Differentiation  Generally how functions change with time.  Rate of Change: could be average or instantaneous	
Rate of Change: could be average or instantaneous  Average - change in distance /change in time  Be close to the change (smaller distance and smaller time) to have exact change  This is the secant line (y-yo) = m(x-xo)  m is d(to+dt) - d(to) / dt  Instantaneous-  if the average change was being calculated over a smaller distance this would resemble the velocity at the instant time.	
would resemble the velocity at the instant time. Calculate the average, but with limit $dt \to 0$ . This would minimize the change in time to a minimum whereby the distance travelled almost zero - we can find the result. For the graphical interpretation: as we move the distance between the two points, the secant line becomes a tangent The slope of the tangent is the derivative at the point! m is the derivative $ (y-yo) = m(x-xo) $ Eg: $v = dt/dt$ $ d(to+dt) - d(to) / dt $	
d(to+dt) - d(to) / dt  Try to get dt at the minimum: limit dt → 0  Insert the function that gives us the d with the variables and find the distance.    lim dt → 0, of d(to+dt) - d(to) / dt - you're given to  This is what the differentiate does!  Differentiate the function and insert the to.	
When you do derivatives, you take a higher version of a polynomial to a lower version of the polynomial, to calculate a higher degree variable from a lower degree  Lower degree variable (high polynomial version) → High degree variable (low polynomial version)	
Adding derivatives: Add individuals and combine Multiplying by a scalar: put it out and multiply after deriving	
Basic Rules  Power Rule: $f'(x) = xx \wedge (n-1) \rightarrow drop$ the power as the coefficient, and subtract 1 from the top. Product Rule: $f'(w.l) = w'*l + w*l'$ Chain Rule: $f'(g(f(x)) \rightarrow f'(g(x))*g'(x) \rightarrow this$ is when $f(x)$ depends on $g(x)$ and both of the derivatives are needed $var('k')$	
v.differentiate() v.diff()  Linear Approximation  If the increasement in the x value (the variable part of the derivative - usually time) is small enough, we can approximate what it would be for that increment using the tangent line equation we derived for the point we know.  Given 2 points, and their relationship equation, find the slope of the line at that point, and make the line	
Given 2 points, and their relationship equation, find the slope of the line at that point, and make the line equation. Then use the new point to find the value of the graph at the new position. (Has to be close to make sense)  Line Tangent  Find the function used to approximate  Find the two points used for approximation  Y-yo = m(x-xo)  Find m by diff of the function (and inserting xo)  Approximate  Plug the new x to find the corresponding y.  Y = m(x-xo)+yo  (V-V_appx)/V   Higher Order Derivatives	
Related Rates  If we're trying to solve for rates that are related by a formula.  Before everything, define what is changing, and what is staying the same (what are the rates given, what are the constants given)  The constants variables don't change, and are taken out of the diff  Write down the relation formula, and find the derivative on each side.  Then compute. (Be aware: take out constants, and drive the equations) $V = \pi r 2h$ .	
$V = \pi r 2h.$ $d/dt (V) = d/dt (\pi r 2h)$ If h is constant: $dV/dt = 2\pi r h (dr/dt)$ If r is constant: $dV/dt = \pi r 2 (dh/dt)$ If neither is constant: $dV/dt = 2\pi r h (dr/dt) + \pi r 2 (dh/dt)$ Optimization (non-partial)	
Find the function you're optimizing for  Usually, it's the constants and use them to define one unknown  Add it to the optimized function to simplify a bit  Find the derivative  Find the critical point - where the derivative == 0  At the critical point, decide if it's max or min  Take 2 samples, 1 larger, and 1 smaller than the critical point  Insert to the derivative function  If the pattern is 0 +++ → Min  If the pattern is +++ 0 → Max	
Second derivative to see concavity (where the second derivative is 0)  This is the inflection point - where concavity changes  - is concave down  + is concave up  Second derivative test - concavity and critical points  The second derivative at critical point is positive (U) → minimum  The second derivative at critical point is negative (n) → maximum  The second derivative at critical point is 0 (the critical point == inflection point)  → inconclusive	
→ inconclusive  Extrema:  Remember when optimizing a function within bounds [x1,x2] exclude xs (critical points) that don't fit into our domain.  And if we're looking for global optimization:  Consider <i>endpoints</i> and critical points  Compare all of the values on the OG function to see which one is greater  EAGE  A(x) == sqrt(x^2 + (x^4-3*x^2+3)^2)  Dprime = diff(d,x)  Xcritical = solve(dprime == 0, x) [0].rhs()	
Acritical = solve(dprime == 0, x) [0].rns()  print('xcritical is', n(Xcritical))  D2prime = diff(dprime,x)  d2prime(n(xcritical))  print('minimal distance =', n(d(xcritical)))  print('maximal distance =', n(d(-2)))  Partial Derivatives  The partial derivative according to one variable treats the others as <i>constants!!!!</i> When you're multiplying, it comes out. When you're adding it's 0. [9]	
When you're multiplying, it comes out. When you're adding it's 0. $(x,y) = x*y*\sin(x)*e^{x}y$ . Ediff(x), f.diff(y)  Higher Order It's the same thing of doing the derivative again, but there are 4 combinations cause we have 2 partials	
SAGE $F(x,y) = x^2 + x * \sin(y)$ $Show((f.diff(x)).diff(x), (f.diff(x)).diff(y))$ $Show((f.diff(y)).diff(x), (f.diff(y)).diff(y))$ $Fangent Plane$	
Tangent Plane  Z-zo = m(x-x0) + n(y-y)  Given the equation of the function  And points  Find zo by putting x and y into the function  M is partial derivative according to x (evaluated at the point)  N is partial derivative according to y (evaluated at the point)  We can extend to higher dimensions by adding w(p-po)	
Optimization for Second Partial Derivatives  Partial of X and Partial of Y == 0, that's the (x,y) where the critical point happens  The second partial derivative test:	
If D is > 0 Pure double partial of x > 0, min (concave up) Pure double partial of y > 0, max (concave down)  If D is < 0 Saddle point  If D is = 0	
If D is = 0 Inconclusive  Multivariable Absolute Extrema  Define the domain (strictly!!!)  Critical Points  px ==0, py==0  Take the ones in the domain  Plug in (x,y) into OG and evaluate  Line Boundaries (1 variable is constant, other is found)  Plug in the constant, and derive the other to find where it would be maxed out.  Derivation == 0	
Derivation == 0 Find points (you can see if it's max or min from f"(x) but there's no use here Evaluate points in the OG function The corner points Plug into OG and evaluate Comparison for max and mins  Vector → Addition and Scalar multiplication, dot product (0 perpendicular) v.w =  v   w  cos (teta) Magnitude of v → v.v	
However, we know partial derivatives are special cases of directional derivatives, where the px is in the movement to (1,0) and py is in the (0,1) direction  Thus there is a new formula for it	
the px is in the movement to (1,0) and py is in the (0,1) direction  Thus there is a new formula for it  This is for anything that:  starting from <xo,yo> and  going to <a,b   > px evaluated at initial</a,b   ></xo,yo>	
Gradient Vector (nabla(f))  It's the <px,py> → partial derivatives evaluated at the starting point Always orthogonal to the level curves → pointing to the center → The steepest ascent SAGE E.gradient()</px,py>	
Constrained Optimization  The constraint is the path within the graph. The nabla f (the gradient) is always pointing to the steepest ascent. So if there is a component of the nabla on our path, we can still grow. If the only way to increase is to jump out of the path (the nabla/ <i>gradient is perpendicular to the path</i> ), we have reached a max of our path.	
Lagrange Multipliers	
grad(f) is perpendicular to the level curves At the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y terms to similar side and calculate the partial derivatives  px,py  Now grad(f) and and grad(g) point to the similar direction → the steepest ascent → the max value is thus at the point (x*,y*)  But they're not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) → the partial derivatives of f	
grad(f) is perpendicular to the level curves At the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y terms to similar side and calculate the partial derivatives  px,py  Now grad(f) and and grad(g) point to the similar direction → the steepest ascent → the max value is thus at the point (x*,y*)  But they're not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)	
grad(f) is perpendicular to the level curves At the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y terms to similar side and calculate the partial derivatives  px,py  Now grad(f) and and grad(g) point to the similar direction → the steepest ascent → the max value is thus at the point (x*,y*)  But they're not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) → the partial derivatives of f  grad(g) → the partial derivatives of g  grad(f) = lamda x grad(g)  Disassociate elements as there are 2/3 things in the grad_f and grad_g  Add the constraint function to the system  Equalize and place in to solve for x* and y*	
grad(f) is perpendicular to the level curves At the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y terms to similar side and calculate the partial derivatives  px,py  Now grad(f) and and grad(g) point to the similar direction → the steepest ascent → the max value is thus at the point (x*,y*)  But they're not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) → the partial derivatives of f  grad(g) → the partial derivatives of g  grad(f) = lamda x grad(g)  Disassociate elements as there are 2/3 things in the grad_f and grad_g  Add the constraint function to the system  Equalize and place in to solve for x* and y*	
At the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y terms to similar side and calculate the partial derivatives px.py  Now grad(f) and and grad(g) point to the similar direction → the steepest ascent → the max value is thus at the point (x*,y*)  But they're not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) = the partial derivatives of f  grad(g) → the partial derivatives of g  grad(f) = lamda x grad(g)  Disassociate elements as there are 2/3 things in the grad_f and grad_g  Add the constraint function to the system  Equalize and place in to solve for x* and y*  Try out the the points to see if it's max or min	
prad(f) is perpendicular to the level curves  A the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y terms to similar aide and calculate the partial derivatives  Sp.py  Yow grad(f) and and grad(g) point to the similar direction — the steepest ascent — the max value is thus at the point (x*,y*)  at they ir not requal (scalar multiplies of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) = the partial derivatives of f  grad(g) — the partial derivatives of g  grad(f) = almad x grad(g)  Disassociate elements as there are 2/3 things in the grad_f and grad_g  Add the constraint function to the system  Equalize and place in to solve for x* and y*  Try out the the points to see if it's max or min  **Try out the the points to see if it's max or min  **Try out the the points to see if it's max or min  **Try out the inputs for the lagrange formula  processes the degree of the polymornial, but take out own a degree of abstraction (v — d)  that input all the process of derivation. Antiderivative.  Increases the degree of the polymornial, but take us down a degree of abstraction (v — d)  What function would derivate to give us the function we have at hand?  's the area under the graph.'	
grad(f) is perpendicular to the level curves  At the max position in the path, the grad(f) should be perpendicular to the constraint function as well  Max is the critical point (x*,y*) where we need to jump out  Try to make the constraint into a function and find it's gradient as well (g(x) is furn)  Aggregate x and y terms to similar side and calculate the partial derivatives  Dxpy  Now grad(f) and and grad(g) point to the similar direction — the steepest ascent — the max value is thus at the point (x*,y*)  Southey it not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplier (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) — the partial derivatives of f  grad(g) — the partial derivatives of g  grad(g) — the partial derivatives of g  grad(f) = lamba x grad(g)  Disassociate elements as there are 2/3 things in the grad_f and grad_g  Add the constraint function to the system  Equalize and place in to solve for x* and y*  Try out the the points to see if it's max or min  **Output Plot - to see the level curve of objective function and constraint function's tangency points (critical points)  **Output Plot - to see the level curve of objective function and constraint function's tangency points (grad grad grad grad grad grad grad grad	).
grad(f) is perpendicular to the level curves  At the max position in the path, the grad(f) should be perpendicular to the constraint function as  well  Max is the critical point (x*,**) where we need to jump out  Try to make the constraint into atmicron and find if a gradient as well (g(x) is fure)  Agorgate x and y terms to similar side and calculate the partial derivatives  px,py  Yor grad(f) and and grad(g) point to the similar direction the steepest ascent the max  aliance is thus at the point (x*, y*)  But they're not equal (scalar multiples of each other)  grad(f) = lagrangeMultiplire (scalar) x grad(g)  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) = dragangeMultiplire (scalar) x grad(g)  Process:  Define the objective function (g)  grad(f) = lagrangeMultiplire (scalar) x grad(g)  Define the constraint function to the system  Equalize and place in to solve for x* and y*  Try nut the the points to see if it's max or min   **Add the constraint function to the system  Equalize and place in to solve for x* and y*  Try nut the the points to see if it's max or min  **  **Add the constraint function to the system  Equalize and place in to solve for x* and y*  Try nut the the points to see if it's max or min  **  **  **  **  **  **  **  **  **	).
grad(f) is perpendicular to the level curves  At the max position in the path, the grad(f) should be perpendicular to the constraint function as  swell  My as is the critical point (**,**) where we need to jump out  Ty to make the constraint into a function and find it's gradient as well (g(x) is fucn)  Aggregate x and y remus to similar side and calculate the partial derivatives  px.py  Now grad(f) and and grad(g) point to the similar direction — the steepest ascent. — the max  and is thus at the point (x*,**) where we need to jump out  Process:  Define the objective function (f)  Define the constraint function (g)  grad(f) — the partial derivatives of g  grad(f) — the partial derivatives of g  grad(g) — the partial derivative of g  grad(g) — the parti	).
stack(s) is perpendicular to the level curves  It the max position is the path, the good(s) should be perpendicular to the constraint function as  Self-une is the critical pairs (e^xy) where we need as jump out  Try or make the constraint into a function and find its guident as well, (g(x)) is face)  Agongue a valy errant to similar side and calculate the partial derivatives  (a.g.)  You good(s) and and goad(g) point to the similar direction — the steepest ascent — the nox  out new year or qualified (color) signal(g)  Yourses:  Define the objective function (f)  Define the constraint function (g)  grat(g) — the paired function (g)  grat(g) — and a paired function (g)  grat(g) — and a paired function (g)  grat(g) — the paired (g)  All the constraint function (g)  grat(g) — the paired (g)  All the constraint function (g)  grat(g) — the paired (g)  grat(g)	).
pad(s) is perpendicular to the level curves  the next position in the path, the gradidy should be perpendicular to the constraint function as  the the constraint into a function and find it's gradient as well (gay is then)  Agongate a vary terms to similar die and calculate has partial derivatives  pages of the constraint into a function and find it's gradient as well (gay is then)  Agongate a vary terms to similar die and calculate has partial derivatives  pages of the partial derivative of pages of the partial derivative of pages  to grad(t) = lagrange/Multiplier (scalar) x grad(g)  Process  Define the objective function (t)  Define the objective function (t)  grad(t) = lagrange/Multiplier (scalar) x grad(g)  Process  Define the objective function (t)  grad(t) = departial derivatives of f grad(t) = lagrange/Multiplier (scalar) x grad(g)  Define the constraint function (s)  grad(t) = departial derivatives of f grad(t) = function x grad(g)  And the constraint function to the vycous  Regulation and place in the partial derivatives of g grad(t) = lambala (sign)  Process  Try out the the points to see if it's max or min.  Try out the the points to see if it's max or min.  Try out the the points to see if it's max or min.  The immediate and place in the objective function and constraint functions  The immediate of derivation and derivative of the sequentions  grad(t) = (a.2, 3-w-2+y-2=6-6-1/4, x, j, annibala)) welve for the equations, and constraint into (sold)  The immediate of derivation and derivative of the sold of the sequential of the sequentia	).
spail(1) is perpendicular to the level curves  to the may position in the path, the good(2) should be perpendicular to the constraint function as  with the may position in the path, the good(2) should be perpendicular to the constraint function as  with may be position in the path, the good(2) should be perpendicular to the constraint function as  fly to note the constraint and a function and find it's guident as well. (4)(3) in func)  Aggregate as and y terms to similar desertion:— the steepest access—the max  place is they as the pount (2 × y²) should be a function of the path of the path  for path (2) = Ingrange-Multiplier (exalar) x grad(g)  Forecas:  Define the objective function (1)  Define the objective function (2)  good(1) = Ingrange-Multiplier (exalar) x grad(g)  Forecas:  Define the objective function (2)  good(2) = Objective functions of (2)  good(3) = Objective functions of (2)  good(3) = Objective functions of (2)  good(3) = Objective functions of (3)  good(3) = Objective functions of (4)  good(3) = Objective functions of (4)  good(3) = Objective functions of (4)  good(4) = Objective functions of (4)  g	).
ANCE.  SACE.  A contract the contract of the path (a) specify should be perpendicular to the constraint function as electric protection of the path (b) goodly should be perpendicular to the constraint function as electric to protect the path (b) goodly should be perpendicular to the constraint function and that the path (b) goodly should be perpendicular to should derivate by goodly should be perpendicular to the path (b) goodly should be perpe	).
profit is perpendicular to the level curves  Acceptation in the position in position and position good position in the concretion to the concretion and position in position and position in position in progress or control and make the concretion for some control and find it is guident as well. ((i)) in the position of the concretion for some control and district the concretion for control and position for spatial electronics ((ii)) in the position of the control and position for spatial electronics ((iii)) in the position of the control and position for spatial electronics ((iii)) in the control and position for spatial electronics ((iii)) in the control and position for spatial electronics ((iii)) in the control and position ((iii)) in the	).
sex of the propositionals to the level convents of the propositional in the control and conference of the control of the contr	
professional properties with a fine level entered.  Many is the created grown (e. 25) which is perpondicular to the constraint function as edit.  Many control grown (e. 25) which is constituted that the partial desiration is a constraint of the c	
part of the proposed to the plant of the proposed colors to the constraint function as a color.  Make is the extract point (\$\circle{x}^2\	
and it population at the level consist.  March and challed the construct traction and construct function of all constructs and construct traction and constructs.  March and challed the construction of the construct traction of all constructs.  March and challed traction of the construction of the construc	
ACCES  The contraction of the co	
Mean and the second of the sec	
And the common of the control country of the country of the control country of the co	
ACADA  The control common for the control control to personal control	
Account former between the management of the man	
Action to excellent an information of the major country of the major cou	
And the properties of the content of	
And the comparison of the comp	
Control and and and the control and the contro	
The complete of the property of the complete o	
The complete of the property of the complete o	
And the control of th	