

# Pade Approximations

## By

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## INTRODUCTION

Pade polynomials are polynomial ratios defined as:

$$y = P_{m,n}(x) = \frac{Q_m(x)}{D_n(x)} \quad (1)$$

Where  $Q_m(x)$  is defined as:

$$Q_m(x) = a_0 + \sum_{i=1}^m a_i x^i \quad (2)$$

And  $D_n(x)$  is defined as:

$$D_n(x) = 1 + \sum_{i=1}^n b_i x^i \quad (3)$$

The Pade polynomials have more flexibility than ordinary legacy polynomials. The trick is to find the optimum values for  $m$  and  $n$ . This study uses swarm optimization to determine these optimum values within the range of (2, 7). The multiple regression model used to fit Pade polynomials is:

$$y = a_0 + \sum_{i=1}^m a_i x^i - \sum_{i=1}^n b_i y x^i \quad (4)$$

When you use the Pade polynomials to calculate new values, use the following form:

$$y = [a_0 + \sum_{i=1}^m a_i x^i] / [1 - \sum_{i=1}^n b_i y x^i] \quad (5)$$

Unlike the Shammas polynomial fitting, working with Pade polynomials focusing on simply determining the optimum values of the orders  $m$  and  $n$  for  $Q_m(x)$  and  $D_n(x)$ , respectively. As these two polynomials are regular polynomials there are no Shammas polynomial parameters to calculate the powers for the various terms. Thus, the process of approximating various functions using Pade polynomials becomes much simpler. Another advantage for this simplicity is that this report is much shorter than the one for Shammas polynomials approximations—there is one approximation per function.

This study looks at Pade polynomials used to approximate common functions that include:

- Trigonometric functions and their inverses.
- Hyperbolic functions.
- Logarithmic functions.
- Exponential functions.
- Inverse student-t functions.
- The common logarithm of the gamma function.
- The digamma function.
- The trigamma function.

The digamma function is defined as:

$$\psi(x) = \Gamma'(x) / \Gamma(x) = \frac{d \ln(\Gamma(x))}{dx} \quad (6)$$

The following Matlab function implements the code for the digamma function:

```
function y = digamma(x)
%DIGAMMA Summary of this function goes here
% Detailed explanation goes here
    h = 0.001;
    fp = gammaln(x+h);
    fm = gammaln(x-h);
    y = (fp - fm)/2/h;
end
```


The above implementation of the digamma function was suggested by Albert Chan, a member of the hp museum web site, in a post he wrote on that site. The above code gives slightly more accurate results than the expression  $(\gamma(x+h) - \gamma(x-h))/(2h)$ .

The trigamma function is defined as:

$$\psi_1(x) = \frac{d^2}{dx^2} \ln(\Gamma(x)) \quad (7)$$

The following Matlab function implements the code for the trigamma function:

```
function y = trigamma(x)
%DIGAMMA Summary of this function goes here
% Detailed explanation goes here
    h = 0.001;
    fp = log(gamma(x+h));
    fm = log(gamma(x-h));
    f0 = log(gamma(x));
    y = (fp - 2*f0 + fm)/h/h;
end
```

 The approximations that I obtain are typically for a defined and suitable interval. It is your responsibility to implement expanded versions of the approximation functions that take wider ranges of arguments and map them onto the interval used. For example, given that my approximation for  $\log_{10}(x)$  uses the range (1, 10), to calculate  $\log_{10}(235)$  use:

$$\log_{10}(235) =$$

$$\log_{10}(2.35 * 100) =$$

$$\log_{10}(2.35) + \log_{10}(100) =$$

$$\log_{10}(2.35) + 2$$

The argument of the  $\log_{10}(x)$  function in the last line falls in the interval (1, 10).

## MATLAB CODE

The algorithm in this study uses particle swarm optimization to obtain the best orders for polynomials  $Q_m(x)$  and  $D_n(x)$  fitting a set of (x, y) data.

This study uses the function PadePoly () to perform various Pade polynomial curve fitting:

```
function PadePoly (fx, xRange, Lb, Ub, runNum, sFxName, diaryFilename)
%SHAMPOLY2 Summary of this function goes here
% Detailed explanation goes here
clc
global bDeleteIfExists
global bUseDiary
global xdata
global ydata
global orderA
global orderB
warning('off', 'all')
if isempty(sFxName)
    sFxName = getFuncName (fx) ;
end
xdata = xRange';
ydata = xdata;
for i=1:length(xdata)
    ydata(i)=fx(xdata(i));
end
xmin = min(xdata);
xmax = max(xdata);
ymin = min(ydata);
ymax = max(ydata);
xdata = (xdata - xmin)/(xmax - xmin) + 1;
ydata = (ydata - ymin)/(ymax - ymin) + 1;
```

```

fprintf('Fitting %s in range (%f, %f)\n', sFxName, xmin ,xmax);

options = optimoptions('particleswarm', 'Display', 'iter');
[x,psAICc] = particleswarm(@optimFunc,2,Lb,Ub,options);
orderA = round(x(1));
orderB = round(x(2));
if bUseDiary
    diaryFilename = strrep(diaryFilename, ".txt", strcat("_",
num2str(orderA),"x",num2str(orderB),"_run", num2str(runNum),".txt"));
    if exist(diaryFilename, 'file')==2
        if bDeleteIfExists
            delete(diaryFilename);
        else
            return;
        end
    end
end
X = [];
for i=1:orderA
    xs = xdata.^i;
    X = [X;xs'];
end
for i=1:orderB
    xs = ydata.*xdata.^i;
    X = [X;xs'];
end
X = X';
lm = fitlm(X,ydata);
if bUseDiary
    diary(diaryFilename)
end
fprintf('Fitting %s in range (%f, %f)\n', sFxName, xmin ,xmax);
format long
disp(lm);
anva = anova(lm,'summary');
disp(anva);
format short
fprintf('orderA = %f, orderB = %f\n', orderA, orderB);
fprintf("Xmin = %f and Xmax = %f\n", xmin, xmax);
fprintf("Ymin = %f and Ymax = %f\n", ymin, ymax);
sMd11 = "y = [Intercept";
j = 1;
for i=1:orderA
    if i<2
        sMd11 = strcat(sMd11, " + cx", num2str(j),"*x");
    else
        sMd11 = strcat(sMd11, " + cx", num2str(j),"*x^",num2str(i));
    end
    j = j + 1;
end
sMd11 = strcat(sMd11, "] /");
sMd12 = "[ 1";
for i=1:orderB
    if i<2
        sMd12 = strcat(sMd12, " + cx", num2str(j),"*y*x");
    else
        sMd12 = strcat(sMd12, " + cx", num2str(j),"*y*x^",num2str(i));
    end
end

```

```

    end
    j = j + 1;
end
sMdl2 = strcat(sMdl2, "]);
fprintf("Model is %s\n\t\t%s\n", sMdl1, sMdl2);
fprintf('Fitting %s in range (%f, %f)\n', sFxName, xmin, xmax);
n = length(xdata);
sumsq = 0;
for i=1:n
    yc = lm.Coefficients{1,1};
    for j=1:orderA
        yc = yc + lm.Coefficients{j+1,1} * xdata(i)^j;
    end
    for j=1:orderB
        yc = yc + lm.Coefficients{j+orderA+1,1} * ydata(i)*xdata(i)^j;
    end
    sumsq = sumsq + (ydata(i) - yc)^2;
end

k = orderA + orderB + 1;
fprintf('MSS of errors squared = %e\n', sqrt(sumsq)/n);
AIC = lm.ModelCriterion.AIC;
AICc = AIC + 2*k*(1 + (k+1)/(n-k-1));
fprintf('Particle swarm AICc = %e\n', psAICc);
fprintf('AIC = %e\n', AIC);
fprintf('AICc = %e\n', AICc);

if bUseDiary
    diary off
end
end

function AICc = optimFunc(x)
    global xdata
    global ydata
    global orderA
    global orderB

    orderA = round(x(1));
    orderB = round(x(2));
    X = [];
    for i=1:orderA
        xs = xdata.^i;
        X = [X;xs'];
    end
    for i=1:orderB
        xs = ydata.*xdata.^i;
        X = [X;xs'];
    end
    X = X';
    lm = fitlm(X,ydata);

    n = length(xdata);
    k = orderA + orderB + 1;
    AIC = lm.ModelCriterion.AIC;
    AICc = AIC + 2*k*(1 + (k+1)/(n-k-1));
    if isinf(AICc), AICc = -1e+99; end
end

```

```

end

function sFx = getFuncName(fx)
    sFx = func2str(fx);
    if sFx(1:2)=="@"
        i = strfind(sFx,"");
        sFx = sFx(i(1)+1:end);
    elseif sFx(1)=="@"
        sFx = strcat(sFx(2:end), ".m");
    else
        % return sFx as is
    end
end

```

The parameters of function PadePoly () are:

- The parameter fx is the handle (or inline function) for the function being approximated. An example is @(x)cos(x) which also shows the **recommended format** for the argument of parameter fx.
- The parameter xRange is the array that specifies the minimum value, increment value, and maximum value for the range of approximation.
- The parameter Lb is is the array of lower limits for the orders of polynomials  $Q_m(x)$  and  $D_n(x)$ . An example is [2 2].
- The parameter Ub is is the array of upper limits for the orders of polynomials  $Q_m(x)$  and  $D_n(x)$ . An example is [7 7].
- The parameter runNum specifies the run number. The arguments for this parameter have nothing to do with the calculations and serve in fine tuning the name of the diary files, when used.
- The optional parameter sFxName is the name of the approximated function. An example is “cos(x)”.
- The parameter diaryFilename is the name of the diary file. An example is “cos\_1.txt”.

The above listing performs the following tasks:

1. Initialize the data for the curve fitting. The function uses the global variables xdata and ydata to store the data for the polynomial fitting.
2. Normalizes the values for xdata and ydata to fall in the range (1, 2). The function stores the minimum and maximum values for the two variables.
3. Set the optimization options and then call the Matlab function particleswarm(). The function call returns the optimized values of orderA and orderB and the *corrected* Akaike information criterion (AICc). The arguments for this function call are:

- a. The handle to the local function `optimFunc()` that calculates the root mean sum of errors squared.
  - b. The number of optimized variables which is 2.
  - c. The lower and upper bounds arrays, `Lb` and `Ub`, respectively,
  - d. The optimization parameters for function `particleswarm()`.
4. Retrieve the optimum values and perform a Pade polynomial.
  5. Display the results of the regression and its associated ANOVA table.
  6. Display the Pade polynomial powers.
  7. Display the minimum and maximum values for `xdata` and `ydata`.
  8. Display the model of  $Q_m(x)/D_n(x)$  in terms of the regression coefficients. This output appends a `c` to the names of the generic variables listed. For example, `cx1` refers to the regression coefficient associated with the generic variable `x1`.
  9. Display the range of the approximated function.
  10. Calculate and display the value of the mean square root of the sum of squared errors. This statistic serves as a check that the Pade polynomial performs well in checking the training data.
  11. Calculate and display the *corrected* Akaike information criterion. This statistic is calculated using:

$$AIC = n * \ln(SSE/n) + 2*k \quad (8)$$

$$AICc = AIC + 2*k*(k+1)/(n-k-1) \quad (9)$$

Where  $n$  is the number of observations,  $k$  is the total number of regression coefficients (including the intercept), and  $SSE$  is the sum of squared errors. The program obtains the value of  $AIC$  using `lm.ModelCriterion.AIC`. The program uses equation (3) to calculate the value for  $AICc$ .

12. Close the diary file, if one is used.

The function `optimFunc()` obtains the array `x` containing the current values of `A` and `B`, and the best Pade polynomial order. The function calculates the transformed variables needed to perform a curve fit for a Pade polynomial. This task calls the Matlab function `fitlm()`. The `optimFunc()` function returns the  $AICc$  as its result. I am using this statistic since the optimization is dealing with different Pade polynomial orders and thus a varying number of polynomial coefficients.

The function `getFuncName()` returns a string-type function name given a handle of a function. The best way to take advantage of this function is to supply arguments



like  $\text{@}(x)\cos(x)$ . Such arguments allow the function to discard the part that declares the variable(s) and return the part that comes after the first closed parenthesis (e.g.  $\cos(x)$ ). If you supply an argument like  $\text{@}fx1$  which refers to the file  $fx1.m$  that defines the function  $fx1()$  then the function  $\text{getFuncName}()$  returns  $fx1.m$ . This string value indicates that you are rereferencing a separate Matlab file that implements the code for  $fx1$ .

Under the current calculation scheme, note that, the function  $\text{Pade}()$  does not explicitly iterate over different values of orders of polynomials  $Q_m(x)$  and  $D_n(x)$ . It delegates that task to the Matlab function  $\text{particleswarm}()$ .

The following Matlab script  $\text{goAll}()$  performs the various Pade polynomial fittings for the various tested functions:

```
% Version 1.0.0 8/14/2020
global bUseDiary
global bDeleteIfExists

bUseDiary = true;
bDeleteIfExists = false; % or false
runNum = 1;
bShutdown = false;

tic;

lstA = [2 7];
lstB = [2 7];
Lb = [lstA(1) lstB(1)];
Ub = [lstA(2) lstB(2)];

PadePoly(@ (x) acos(x), [0:.01:1], Lb, Ub, runNum, "arccos(x)", "arccos.txt")
PadePoly(@ (x) asin(x), [0:.01:1], Lb, Ub, runNum, "arcsin(x)", "arcsin.txt")
PadePoly(@ (x) atan(x), [0:.01:1], Lb, Ub, runNum, "arctan(x)", "arctan.txt")
PadePoly(@ (x) sin(x), [0:.01:1], Lb, Ub, runNum, "sin(x)", "sin.txt")
PadePoly(@ (x) cos(x), [0:.01:1], Lb, Ub, runNum, "cos(x)", "cos.txt")
PadePoly(@ (x) tan(x), [0:.01:1], Lb, Ub, runNum, "tan(x)", "tan.txt")
PadePoly(@ (x) sinh(x), [0:.01:5], Lb, Ub, runNum, "sinh(x)", "sinh.txt")
PadePoly(@ (x) cosh(x), [0:.01:5], Lb, Ub, runNum, "cosh(x)", "cosh.txt")
PadePoly(@ (x) tanh(x), [0:.01:3], Lb, Ub, runNum, "tanh(x)", "tanh.txt")
PadePoly(@ (x) erf(x), [0:.01:2.1], Lb, Ub, runNum, "erf(x)", "erf.txt")
PadePoly(@ (x) exp(x), [0:.01:2], Lb, Ub, runNum, "exp(x)", "exp.txt")
PadePoly(@ (x) log(x), [1:.01:10], Lb, Ub, runNum, "ln(x)", "ln.txt")
PadePoly(@ (x) log10(x), [1:.01:10], Lb, Ub, runNum, "log(x)", "log.txt")
PadePoly(@ (x) 10.^x, [0:.01:1], Lb, Ub, runNum, "10^x", "pwr10.txt")
PadePoly(@ (x) tinva(0.95,x), [2:100], Lb, Ub, runNum, "tinva(0.95,x)", "tinva1.txt")
PadePoly(@ (x) tinva(0.975,x), [2:100], Lb, Ub, runNum, "tinva(0.975,x)", "tinva2.txt")
PadePoly(@ (x) log10(gamma(x)), [2:100], Lb, Ub, runNum, "log10Gamma(x)", "log10Gamma.txt")
PadePoly(@ (x) digamma(x), [1:100], Lb, Ub, runNum, "digamma(x)", "digamma.txt")
PadePoly(@ (x) trigamma(x), [1:100], Lb, Ub, runNum, "trigamma(x)", "trigamma.txt")

toc;
```

```

for i=1:7
    beep;
    pause(3)
end

if bShutdown
    system('shutdown -s');
else
    fprintf("\n\nDone!\n\n");
end

```


The above listing has the following global and operational variables:

- The global variable `bUseDiary` is a Boolean flag used to tell the function `PadePoly()` if you want to copy the screen output to diary text files.
- The global variable `bDeleteIfExists` is a Boolean flag used to tell the function `PadePoly()` whether you want to delete diary files if they exist.
- The Boolean variable `bShutdown` tells the Matlab script whether to shut down the computer when done

You can edit the script in `goAll.m` to perform Pade polynomial fitting for other functions you are interested in or for other Pade polynomial orders.

## GENERAL COMMENTS ON RESULTS

The next sections show the results of fitting various common functions each with a variety of Pade polynomials. There is a summary table for the fitted functions showing the Pade polynomial orders, the F statistic, the AICc statistic, the root mean sum of errors squared.

 Remember that the function `PadePoly()` performs data transformation on the  $x$  and  $y$  values, mapping them both in the range of  $(1, 2)$ . When using any of the Pade approximations shown below, perform the following:

1. Transform you  $x$  value(s) using the  $x_{\min}$  and  $x_{\max}$  values associated with the function approximation you are using and employing  $(x - x_{\min})/(x_{\max} - x_{\min}) + 1$ .
2. Calculate the  $y$  value using the Pade polynomial.
3. Revere map the calculate  $y$  value, using the  $y_{\min}$  and  $y_{\max}$  values, and applying the expression  $(y - 1)*(y_{\max} - y_{\min}) + y_{\min}$ .

## RESULTS FOR THE ARC COSINE

Fitting  $\arccos(x)$  in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10}$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	2.74411876998652	0	Inf	0
x1	-4.75440799756697	0	-Inf	0
x2	3.43983951559669	0	Inf	0
x3	-1.54894562520587	0	-Inf	0
x4	0.575961766772712	0	Inf	0
x5	-0.17299703478946	0	-Inf	0
x6	0.0319923903691364	0	Inf	0
x7	-0.00257872204993489	0	-Inf	0
x8	1.37783118927832	0	Inf	0
x9	-0.629725985821115	0	-Inf	0
x10	0.0954032517914815	0	Inf	0

Number of observations: 101, Error degrees of freedom: 90

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	6.03050467942528	100	0.0603050467942528		
Model	6.03050467942528	10	0.603050467942528	Inf	0
Residual	0	90	0		

orderA = 7.000000, orderB = 3.000000

Xmin = 0.000000 and Xmax = 1.000000

Ymin = 0.000000 and Ymax = 1.570796

Model is  $y = [\text{Intercept} + cx_1*x + cx_2*x^2 + cx_3*x^3 + cx_4*x^4 + cx_5*x^5 + cx_6*x^6 + cx_7*x^7] / [1 + cx_8*y*x + cx_9*y*x^2 + cx_{10}*y*x^3]$

Fitting  $\arccos(x)$  in range (0.000000, 1.000000)

MSS of errors squared = 9.165132e-10

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE ARC SINE

Fitting  $\arcsin(x)$  in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10} + x_{11}$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.234940453381004	0	Inf	0
x1	0.74104922101633	0	Inf	0
x2	-2.25026340524683	0	-Inf	0
x3	1.94299333200437	0	Inf	0

x4	-0.699592168359401	0	-Inf	0
x5	0.091672916443102	0	Inf	0
x6	1.48857616520442	0	Inf	0
x7	-0.150354831868603	0	-Inf	0
x8	-0.831112075749417	0	-Inf	0
x9	0.556941620367831	0	Inf	0
x10	-0.136018141698462	0	-Inf	0
x11	0.0111669207831689	0	Inf	0

Number of observations: 101, Error degrees of freedom: 89

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
<hr/>					
Total	6.03050467942538	100	0.0603050467942538		
Model	6.03050467942538	11	0.54822769812958	Inf	0
Residual	0	89	0		

orderA = 5.000000, orderB = 6.000000

Xmin = 0.000000 and Xmax = 1.000000

Ymin = 0.000000 and Ymax = 1.570796

Model is  $y = [\text{Intercept} + \text{cx1} \cdot x + \text{cx2} \cdot x^2 + \text{cx3} \cdot x^3 + \text{cx4} \cdot x^4 + \text{cx5} \cdot x^5] /$

$[1 + \text{cx6} \cdot y \cdot x + \text{cx7} \cdot y \cdot x^2 + \text{cx8} \cdot y \cdot x^3 + \text{cx9} \cdot y \cdot x^4 + \text{cx10} \cdot y \cdot x^5 + \text{cx11} \cdot y \cdot x^6]$

Fitting arcsin(x) in range (0.000000, 1.000000)

MSS of errors squared = 1.936336e-10

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE ARC TANGENT

Fitting arctan(x) in range (0.000000, 1.000000)

Linear regression model:

$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
<hr/>				
(Intercept)	-0.0135261932408763	0	-Inf	0
x1	0.732530003859316	0	Inf	0
x2	-0.586835180957421	0	-Inf	0
x3	0.797757928337211	0	Inf	0
x4	-0.393396378726248	0	-Inf	0
x5	0.248522085670495	0	Inf	0
x6	0.964967258572369	0	Inf	0
x7	-0.810042964004574	0	-Inf	0
x8	0.137378866156981	0	Inf	0
x9	-0.00917906911705593	0	-Inf	0
x10	-0.0671577417687822	0	-Inf	0
x11	-0.00101861480487907	0	-Inf	0

Number of observations: 101, Error degrees of freedom: 89

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
<hr/>					

```

Total      8.80077198802885    100    0.0880077198802885
Model      8.80077198802885     11     0.800070180729895    Inf      0
Residual          0      89              0

orderA = 5.000000, orderB = 6.000000
Xmin = 0.000000 and Xmax = 1.000000
Ymin = 0.000000 and Ymax = 0.785398
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5] /
              [ 1 + cx6*y*x + cx7*y*x^2 + cx8*y*x^3 + cx9*y*x^4 + cx10*y*x^5 + cx11*y*x^6]
Fitting arctan(x) in range (0.000000, 1.000000)
MSS of errors squared = 1.083466e-12
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## RESULTS FOR COSINE

Fitting cos(x) in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.99744263261147	0	Inf	0
x1	1.53975473802235	0	Inf	0
x2	-1.06223383917815	0	-Inf	0
x3	0.113655014741225	0	Inf	0
x4	0.304952088808806	0	Inf	0
x5	-0.117680100338148	0	-Inf	0
x6	0.0213925509106876	0	Inf	0
x7	-0.00297381627419662	0	-Inf	0

Number of observations: 101, Error degrees of freedom: 93

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	9.38559236862651	100	0.0938559236862651		
Model	9.38559236862651	7	1.34079890980379	Inf	0
Residual	0	93	0		

```

orderA = 3.000000, orderB = 4.000000
Xmin = 0.000000 and Xmax = 1.000000
Ymin = 0.540302 and Ymax = 1.000000
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3] /
              [ 1 + cx4*y*x + cx5*y*x^2 + cx6*y*x^3 + cx7*y*x^4]
Fitting cos(x) in range (0.000000, 1.000000)
MSS of errors squared = 2.504558e-10
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## RESULTS FOR THE HYPERBOLIC COSINE FUNCTION

Fitting cosh(x) in range (0.000000, 5.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	1.55934916282121	0	Inf	0
x1	-3.10369563975385	0	-Inf	0
x2	4.66652693020443	0	Inf	0
x3	-4.87494386825909	0	-Inf	0
x4	3.21698131564907	0	Inf	0
x5	-1.30015037085423	0	-Inf	0
x6	0.29725294182685	0	Inf	0
x7	-0.0288874680927875	0	-Inf	0
x8	0.688132938573364	0	Inf	0
x9	-0.120566000484616	0	-Inf	0

Number of observations: 501, Error degrees of freedom: 491

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	31.218732615625	500	0.0624374652312499		
Model	31.218732615625	9	3.46874806840277	Inf	0
Residual	0	491	0		

orderA = 7.000000, orderB = 2.000000

Xmin = 0.000000 and Xmax = 5.000000

Ymin = 1.000000 and Ymax = 74.209949

Model is  $y = [\text{Intercept} + cx_1x + cx_2x^2 + cx_3x^3 + cx_4x^4 + cx_5x^5 + cx_6x^6 + cx_7x^7] / [1 + cx_8yx + cx_9y^2]$

Fitting cosh(x) in range (0.000000, 5.000000)

MSS of errors squared = 5.717733e-10

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE ERROR FUNCTION

Fitting erf(x) in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10} + x_{11}$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.0634927794926562	0.163551992466092	0.388211592749748	0.698274432642597
x1	-0.206186311473873	0.954407294219535	-0.216035976173549	0.829180986134864
x2	0.165176348223269	2.31652059597425	0.07130363896195	0.943227707138312
x3	0.8791079054853	2.98952919533215	0.294062324883108	0.769016767974869
x4	-1.22188727848586	2.13725789505277	-0.57170792598976	0.568165050489232
x5	0.652873854026182	0.865274673274095	0.754527867498752	0.451424283164583
x6	-0.149260114136752	0.183761788372226	-0.812247831602575	0.417620013842709
x7	0.0140281514647448	0.0161279336076203	0.869804638711845	0.38545511140998

x8	1.96685368256505	0.0452586936750921	43.4580303330208	1.60125995554417e-103
x9	-1.82884980961066	0.0379019688152698	-48.2521058081251	8.74396904566243e-112
x10	0.839678341953981	0.0204449658452734	41.0701758226758	3.98958209220962e-99
x11	-0.175027545943141	0.00915353159077918	-19.1213133649372	6.03867144018144e-47

Number of observations: 211, Error degrees of freedom: 199

Root Mean Squared Error: 4.78e-08

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: 7.29e+14, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	18.3371112829991	210	0.0873195775380909		
Model	18.3371112829986	11	1.66701011663624	729493008730985	0
Residual	4.54747350886464e-13	199	2.28516256726866e-15		

orderA = 7.000000, orderB = 4.000000

Xmin = 0.000000 and Xmax = 2.100000

Ymin = 0.000000 and Ymax = 0.997021

Model is y = [Intercept + cx1\*x + cx2\*x^2 + cx3\*x^3 + cx4\*x^4 + cx5\*x^5 + cx6\*x^6 + cx7\*x^7] /  
[ 1 + cx8\*y\*x + cx9\*y\*x^2 + cx10\*y\*x^3 + cx11\*y\*x^4]

Fitting erf(x) in range (0.000000, 1.000000)

MSS of errors squared = 7.212629e-11

Particle swarm AICc = -6.688183e+03

AIC = -6.713759e+03

AICc = -6.688183e+03

## RESULTS FOR THE EXPONENTIAL FUNCTION

Fitting exp(x) in range (0.000000, 2.000000)

Linear regression model:

y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.864659858935923	0	Inf	0
x1	-0.66662892088373	0	-Inf	0
x2	0.224882971306153	0	Inf	0
x3	-0.020997224679647	0	-Inf	0
x4	0.820002283472213	0	Inf	0
x5	-0.251379087975406	0	-Inf	0
x6	0.0292917287174262	0	Inf	0
x7	0.000203802681796752	0	Inf	0
x8	6.61006958148164e-05	0	Inf	0
x9	-0.000114334503638729	0	-Inf	0
x10	1.28222327971386e-05	0	Inf	0

Number of observations: 201, Error degrees of freedom: 190

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	15.9274939123249	200	0.0796374695616245		
Model	15.9274939123249	10	1.59274939123249	Inf	0
Residual	0	190	0		

```

orderA = 3.000000, orderB = 7.000000
Xmin = 0.000000 and Xmax = 2.000000
Ymin = 1.000000 and Ymax = 7.389056
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3] /
              [ 1 + cx4*y*x + cx5*y*x^2 + cx6*y*x^3 + cx7*y*x^4 + cx8*y*x^5 + cx9*y*x^6 + cx10*y*x^7]
Fitting exp(x) in range (0.000000, 2.000000)
MSS of errors squared = 5.899982e-15
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## RESULTS FOR THE NATURAL LOGRITHM

Fitting  $\ln(x)$  in range (1.000000, 10.000000)

Linear regression model:

$$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	2.12103478819	0	Inf	0
x1	-7.32802068756791	0	-Inf	0
x2	0	0	NaN	NaN
x3	24.8126032129289	0	Inf	0
x4	-29.5997694083641	0	-Inf	0
x5	8.19029041078807	0	Inf	0
x6	1.82492367231733	0	Inf	0
x7	5.14829823747902	0	Inf	0
x8	-6.73819013764748	0	-Inf	0
x9	-2.69042586262795	0	-Inf	0
x10	9.9311271484996	0	Inf	0
x11	-4.17669832038885	0	-Inf	0
x12	-0.49517305508618	0	-Inf	0

Number of observations: 901, Error degrees of freedom: 889

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	58.921158778179	900	0.0654679541979767		
Model	58.921158778179	11	5.35646897983446	Inf	0
Residual	0	889	0		

```

orderA = 6.000000, orderB = 6.000000
Xmin = 1.000000 and Xmax = 10.000000
Ymin = 0.000000 and Ymax = 2.302585
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5 + cx6*x^6] /
              [ 1 + cx7*y*x + cx8*y*x^2 + cx9*y*x^3 + cx10*y*x^4 + cx11*y*x^5 + cx12*y*x^6]
Fitting ln(x) in range (1.000000, 10.000000)
MSS of errors squared = 8.896563e-12
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```



## RESULTS FOR THE COMMON LOGARITHM

Fitting  $\log(x)$  in range (1.000000, 10.000000)

Linear regression model:

$$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	1.45540511589676	0	Inf	0
x1	-0.513439118636382	0	-Inf	0
x2	-13.3013394674701	0	-Inf	0
x3	22.3461715375533	0	Inf	0
x4	-8.05269520917601	0	-Inf	0
x5	-2.07766207174536	0	-Inf	0
x6	2.87893865791043	0	Inf	0
x7	0.915541424555934	0	Inf	0
x8	-7.4356545028703	0	-Inf	0
x9	4.2111499152529	0	Inf	0
x10	0.573583704223171	0	Inf	0

Number of observations: 901, Error degrees of freedom: 890

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	58.9211587781763	900	0.0654679541979736		
Model	58.9211587781763	10	5.89211587781763	Inf	0
Residual	0	890	0		

orderA = 5.000000, orderB = 5.000000

Xmin = 1.000000 and Xmax = 10.000000

Ymin = 0.000000 and Ymax = 1.000000

Model is  $y = [\text{Intercept} + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5] / [1 + cx6*y*x + cx7*y*x^2 + cx8*y*x^3 + cx9*y*x^4 + cx10*y*x^5]$

Fitting  $\log(x)$  in range (1.000000, 10.000000)

MSS of errors squared = 7.292823e-11

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE COMMON EXPONENT ( $10^X$ )

Fitting  $10^x$  in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.900308834713545	0	Inf	0
x1	-0.613792590815386	0	-Inf	0
x2	0.175326759951948	0	Inf	0
x3	-0.0110643895286522	0	-Inf	0

x4	0.00339167046058943	0	Inf	0
x5	0.708790850944777	0	Inf	0
x6	-0.179054051949656	0	-Inf	0
x7	0.0160929194398677	0	Inf	0

Number of observations: 101, Error degrees of freedom: 93  
R-squared: 1, Adjusted R-Squared: 1  
F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	7.96302009058562	100	0.0796302009058562		
Model	7.96302009058562	7	1.13757429865509	Inf	0
Residual	0	93	0		

orderA = 4.000000, orderB = 3.000000  
Xmin = 0.000000 and Xmax = 1.000000  
Ymin = 1.000000 and Ymax = 10.000000  
Model is  $y = [\text{Intercept} + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4] / [1 + cx5*y*x + cx6*y*x^2 + cx7*y*x^3]$   
Fitting  $10^x$  in range (0.000000, 1.000000)  
MSS of errors squared = 1.120822e-10  
Particle swarm AICc = -1.000000e+99  
AIC = -Inf  
AICc = -Inf

## RESULTS FOR THE SINE FUNCTION

Fitting  $\sin(x)$  in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-5.68503965954338e-05	0.0016865508408706	-0.0337080835144509	0.973182958306001
x1	0.642453006092019	0.00935439914415206	68.679238098756	7.64477851861237e-81
x2	0.448766635814435	0.147771268161347	3.03690048409437	0.0031096796874584
x3	-0.131145401196643	0.0918230027193288	-1.42824126104337	0.156608517160931
x4	-0.0245544620181456	0.0227439458853017	-1.0796043106141	0.283140647017255
x5	0.0074975648864991	0.0247118183343463	0.303399967782962	0.762270117870453
x6	-0.000378998279974461	0.00320252606731495	-0.118343542568639	0.906053464928963
x7	0.0782238325451951	0.195784268503804	0.39954094955119	0.690420698083317
x8	-0.0208053274733243	0.0370350562153575	-0.561773886674887	0.575636126169296

Number of observations: 101, Error degrees of freedom: 92

Root Mean Squared Error: 1.76e-08

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: 3.61e+15, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	8.91856438137271	100	0.0891856438137271		
Model	8.91856438137268	8	1.11482054767159	3.60863200846283e+15	0
Residual	2.8421709430404e-14	92	3.08931624243522e-16		

orderA = 6.000000, orderB = 2.000000

```

Xmin = 0.000000 and Xmax = 1.000000
Ymin = 0.000000 and Ymax = 0.841471
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5 + cx6*x^6] /
              [ 1 + cx7*y*x + cx8*y*x^2]
Fitting sin(x) in range (0.000000, 1.000000)
MSS of errors squared = 9.278072e-13
Particle swarm AICc = -3.392877e+03
AIC = -3.412855e+03
AICc = -3.392877e+03

```

## RESULTS FOR THE HYPERBOLIC SINE FUNCTION

Fitting sinh(x) in range (0.000000, 5.000000)

Linear regression model:

$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10} + x_{11}$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.475800690571069	0	-Inf	0
x1	8.64195038336725	0	Inf	0
x2	-7.52961153097691	0	-Inf	0
x3	1.33379714643916	0	Inf	0
x4	0.455609617918177	0	Inf	0
x5	-0.110999743150955	0	-Inf	0
x6	-3.36452847184026	0	-Inf	0
x7	-0.658320806193701	0	-Inf	0
x8	5.72031085649003	0	Inf	0
x9	-3.99540212994497	0	-Inf	0
x10	1.09169726869538	0	Inf	0
x11	-0.108701903440452	0	-Inf	0

Number of observations: 501, Error degrees of freedom: 489

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	30.8337526139307	500	0.0616675052278614		
Model	30.8337526139307	11	2.80306841944825	Inf	0
Residual	0	489	0		

```

orderA = 5.000000, orderB = 6.000000
Xmin = 0.000000 and Xmax = 5.000000
Ymin = 0.000000 and Ymax = 74.203211
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5] /
              [ 1 + cx6*y*x + cx7*y*x^2 + cx8*y*x^3 + cx9*y*x^4 + cx10*y*x^5 + cx11*y*x^6]
Fitting sinh(x) in range (0.000000, 5.000000)
MSS of errors squared = 5.054090e-11
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## RESULTS FOR THE TANGENT

Fitting tan(x) in range (0.000000, 1.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-4.20574311922127e-05	0	-Inf	0
x1	2.19984561284616	0	Inf	0
x2	-0.213680098049683	0	-Inf	0
x3	-0.239732086406133	0	-Inf	0
x4	0.0225835353341068	0	Inf	0
x5	0.00140998002526337	0	Inf	0
x6	-1.46088400329214	0	-Inf	0
x7	0.594323732991001	0	Inf	0
x8	0.126387134317526	0	Inf	0
x9	-0.0302117503378271	0	-Inf	0

Number of observations: 101, Error degrees of freedom: 91

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	7.61910551705131	100	0.0761910551705131		
Model	7.61910551705131	9	0.846567279672368	Inf	0
Residual	0	91	0		

orderA = 5.000000, orderB = 4.000000

Xmin = 0.000000 and Xmax = 1.000000

Ymin = 0.000000 and Ymax = 1.557408

Model is  $y = [\text{Intercept} + cx_1x + cx_2x^2 + cx_3x^3 + cx_4x^4 + cx_5x^5] / [1 + cx_6yx + cx_7y^2x + cx_8yx^3 + cx_9yx^4]$

Fitting tan(x) in range (0.000000, 1.000000)

MSS of errors squared = 1.149152e-13

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE HYPERBOLIC TANGENT FUNCTION

Fitting tanh(x) in range (0.000000, 3.000000)

Linear regression model:

$$y \sim 1 + x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10}$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.167791028100871	0	Inf	0
x1	-0.935540124306837	0	-Inf	0
x2	2.37070403152777	0	Inf	0
x3	-2.97078649938341	0	-Inf	0
x4	2.29365874096859	0	Inf	0
x5	-0.880228670220663	0	-Inf	0
x6	0.172387240734481	0	Inf	0
x7	-0.0138806590578725	0	-Inf	0
x8	1.61926511122068	0	Inf	0
x9	-0.862043277098288	0	-Inf	0

x10 0.0386730872018001 0 Inf 0

Number of observations: 301, Error degrees of freedom: 290

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	23.2802959868209	300	0.0776009866227363		
Model	23.2802959868209	10	2.32802959868209	Inf	0
Residual	0	290	0		

orderA = 7.000000, orderB = 3.000000

Xmin = 0.000000 and Xmax = 3.000000

Ymin = 0.000000 and Ymax = 0.995055

Model is  $y = [\text{Intercept} + \text{cx1} \cdot x + \text{cx2} \cdot x^2 + \text{cx3} \cdot x^3 + \text{cx4} \cdot x^4 + \text{cx5} \cdot x^5 + \text{cx6} \cdot x^6 + \text{cx7} \cdot x^7] / [1 + \text{cx8} \cdot y \cdot x + \text{cx9} \cdot y \cdot x^2 + \text{cx10} \cdot y \cdot x^3]$

Fitting tanh(x) in range (0.000000, 3.000000)

MSS of errors squared = 1.524299e-10

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE TWO-SIDED T-INVERSE DISTRIBUTION

Fitting tinva(0.975,x) in range (2.000000, 100.000000)

Linear regression model:

$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.979119303945661	0	Inf	0
x1	-1.878994097881	0	-Inf	0
x2	0.00955133125518624	0	Inf	0
x3	1.29765857899649	0	Inf	0
x4	0	0	NaN	NaN
x5	-0.407364182564784	0	-Inf	0
x6	-7.57017719835083e-09	0	-Inf	0
x7	1.90822588885485	0	Inf	0
x8	0	0	NaN	NaN
x9	-1.31549494995822	0	-Inf	0
x10	-0.00434262168361492	0	-Inf	0
x11	0.411626219696284	0	Inf	0

Number of observations: 99, Error degrees of freedom: 89

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	1.4314772743268	98	0.0146069109625184		
Model	1.4314772743268	9	0.159053030480756	Inf	0
Residual	0	89	0		

orderA = 6.000000, orderB = 5.000000

Xmin = 2.000000 and Xmax = 100.000000

```

Ymin = 1.983972 and Ymax = 4.302653
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5 + cx6*x^6] /
              [ 1 + cx7*y*x + cx8*y*x^2 + cx9*y*x^3 + cx10*y*x^4 + cx11*y*x^5]
Fitting tinva(0.975,x) in range (2.000000, 100.000000)
MSS of errors squared = 4.680093e-14
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## RESULTS FOR THE ONE-SIDED T-INVERSE DISTRIBUTION

```
Fitting tinva(0.95,x) in range (2.000000, 100.000000)
```

Linear regression model:

```
y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8
```

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.975312316906565	0	Inf	0
x1	-3.00234264235221	0	-Inf	0
x2	3.08073968338658	0	Inf	0
x3	-1.05372700285936	0	-Inf	0
x4	3.06540517416161	0	Inf	0
x5	-3.1321477062934	0	-Inf	0
x6	1.06675137217174	0	Inf	0
x7	-1.99493718593477e-08	0	-Inf	0
x8	2.3685685960035e-09	0	Inf	0

Number of observations: 99, Error degrees of freedom: 90

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	1.51844154817134	98	0.0154943015119524		
Model	1.51844154817134	8	0.189805193521417	Inf	0
Residual	0	90	0		

```

orderA = 3.000000, orderB = 5.000000
Xmin = 2.000000 and Xmax = 100.000000
Ymin = 1.660234 and Ymax = 2.919986
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3] /
              [ 1 + cx4*y*x + cx5*y*x^2 + cx6*y*x^3 + cx7*y*x^4 + cx8*y*x^5]
Fitting tinva(0.95,x) in range ((2.000000, 100.000000)
MSS of errors squared = 6.748744e-14
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## RESULTS FOR THE COMMON LOGARITHM OF THE GAMMA FUNCTION

```
Fitting log10Gamma(x) in range (2.000000, 100.000000)
```

Linear regression model:

```
y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10
```

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0810158671459593	0	-Inf	0
x1	-0.118627827538114	0	-Inf	0
x2	1.32026727678648	0	Inf	0
x3	-4.09275990701905	0	-Inf	0
x4	5.46139474348187	0	Inf	0
x5	-2.50113320772895	0	-Inf	0
x6	3.66856164077954	0	Inf	0
x7	-3.10237937749939	0	-Inf	0
x8	-1.19225524927864	0	-Inf	0
x9	1.66170491724495	0	Inf	0
x10	-0.0237571328294603	0	-Inf	0

Number of observations: 99, Error degrees of freedom: 88

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	9.07288178684988	98	0.0925804263964273		
Model	9.07288178684988	10	0.907288178684988	Inf	0
Residual	0	88	0		

orderA = 5.000000, orderB = 5.000000

Xmin = 2.000000 and Xmax = 100.000000

Ymin = 0.000000 and Ymax = 155.970004

Model is  $y = [\text{Intercept} + \text{cx1} \cdot x + \text{cx2} \cdot x^2 + \text{cx3} \cdot x^3 + \text{cx4} \cdot x^4 + \text{cx5} \cdot x^5] /$   
 $[1 + \text{cx6} \cdot y \cdot x + \text{cx7} \cdot y \cdot x^2 + \text{cx8} \cdot y \cdot x^3 + \text{cx9} \cdot y \cdot x^4 + \text{cx10} \cdot y \cdot x^5]$

Fitting log10Gamma(x) in range ((2.000000, 100.000000))

MSS of errors squared = 7.841470e-10

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE DIGAMMA FUNCTION

Fitting digamma(x) in range (1.000000, 100.000000)

Linear regression model:

$$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12 + x13$$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	3.55657619628626	0	Inf	0
x1	-29.7038549951656	0	-Inf	0
x2	81.0509857744355	0	Inf	0
x3	-90.6479862422103	0	-Inf	0
x4	28.5446256329591	0	Inf	0
x5	17.8511502495401	0	Inf	0
x6	-10.6516195856764	0	-Inf	0
x7	11.554860392583	0	Inf	0
x8	-36.8291014514652	0	-Inf	0
x9	47.4044612398808	0	Inf	0
x10	-21.2339184432746	0	-Inf	0

x11	-4.24151166138219	0	-Inf	0
x12	4.36669670323192	0	Inf	0
x13	-0.0213638097402183	0	-Inf	0

Number of observations: 100, Error degrees of freedom: 86

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	3.53709271459914	99	0.0357282092383752		
Model	3.53709271459914	13	0.272084054969165	Inf	0
Residual	0	86	0		

orderA = 6.000000, orderB = 7.000000

Xmin = 1.000000 and Xmax = 100.000000

Ymin = -0.577216 and Ymax = 4.600162

Model is  $y = [\text{Intercept} + \text{cx1} \cdot x + \text{cx2} \cdot x^2 + \text{cx3} \cdot x^3 + \text{cx4} \cdot x^4 + \text{cx5} \cdot x^5 + \text{cx6} \cdot x^6] /$

$[1 + \text{cx7} \cdot y \cdot x + \text{cx8} \cdot y \cdot x^2 + \text{cx9} \cdot y \cdot x^3 + \text{cx10} \cdot y \cdot x^4 + \text{cx11} \cdot y \cdot x^5 + \text{cx12} \cdot y \cdot x^6 + \text{cx13} \cdot y \cdot x^7]$

Fitting digamma(x) in range (1.000000, 100.000000)

MSS of errors squared = 3.376550e-11

Particle swarm AICc = -1.000000e+99

AIC = -Inf

AICc = -Inf

## RESULTS FOR THE TRIGAMMA FUNCTION

Fitting tgamma(x) in range (1.000000, 100.000000)

Linear regression model:

$y \sim 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.98764836765494	0	Inf	0
x1	-4.03311154322681	0	-Inf	0
x2	6.4684691231006	0	Inf	0
x3	-5.08078932084451	0	-Inf	0
x4	1.95025824266778	0	Inf	0
x5	-0.292476260537502	0	-Inf	0
x6	2.42316514620585e-06	0	Inf	0
x7	-2.12674752882649e-07	0	-Inf	0
x8	4.07722845370951	0	Inf	0
x9	-6.52993901381203	0	-Inf	0
x10	5.1225557671214	0	Inf	0
x11	-1.96411913323873	0	-Inf	0
x12	0.294273516564833	0	Inf	0

Number of observations: 100, Error degrees of freedom: 87

R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: Inf, p-value = 0

	SumSq	DF	MeanSq	F	pValue
Total	1.20244526290484	99	0.0121459117465136		
Model	1.20244526290484	12	0.100203771908737	Inf	0
Residual	0	87	0		



```

orderA = 7.000000, orderB = 5.000000
Xmin = 1.000000 and Xmax = 100.000000
Ymin = 0.010050 and Ymax = 1.644935
Model is y = [Intercept + cx1*x + cx2*x^2 + cx3*x^3 + cx4*x^4 + cx5*x^5 + cx6*x^6 + cx7*x^7] /
              [ 1 + cx8*y*x + cx9*y*x^2 + cx10*y*x^3 + cx11*y*x^4 + cx12*y*x^5]
Fitting tgamma(x) in range (1.000000, 100.000000)
MSS of errors squared = 5.253660e-12
Particle swarm AICc = -1.000000e+99
AIC = -Inf
AICc = -Inf

```

## SUMMARY

The following table shows the summary of the above results. Notice that the regression coefficients for polynomials  $Q_m(x)$  and  $D_n(x)$  appear as one long vertical list. The output that starts with *Model is y = [Intercept +* tells you which coefficients belong to  $Q_m(x)$  and which ones belong to  $D_n(x)$ .

<i>Function</i>	<i>Order <math>Q(x)</math></i>	<i>Order <math>D(x)</math></i>	<i>F</i>	<i>AICc</i>	<i>MSSE</i>
arccos(x)	7	3	Infinity	-Infinity	9.165132E-10
arcsin(x)	5	6	Infinity	-Infinity	1.936336E-10
arctan(x)	5	6	Infinity	-Infinity	1.083466E-12
cosh(x)	7	2	Infinity	-Infinity	5.717733E-10
cos(x)	3	4	Infinity	-Infinity	2.504558E-10
digamma(x)	6	7	Infinity	-Infinity	3.376550E-11
erf(x)	7	4	7.29493E+14	-6.688183E+03	7.212629E-11
exp(x)	3	7	Infinity	-Infinity	5.899982E-15
ln(x)	6	6	Infinity	-Infinity	8.896563E-12
log10Gamma(x)	5	5	Infinity	-Infinity	7.841470E-10
log(x)	5	5	Infinity	-Infinity	7.292823E-11
10^x	4	3	Infinity	-Infinity	1.120822E-10
sinh(x)	5	6	Infinity	-Infinity	5.054090E-11
sin(x)	6	2	3.60863200846283e+15	-3.392877E+03	9.278072E-13
tanh(x)	7	3	Infinity	-Infinity	1.524299E-10
tan(x)	5	4	Infinity	-Infinity	1.149152E-13
tinv(0.95,x)	3	5	Infinity	-Infinity	6.748744E-14
tinv(0.975,x)	6	5	Infinity	-Infinity	4.680093E-14
tgamma(x)	7	5	Infinity	-Infinity	5.253660E-12

## CONCLUSIONS

The results of the Pade approximations show that the Pade polynomials perform an excellent job in approximating various functions. All the coefficients of determination obtained for the optimum Pade polynomials are 1 (or extremely close to it). The optimum orders for polynomials  $Q_m(x)$  and  $D_n(x)$  vary for different functions. This variation shows that the particle swarm optimization succeeds in getting optimum orders for polynomials  $Q_m(x)$  and  $D_n(x)$  and is not always attracted to the order 7—the maximum order allowed.

**DOCUMENT HISTORY**

<i>Date</i>	<i>Version</i>	<i>Comments</i>
9/5/2020	1.00.00	Initial release.
9/6/2020	1.00.01	Corrections for equation 1 and ranges in the output.
9/8/2020	1.00.02	Minor equation edits.
9/16/2020	1.00.03	Edited equation 5.