

Phys 512 Lecture 2

Polynomial Interpolation/ Integration

Interpolation

- Let's say we have a function y_i tabulated at some values x_i but we want to know it at arbitrary x .
- If the new values are between current values, we call this interpolation. If outside, extrapolation. Extrapolation decidedly dodgier.
- How should we do this?

Simple Solutions

- Dumbest thing we can do is find the x_i nearest our target x , and take y_i . This is nearest neighbor. Is this going to be accurate? Is it ever going to go crazy?
- Next dumbest thing is find the interval x_i, x_{i+1} that x sits in. Then draw a line between (x_i, y_i) and (x_{i+1}, y_{i+1}) and evaluate it at x . This is linear interpolation. Will this be accurate? Is it every going to go crazy?
- NB - by “crazy” we usually mean that the interpolated y is far from the spread covered by y_i and its neighbors.
- For linear, y will be between y_i and y_{i+1} , so it can't go crazy.

Higher Order

- If we want more accuracy **AND** our function is “smooth”, we can win by Taylor expanding.
- Next order is quadratic. We could take y_{i-1}, y_i, y_{i+1} and draw a parabola.
- This is almost certainly a bad idea! Why?

```

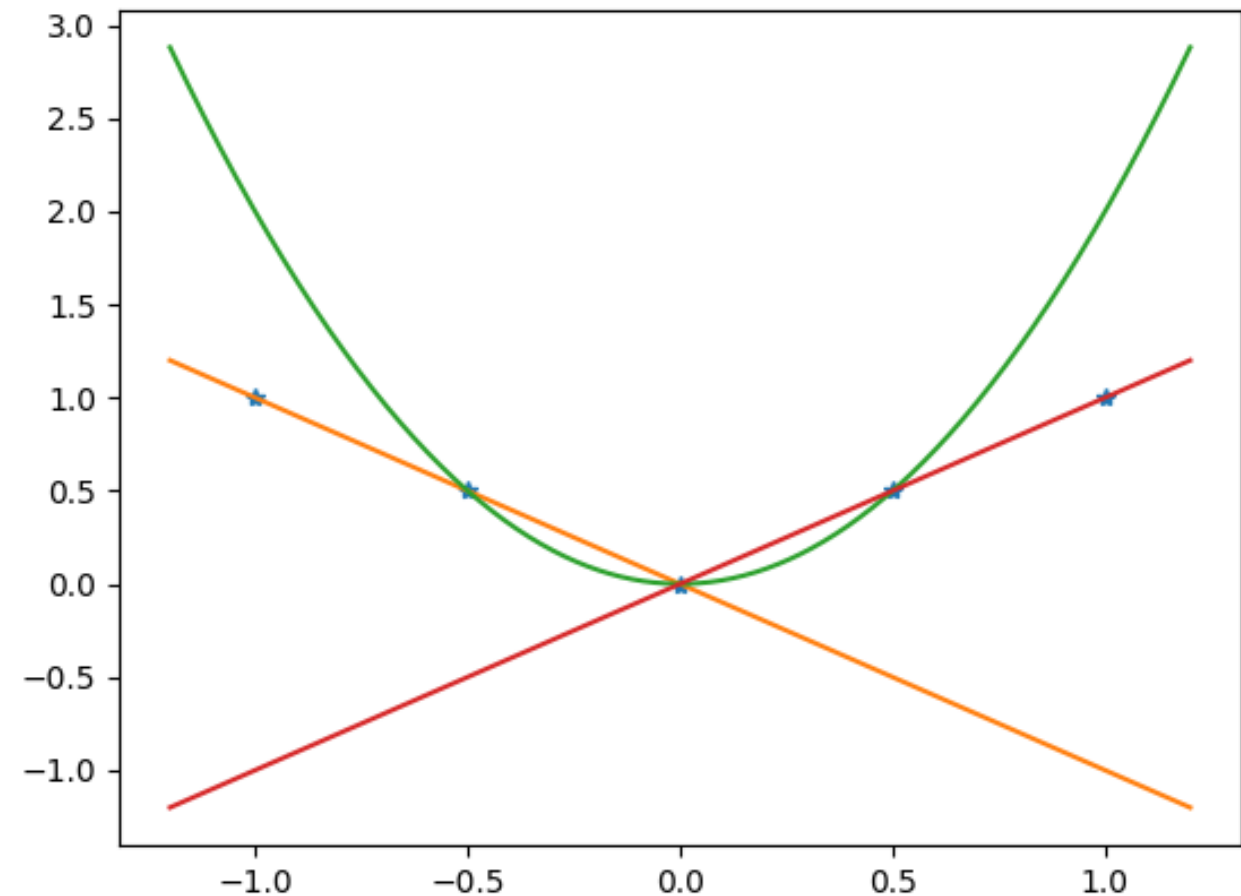
import numpy as np
from matplotlib import pyplot as plt

x=np.linspace(-1,1,5)
y=np.sqrt(np.abs(x))
y=np.abs(x)

xx=np.linspace(-1.2,1.2,1000)

plt.clf()
plt.plot(x,y,'*')
for i in range(len(x)-2):
    pp=np.polyfit(x[i:i+3],y[i:i+3],2)
    yy=np.polyval(pp,xx)
    plt.plot(xx,yy)
plt.savefig('parabolas.png')

```



How would I decide on x_i ? Natural thing is to take nearest neighbor.

However, that changes halfway between points. I then move to a different parabola. In general, interpolation will be discontinuous. This is (almost certainly) bad!

NB - no guarantee anymore that y is bracketed by function values.

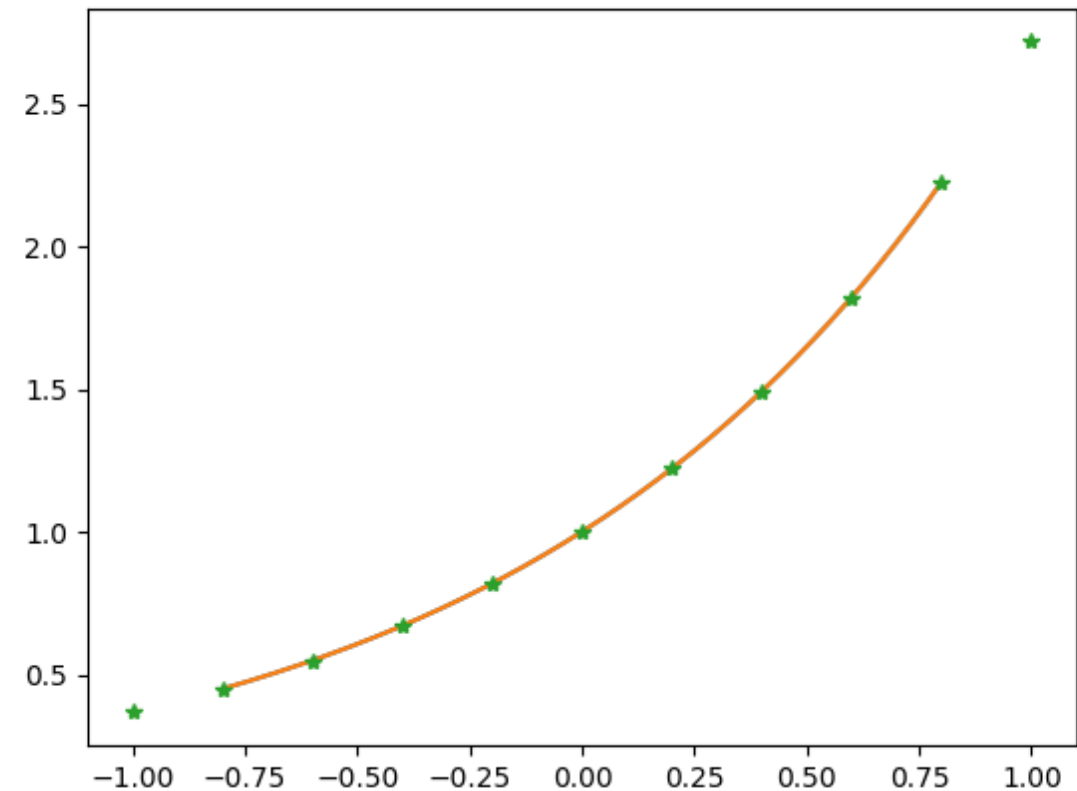
```

fun=np.exp
xmin=-1
xmax=1
x=np.linspace(xmin,xmax,11)
dx=np.median(np.diff(x))
y=fun(x)

xx=np.linspace(x[1],x[-2]-1e-13,1001) #skip the first/last region
                                         #since we aren't double-bracketed

yy_true=fun(xx)
yy=0*yy_true
for i,myx in enumerate(xx):
    j=np.int((myx-xmin)/dx)
    pp=np.polyfit(x[j-1:j+3],y[j-1:j+3],3)
    yy[i]=np.polyval(pp,myx)
plt.clf();
plt.plot(xx,yy_true);
plt.plot(xx,yy);
plt.savefig('cubic_interp.png')
print('mean error is ' + repr(np.mean(np.abs(yy-yy_true))))

```



- Cubic polynomials don't suffer from discontinuity since interval is well defined.
- Mean error has done pretty well! $\sim 1e-5$
- However - we are doing a polynomial fit for every point. This can be quite slow.

Simple Polynomial Construction

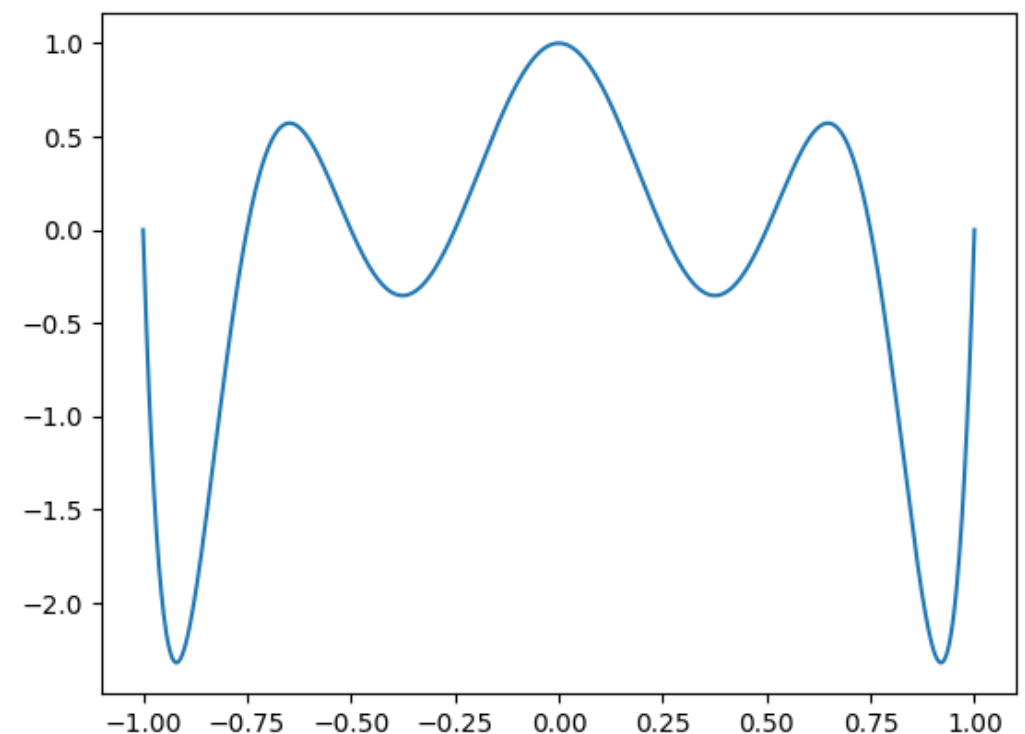
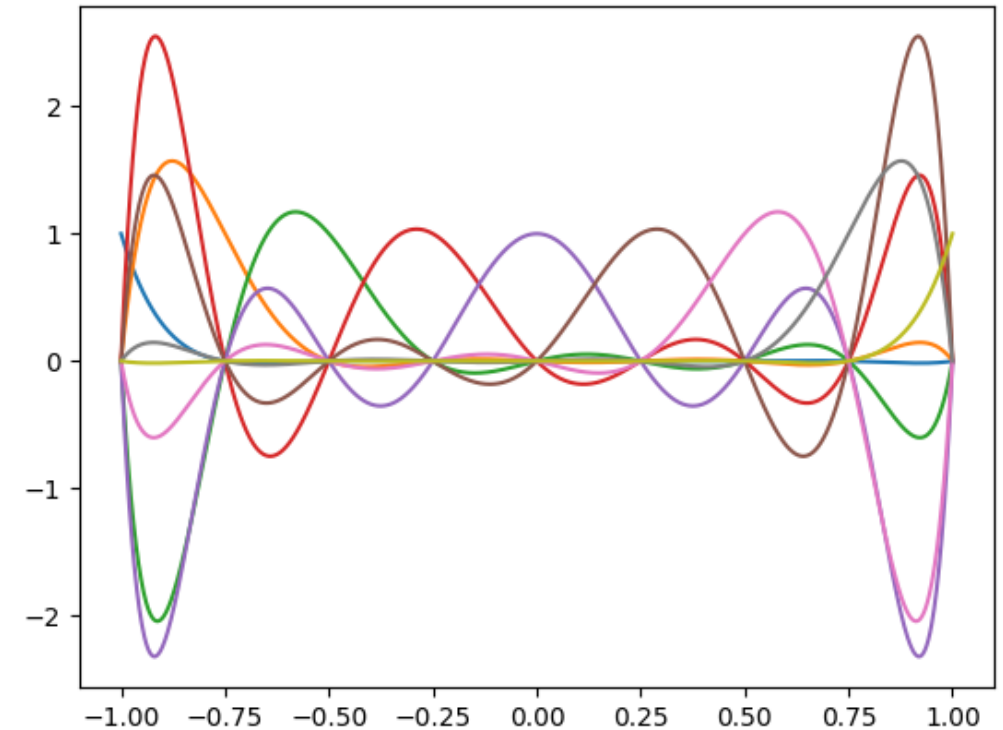
- How can I construct a polynomial that goes through n points?
- Well, I can construct a polynomial that is zero at $n-1$ points, say x_1 through x_{n-1} . NB - $n-1$ is because we zero index.
- $(x-x_1)(x-x_2)(x-x_3)\dots(x-x_{n-1})$ by construction is zero.
- What is it at x_0 ? well, $(x_0-x_1)(x_0-x_2)\dots(x_0-x_{n-1})$.
- If I take the ratio, I have a polynomial P_0 that is 1 at x_0 and zero at all other x_i .
- I can now take $\sum P_i y_i$ to have a polynomial that goes exactly through all y_i .

What Those Look Like

```
ord=8
x=np.linspace(-1,1,ord+1)
xx=np.linspace(x[0],x[-1],1001)
plt.clf()
for i in range(len(x)):
    x_use=np.append(x[:i],x[i+1:])
    x0=x[i]
    mynorm=np.prod(x0-x_use)
    p0=1.0
    for xi in x_use:
        p0=p0*(xi-xx)
    p0=p0/mynorm
    plt.plot(xx,p0)
    if i==4:
        bad_p0=p0.copy()

plt.savefig('delta_polys_out.png')
plt.clf()
plt.plot(xx,bad_p0)
plt.savefig('delta_polys_one.png')
```

- This should make you nervous. At high order, polys could jiggle quite a bit between points. OK iff your function is smooth, in the sense that $(ord \cdot dx)^n f^{(n)}/n!$ is converging.



Poly Interpolation ctd.

- Cubic interpolation from earlier look OK. At least was continuous.
- I didn't need to do the polynomial fit for each interpolated value. Rather, I could fit every interval and store coefficients.
- Then, when interpolating, look up the segment, take the relevant coefficients, and evaluate.
- Note that nowhere have we assumed the x_i are equally spaced. The lookup is faster when they are, but still only $\log_2(n)$ when they aren't.

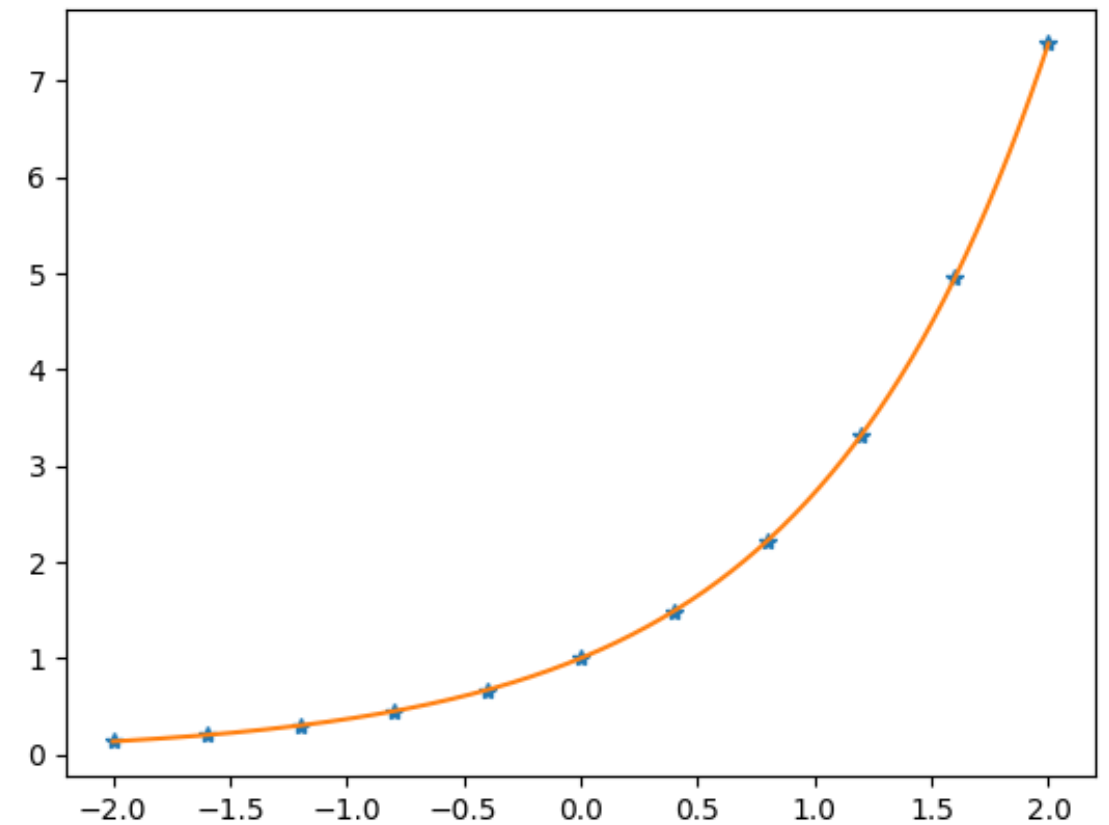
Cubic Splines

- My old cubic interpolation was continuous. Were its derivatives?
- An important class of interpolation forces the function and the first n derivatives to be continuous. These are called splines.
- By far most common is requirement that second derivate is continuous (so first deriv is guaranteed smooth). Specifying function values and derivatives at edges is $2+2=4$ values, so we will need a cubic to fit them.
- Cubic splines are so common, we usually drop the cubic, just call them splines.
- My 2nd deriv has to match left and right neighbors. But what about at ends? You need to specify. Most common is set f'' to zero on edges, but can also set f' to specific values, or require periodic boundary conditions (right edge has to match left).

```
import numpy as np
from matplotlib import pyplot as plt
from scipy import interpolate

x=np.linspace(-2,2,11)
y=np.exp(x)
xx=np.linspace(x[0],x[-1],2001)

spln=interpolate.splrep(x,y)
yy=interpolate.splev(xx,spln)
plt.clf();
plt.plot(x,y, '*')
plt.plot(xx,yy)
plt.savefig('spline_out.png')
```



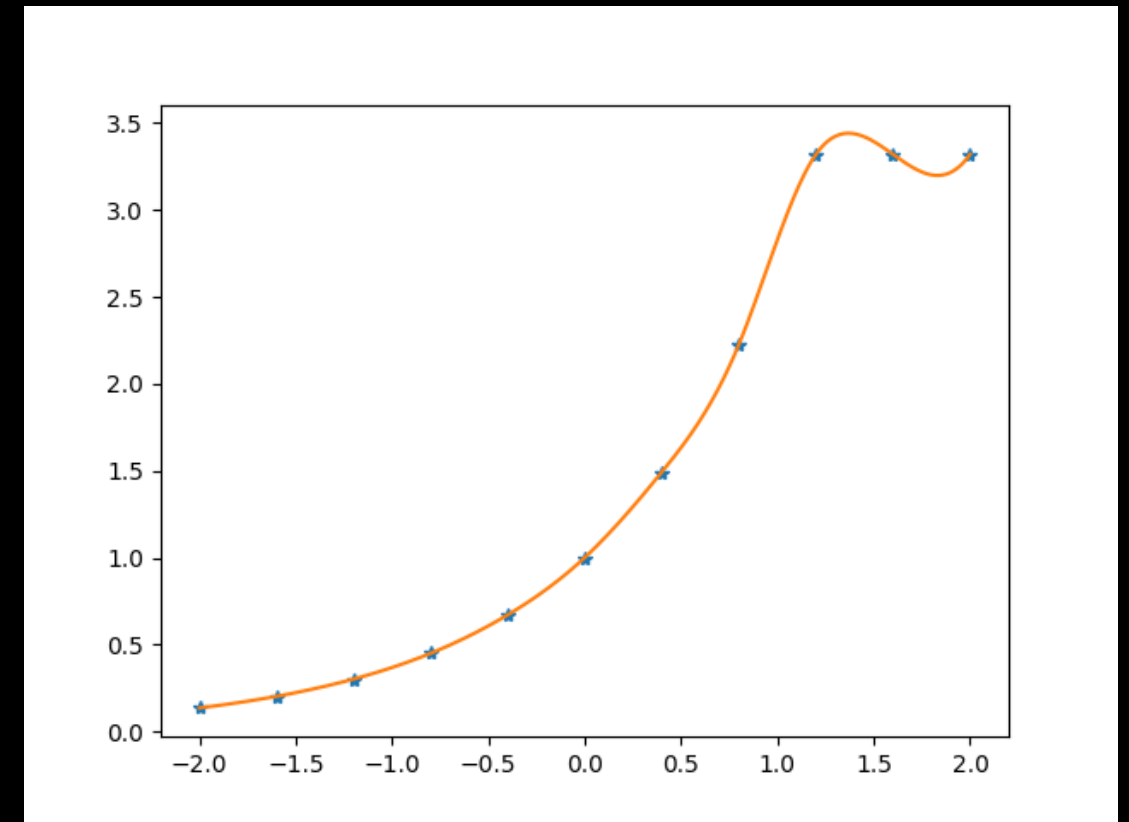
- Spline in use. Lives in `scipy.interpolate`
- First, set up the spline fit with `splrep`.
- Then evaluate with `splev`.
- Broader range of options in `BSpline` class (also in `scipy.interpolate`).

```

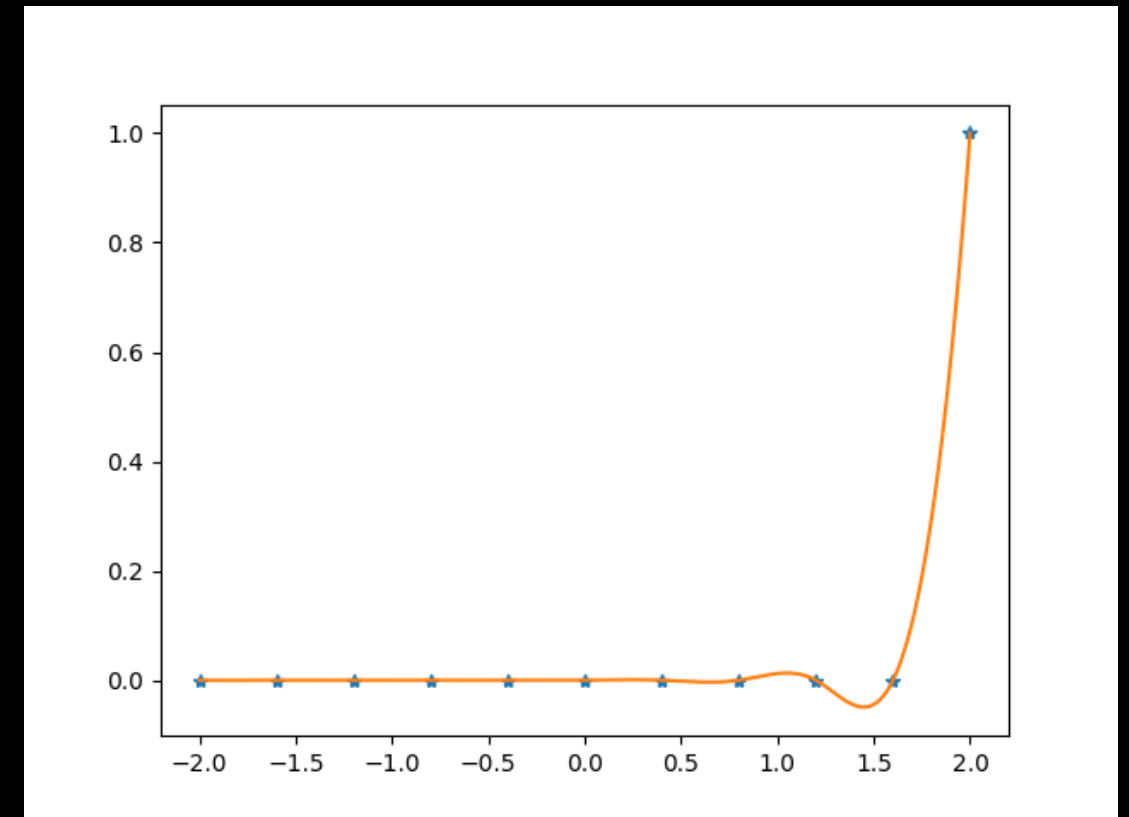
x=np.linspace(-2,2,11)
y=np.exp(x)
y[-2:]=y[-3]
xx=np.linspace(x[0],x[-1],2001)

spln=interpolate.splrep(x,y)
yy=interpolate.splev(xx,spln)
plt.clf();
plt.plot(x,y,'*')
plt.plot(xx,yy)
plt.savefig('spline_out.png')

```



- Be aware - splines can ring near jumps/kinks. This might be OK, this might not be. But you should not be caught by surprise.
- Another option is cubic Hermite polynomials - similar to spline, but $y(x \in (x_1, x_2)) \in (y_1, y_2)$ (scipy.interpolate.PchipInterpolator)



Rational Functions

- Another useful class is rational functions, ratios of two polynomials.
- Can be especially useful when your function has poles.
- Nominally non-linear: $p(x)/q(x)=y(x)$. Without loss, set $q(x)=1+ax+bx^2+\dots$
- For simple case of number of degrees matches number of points can get around: $p(x)=q(x)y(x) = y(x)+qq(x)y(x)$
- Matrix: $[1 \ x \ x^2 \ x^3 \dots \ -yx \ -yx^2 \ -yx^3 \dots][p;q]=y$

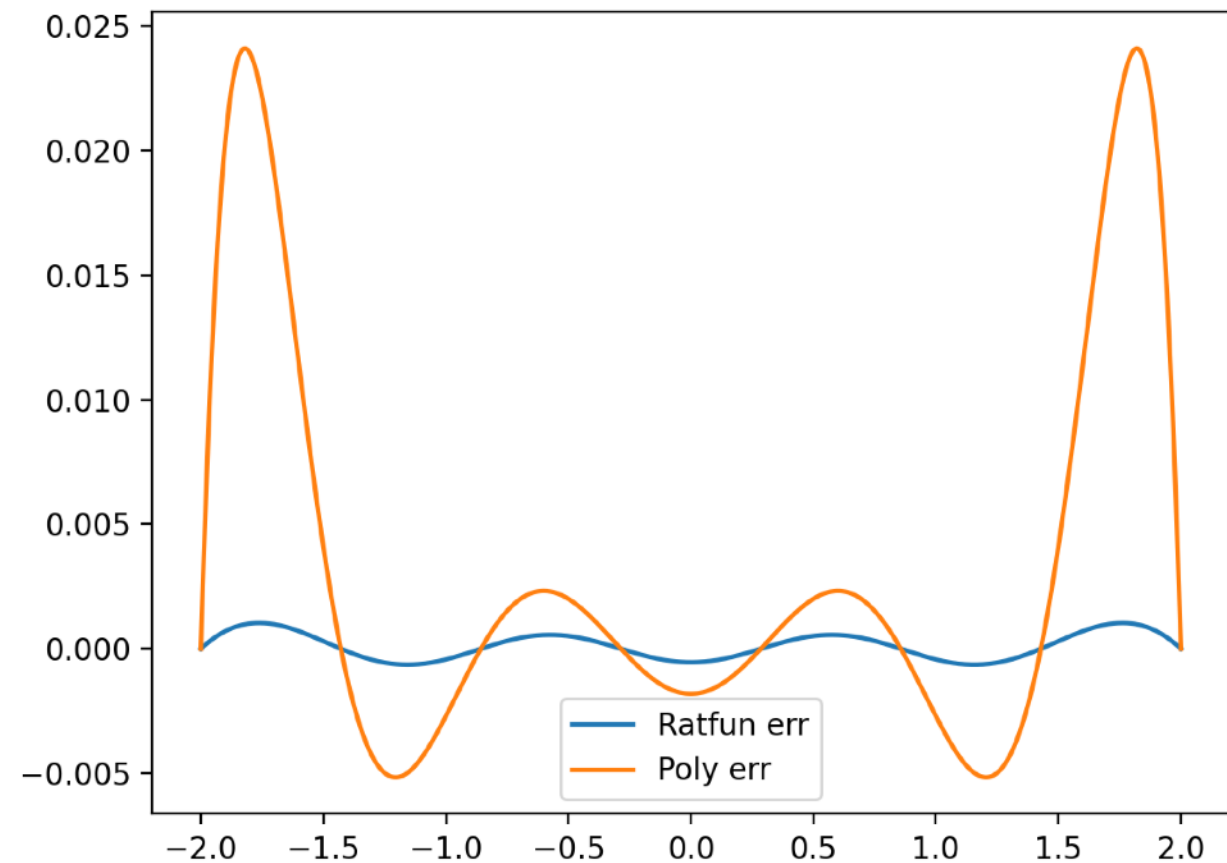
```
def rat_eval(p,q,x):
    top=0
    for i in range(len(p)):
        top=top+p[i]*x**i
    bot=1
    for i in range(len(q)):
        bot=bot+q[i]*x**(i+1)
    return top/bot

def rat_fit(x,y,n,m):
    assert(len(x)==n+m-1)
    assert(len(y)==len(x))
    mat=np.zeros([n+m-1,n+m-1])
    for i in range(n):
        mat[:,i]=x**i
    for i in range(1,m):
        mat[:,i-1+n]=-y*x**i
    pars=np.dot(np.linalg.inv(mat),y)
    p=pars[:n]
    q=pars[n:]
    return p,q
```

```
#we can use numpy's polynomial fitter to see how that does
pp=np.polyfit(x,y,n+m) #use same number of terms
yy_poly=np.polyval(pp,xx)
plt.plot(xx,yy_poly-yy)
plt.savefig('ratfit_vs_poly.png')
```

```
n=4
m=5
x=np.linspace(-2,2,n+m-1)
y=np.exp(-0.5*x**2)
p,q=rat_fit(x,y,n,m)
pred=rat_eval(p,q,x)

xx=np.linspace(-2,2,1001)
yy=np.exp(-0.5*xx**2)
yy_interp=rat_eval(p,q,xx)
plt.ion()
plt.clf()
plt.plot(xx,yy_interp-yy)
```





Integration

- Interpolation & numerical integration are closely coupled
- Interpolation schemes are often easy to integrate analytically.
- Usually end up as a set of coefficients times function values, where coefficients are set by scheme.
- Can think of this as finding the “average” value in a region, based on some interpolation scheme.

Integration with Linear

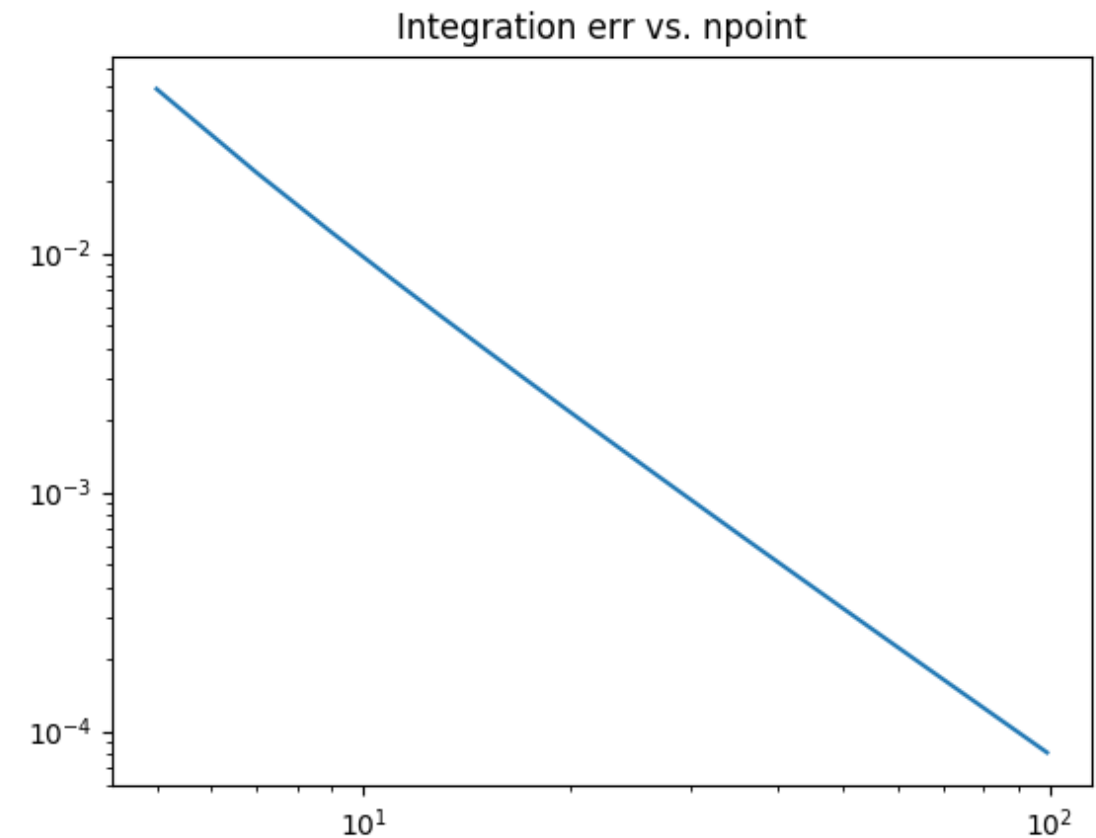
- Break function into series of regions, draw a line between points.
- What is the average value of y if it is based on a line between y_i and y_{i+1} ? just $0.5(y_i + y_{i+1})$.
- If points are dx apart, then $\text{area}/dx = 0.5(y_0 + y_1) + 0.5(y_1 + y_2) \dots + 0.5(y_{n-2} + y_{n-1}) = 0.5(y_0 + y_{n-1}) + \sum y_i, i=1..n-2$.
- How should error scale with # of points?


```

x0=-1
x1=1
nn=np.arange(5,101,2)
errs=np.zeros(nn.size)
for i,npt in enumerate(nn):
    x=np.linspace(x0,x1,npt)
    y=np.exp(x)
    dx=np.median(np.diff(x))
    myint=0.5*(y[0]+y[-1])+np.sum(y[1:-1])
    myint=myint*dx

    targ=np.exp(x1)-np.exp(x0)
    errs[i]=np.abs(myint-targ)
plt.loglog(nn,errs)
plt.title('Integration err vs. npoint')
plt.savefig('linear_integral_errs.png')
pp=np.polyfit(np.log10(nn),np.log10(errs),1)
print('error is scaling as step size to the power ' + repr(pp[0]))

```



- Scaling is going as step size squared, as expected.

But Wait!

- If error is going like dx^2 , can I use that for fun and profit?
- $f(dx) = f_{\text{true}} + a dx^2 + \dots$ $f(2dx) = f_{\text{true}} + a(2dx)^2 + \dots$
- $4f(dx) - f(2dx) = 4f_{\text{true}} - f_{\text{true}} + \dots = 3f_{\text{true}} + \dots$ or $f_{\text{true}} = (4f(dx) - f(2dx))/3$
- 3 points: $f(dx) = (y_0 + 2y_1 + y_2)dx/2$. $f(2dx) = (y_0 + y_2)dx$ (NB - dx went to $2 dx$, cancelling usual factor of 2)
- $4f(dx) - f(2dx) = (2y_0 + 4y_1 + 2y_2 - y_0 - y_2)dx/3 = (y_0 + 4y_1 + y_2)dx/3$
- We have cancelled 2nd order error term. Should be more accurate.

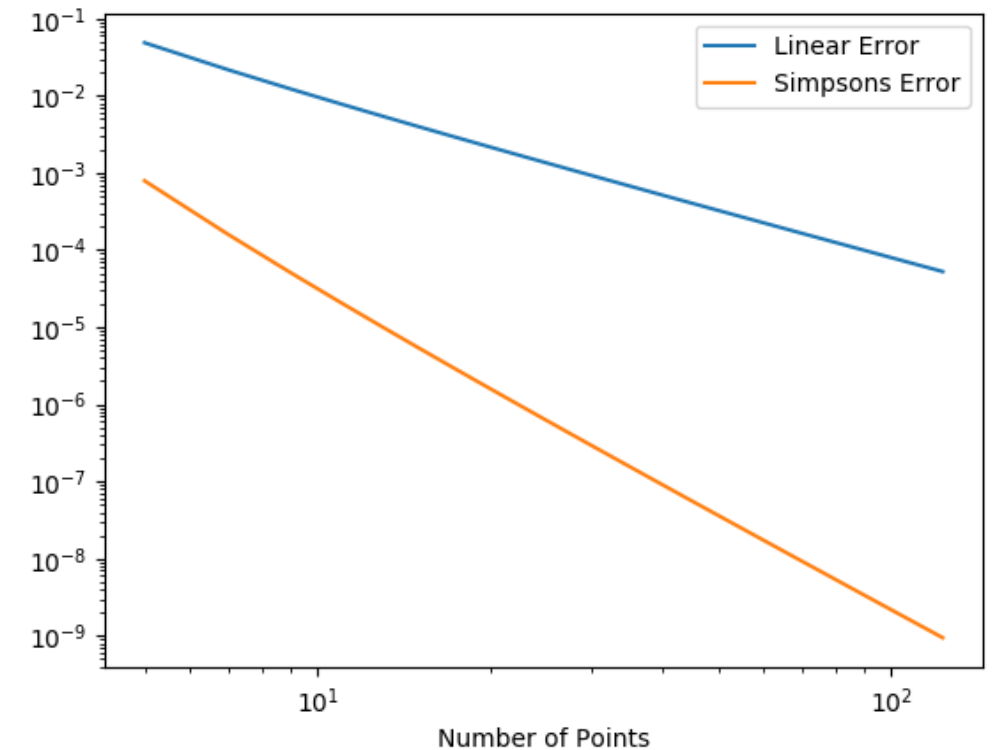
Equivalent

- We could also fit a parabola to 3 points. For simplicity take $x=-1,0,1$. There's a trapezoid going through y_0 and y_2 , with a parabola that goes through y_1 minus $(y_0+y_2)/2$.
- Parabola is $(y_1-(y_0+y_2)/2)(1-x^2)$. Integral is $(x-x^3/3)$, evaluates to $4/3$ over $2dx$, so average is $2/3$. Leaves $(y_0+y_2)/2*(2dx)+2/3(y_1-(y_0+y_2)/2)2dx=dx(y_0+4y_1+y_2)/3$.
- This is exactly what we had before! Cancelling 2nd order error term is identical to fitting quadratic & integrating.
- This second-order scheme is called Simpson's rule.
- How should error scale? Hint - what is the average value of x^3 ?

```

nn=np.arange(5,125,2)
x0=-1
x1=1
ints_lin=np.zeros(len(nn))
ints_quad=np.zeros(len(nn))
for i,npt in enumerate(nn):
    x=np.linspace(x0,x1,npt)
    y=np.exp(x)
    dx=np.median(np.diff(x))
    ints_lin[i]=dx*(0.5*y[0]+0.5*y[-1]+np.sum(y[1:-1]))
    ints_quad[i]=dx/3.0*(y[0]+y[-1]+4*np.sum(y[1:-2])+2*np.sum(y[2:-1:2]))
targ=np.exp(x1)-np.exp(x0)
plt.clf();
errs_lin=np.abs(ints_lin-targ)
errs_quad=np.abs(ints_quad-targ)
pp=np.polyfit(np.log(nn),np.log(errs_quad),1)
print('Simpsons scaling is ' + repr(pp[0]))
plt.loglog(nn,errs_lin)
plt.loglog(nn,errs_quad)
plt.xlabel('Number of Points')
plt.legend(['Linear Error','Simpsons Error'])
plt.savefig('simpson_errs.png')

```

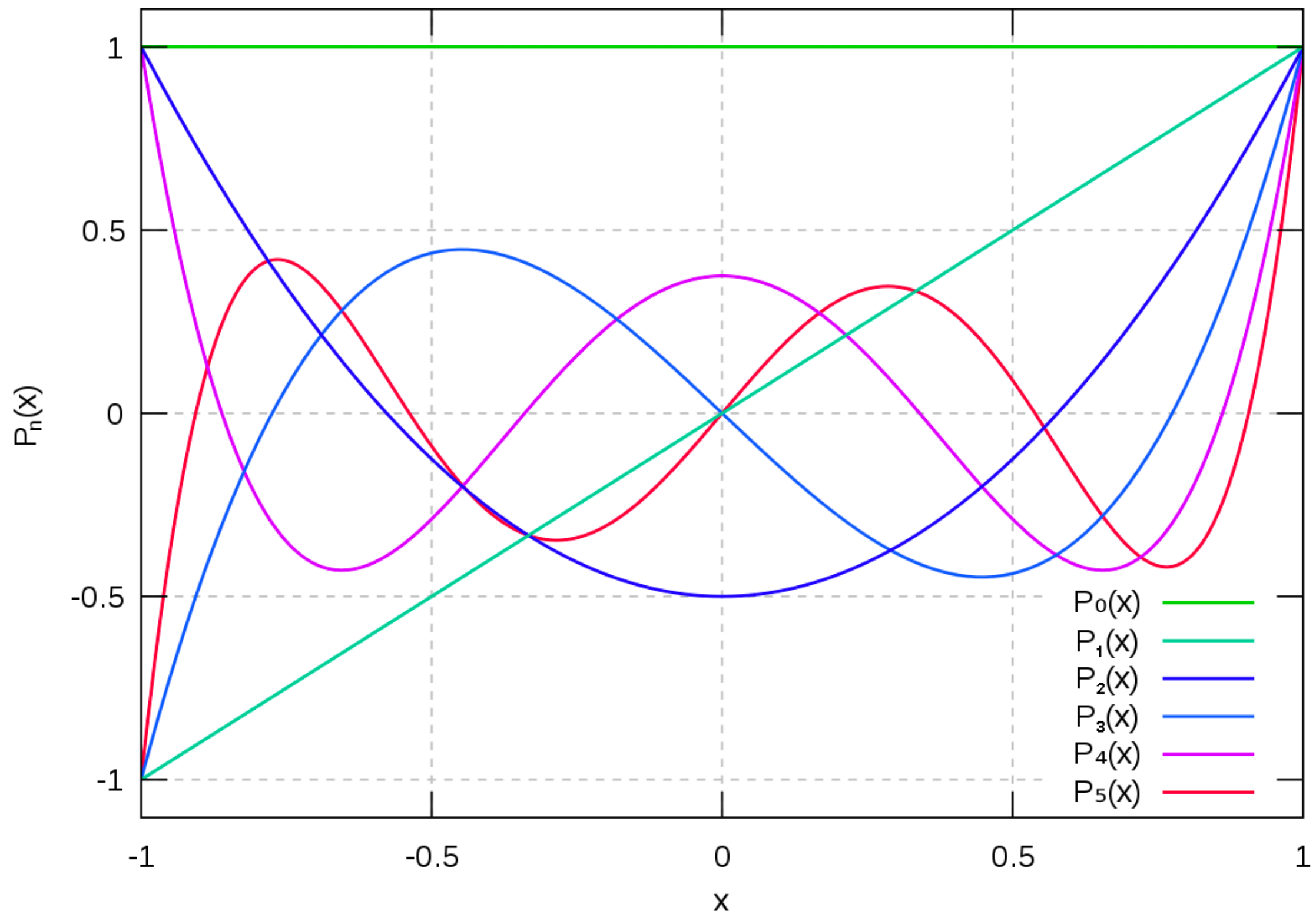


- Simpsons is far more accurate than trapezoid.
- Error goes like dx^4 , since x^3 term integrates to zero.
- I didn't have to make any more function calls, just used the ones I had more cleverly.
- NB - would this work with an even number of y_i ?

Can We Turn it up to 11?

- Yes! Regular polynomials ($x, x^2, x^3 \dots$) are not what we want, though.
- Legendre polynomials are an important class. They arise in separation of variables in spherical coordinates.
- We could think of regular polynomials as defined by a recurrence relation. $F_{n+1} = xF_n$.
- Legendre polynomials best generated with a different recurrence relation. $(n+1)P_{n+1} = (2n+1)xP_n - nP_{n-1}$. $P_0 = 1$, $P_1 = x$.

legendre polynomials



Legendre ctd.

- They have the important property that they are orthogonal on the interval $(-1,1)$. $\int P_n P_m \propto \delta_{nm}$
- Given this, what is $\int P_n dx$ from -1 to 1 ?
- 2 for P_0 , and zero for everything else.
- I can fit Legendre polynomials to a set of data, and integral will just be P_0 coefficient(!).
- How do I get this?

Legendre Fitting

- $y_i = \sum c_j P_j(x_i)$. If I can figure out the c_j then I'm in business.
- But this is just a matrix equation! $y = Pc$. If we have as many polynomials as we have points, then the matrix P is square, and we can just get $c = P^{-1}y$. Pull c_0 , and then we're done.
- But, c_0 is just $\sum P^{-1}_{0,k} y_k$, so I can just take the first column of P^{-1} . This gives me my weights.
- Now I can integrate to whatever order I want (making sure I have a suitable number of y_i for my chosen order).

Code to Make Coeffs

```
def legendre_mat(npt):  
    #Make a square legendre polynomial matrix of desired dimension  
    x=np.linspace(-1,1,npt)  
    mat=np.zeros([npt,npt])  
    mat[:,0]=1.0  
    mat[:,1]=x  
    if npt>2:  
        for i in range(1,npt-1):  
            mat[:,i+1]=((2.0*i+1)*x*mat[:,i]-i*mat[:,i-1])/(i+1.0)  
    return mat  
  
def integration_coeffs_legendre(npt):  
    #Find integration coefficients using  
    #square legendre polynomial matrix  
    mat=legendre_mat(npt)  
    mat_inv=np.linalg.inv(mat)  
    coeffs=mat_inv[0,:]  
    coeffs=coeffs/coeffs.sum()*(npt-1.0)  
    return coeffs
```

Code to Integrate Stuff

```
def integrate(fun,xmin,xmax,dx_targ,ord=2,verbose=False):
    coeffs=legendre.integration_coeffs_legendre(ord+1)
    if verbose: #should be zero
        print("fractional difference between first/last coefficients is "+repr(coeffs[0]/coeffs[-1]-1))

    npt=np.int((xmax-xmin)/dx_targ)+1
    nn=(npt-1)%(ord)
    if nn>0:
        npt=npt+(ord-nn)
    assert(npt%(ord)==1)

    x=np.linspace(xmin,xmax,npt)
    dx=np.median(np.diff(x))
    dat=fun(x)

    #we could have a loop here, but note that we can also reshape our data, then som along columns, and only then
    #apply coefficients. Some care is required with the first and last points because they only show up once.
    mat=np.reshape(dat[:-1],[(npt-1)/(ord),ord]).copy()
    mat[0,0]=mat[0,0]+dat[-1] #as a hack, we can add the last point to the first
    mat[1:,0]=2*mat[1:,0] #double everythin in the first column, since each element appears as the last element in the previous row

    vec=np.sum(mat,axis=0)
    tot=np.sum(vec*coeffs[:-1])*dx
    return tot
```


Code to Call it +Output

```
if True:
    print("Integrating sin")
    fun=np.sin
    xmin=0
    xmax=np.pi
    targ=2.0
    dx_targ=0.1
else:
    print("Integrating Lorentzian")
    fun=lorentz
    xmin=-5
    xmax=5
    targ=np.arctan(xmax)-np.arctan(xmin)
    dx_targ=0.5

for ord in range(2,16,2):
    val=integrate(fun,xmin,xmax,dx_targ,ord)
    print('For order ' + repr(ord) + ' error is ' + repr(np.abs(val-targ)))
```

```
def lorentz(x):
    return 1.0/(1.0+x**2)
```

```
Integrating sin
For order 2 error is 1.0333694131503535e-06
For order 4 error is 3.809155213474469e-09
For order 6 error is 7.276845792603126e-12
For order 8 error is 1.0769163338864018e-13
For order 10 error is 0.0
For order 12 error is 1.9984014443252818e-15
For order 14 error is 2.6645352591003757e-15
```

```
Integrating Lorentzian
For order 2 error is 0.0038935163714279852
For order 4 error is 0.01097767769723701
For order 6 error is 0.002621273236311783
For order 8 error is 0.01837703807845159
For order 10 error is 0.005032084054994446
For order 12 error is 0.001118349714313016
For order 14 error is 0.0003964865376655524
```

What Happened?

- In all cases, we used roughly the same number of function evaluations.
- Sin is a smooth function. Its error rapidly went to zero as we increased the order. If you know you're integrating a sin, crank away!
- Lorentzian is not a smooth function since it has poles at $\pm i$. Its power series expanded at zero does not converge for $|x| > 1$. Integral is less accurate, and does not improve very rapidly as we increase order.
- Lorentzian sometimes gets worse at higher order!

Error Estimate

- Usual scheme is to pick an order, then vary step size until accuracy is good.
- How do I know accuracy? If I'm in happy Taylor regime, errors predictable. Compare $f(4dx)$ & $f(2dx)$ against $f(2dx)$ & $f(dx)$. Did differences shrink as expected? If not, try smaller step size.
- If you beat hard enough, eventually Taylor wins out.

Variable Step Size

- For Lorentzian, areas well away from poles should integrate nicely. Only around $|x| < \sim 1$ is problematic.
- If I keep track, I will be able to see that away from the origin I converge, but less well at origin.
- I can find regions that behave, and not shrink dx when their errors are small.
- Regions that do not behave: shrink dx by a factor of 2, and try again.
- Life experience: Bad functions are usually bad in a small piece.
- Variable step size integration can easily save factors of \sim hundred.