac{dv}{du} * \frac{du}{dx}$$







How to handle derivatives of multivariable functions?

Partial Derivatives: Taking derivative of each variable and holding others as constants

Notations:
$$\frac{\partial f}{\partial x} = \lim_{\Delta x \to 0} \frac{f(x + \Delta x, y) - f(x, y)}{\Delta x}$$

$$f_x = rac{\partial f}{\partial x}$$
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- Application: Jacobians

$$\mathbf{J} = \begin{bmatrix} \frac{\partial F_1}{\partial x_1} & \frac{\partial F_1}{\partial x_2} & \cdots & \frac{\partial F_1}{\partial x_n} \\ \frac{\partial F_2}{\partial x_1} & \frac{\partial F_2}{\partial x_2} & \cdots & \frac{\partial F_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1} & \frac{\partial F_m}{\partial x_2} & \cdots & \frac{\partial F_m}{\partial x_n} \end{bmatrix}$$







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Cross Partial Derivatives

$$\frac{\partial}{\partial y} \left(\frac{\partial f}{\partial x} \right) = \frac{\partial}{\partial x} \left(\frac{\partial f}{\partial y} \right) = \frac{\partial^2 f}{\partial y \partial x}$$









Total Derivatives: if there is a function f(x,y), then the total derivative is represented as sum f partial derivatives of each variable times the derivative of that variable





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In this example, assuming function 'f' is not directly dependent on 't' and 't' is independent variable, the total derivative can be represented as,

$$\frac{df}{dt} = \frac{\partial f}{\partial x}\frac{dx}{dt} + \frac{\partial f}{\partial y}\frac{dy}{dt}$$







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Taylor Series: Approximations of functions. At x=0, this series is also termed as Maclaurin series.

$$f(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \frac{f'''(a)}{3!}(x-a)^3 + \cdots$$

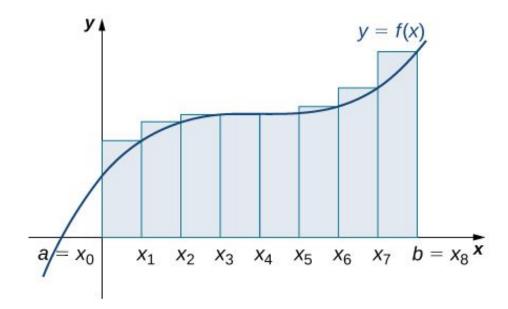








Integration: it is analogous to summation. It is also termed as antiderivative





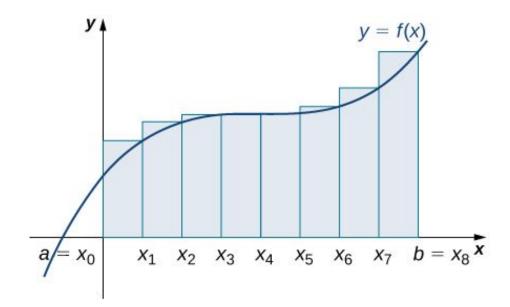




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Types:

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- Definite integrals: bounds are defined









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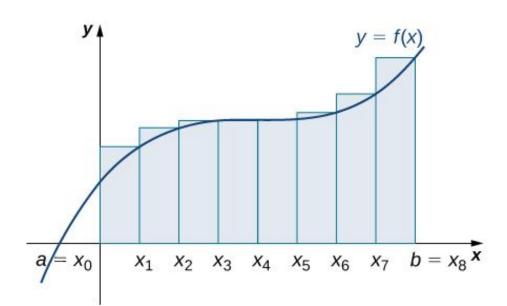
Example:

$$y_1 = x^2 + 20$$

 $y_2 = x^2 + 100$

$$y_1^l = y_2^l = 2x$$

Thus,
$$\int 2x \, dx = x^2 + c$$

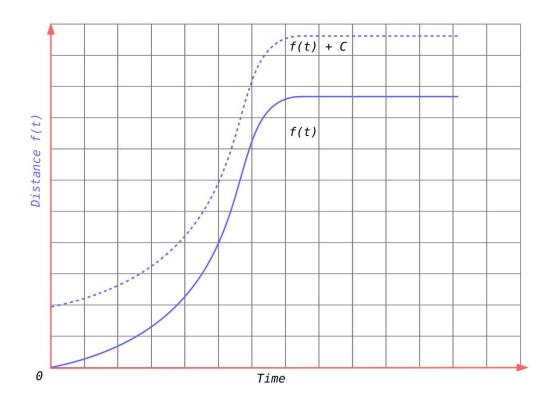








Bounds





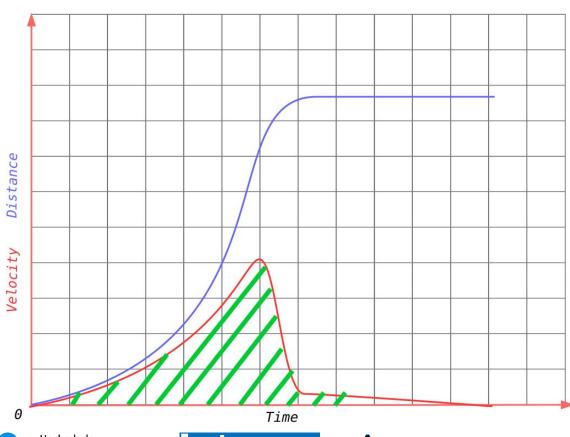


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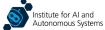






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What about discrete functions?





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What about discrete functions?

Approximate!

$$\int_{a}^{b} f(x)dx \approx \frac{h}{2} \sum_{k=0}^{n-1} (s_{k+1} + s_k)$$

h – small, positive, fixed epsilon

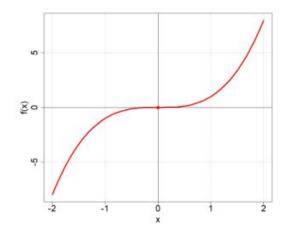


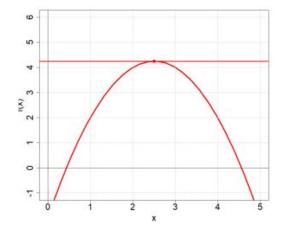




Optimisation

Inflection Point vs Critical Point









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References

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Thank You!