CSE 401: Numerical Analysis

Term Project Report

Submitted to:

Prof. Stephen Bond

Prepared by:

Anirudh Vemula

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UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN
CIVIL AND ENVIRONMENTAL ENGINEERING DEPARTMENT
CONSTRUCTION MANAGEMENT PROGRAM

Introduction:

Valuation of real estate is generally performed using a *comparison* approach, wherein *adjustments* are made to recent sales of properties having "similar" characteristics (sq. footage, number of bedrooms/bathrooms, age, etc.) to estimate the sales price. This procedure is highly subjective (since the appraiser is at liberty regarding the choice of comparables) and suffers from a number of disadvantages, primarily due to a very small sample size (typically 3-5).

One way to address this problem is to employ least squares regression to establish a correlation amongst these variables. Unlike comparison approach, the explicit dependence of selling price on some of these characteristics can be studied (do *granite countertops* or *parking space* really matter?). Furthermore, literature suggests that a nonlinear relationship exists between the dependent variable (sales price) and independent variables (living area, bathrooms, etc). Therefore, this study involves the following objectives:

- Examine the relationship between the dependent and independent variables.
- Develop a linear and nonlinear relationship, which can be determined using linear least squares regression.
- Check for rank deficiency and inspect its numerical conditioning for regression.
- Solve the least squares problem using three different techniques (Normal Equations, Orthogonal/Householder Transformations, and Singular Value Decomposition).
- Finally, compare the results for each method; and also with observed data.

For this purpose, real sales data of condominiums sold in Streeterville, Chicago were used (courtesy of Draper and Kramer, www.draperandkramer.com). Each of these objectives is elaborated in the following sections.

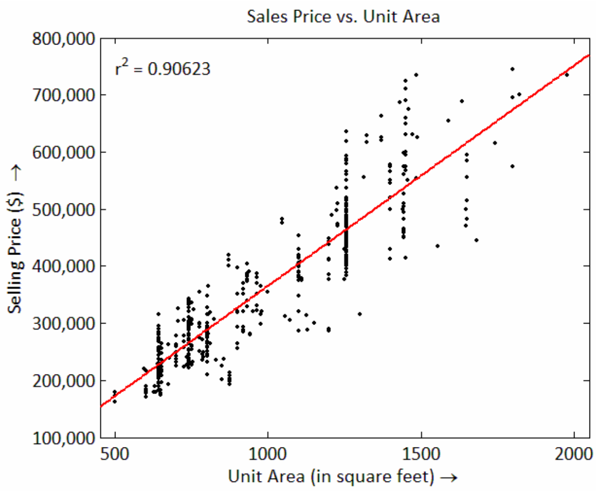
Section 1 – Relationship between variables:

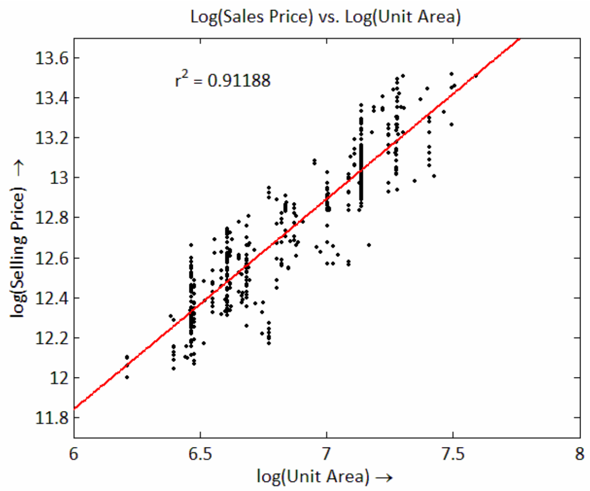
The sales price of a condominium unit was assumed to be dependent on a number of characteristics which could be quantified using following explanatory variables:

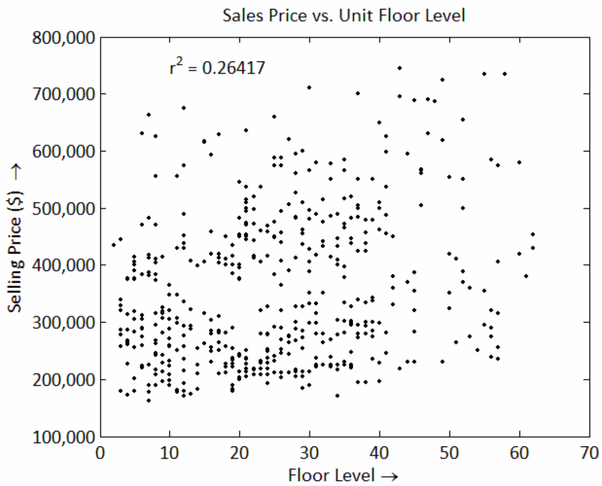
- Square footage of living area (fundamental governing characteristic, +ve correlation)
- Unit floor level (units having unobstructed view sell for a premium)
- Age (older units have larger depreciation, hence lower in value)

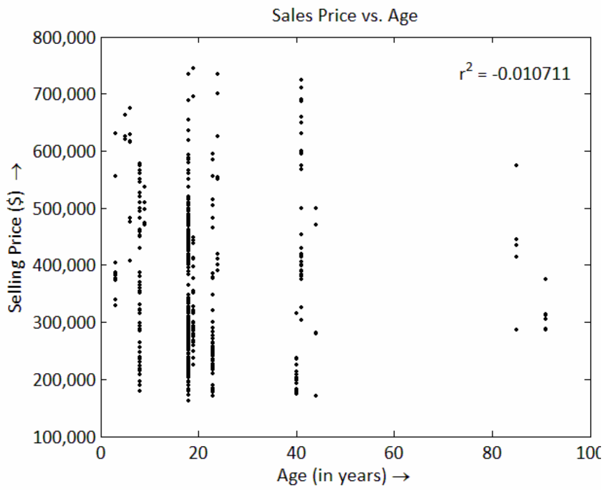
- Number of Bedrooms and Bathrooms in a unit (generally +ve correlation)
- Number of cars in household and parking space availability (Y/N)
- Central Air Conditioning (Y/N)

The most effective method to examine the relationship between variables is to plot each of these variables versus the dependent variable. Some of these plots are given below:









It is obvious from these plots (small correlation coefficients) that most of these variables do not affect the price of a unit and hence redundant. However, in the current study none of these were dropped since the main goal is to study the computational aspects rather than simply maximizing the correlation (which can be achieved through an iterative approach dropping independent variable having least significance (t statistic) at each step).

Section 2 – Linear and Nonlinear models:

The following models were developed to estimate the sales price of a unit based on above stated characteristics. Since our objective is employ linear least squares regression, the function should be linear in terms of coefficients for each of these variables (see below)

$$y = f(t,x) = x_1\,\phi_1(t) + x_2\,\phi_2(t) + \cdots + x_8\,\phi_8(t), \qquad \phi_i \text{ is a function of } t \text{ only.}$$

This allows the problem to be written in matrix notation as: $A\,x \cong b, \quad a_{ij} = \phi_j(t_i) \quad b_i = y_i$

$$\boxed{SP = x_0 + x_1\,SF + x_2\,Floor + x_3\,Age + x_4\,Cars + x_5\,Bed + x_6\,Bath + x_7\,CenAir + x_8\,Park} \quad \Rightarrow$$

$$A = \begin{bmatrix} 1 & Ar_1 & F_1 & Age_1 & Bed_1 & Bath_1 & Cars_1 & Park_1 & Cen.Air_1 \\ 1 & Ar_2 & F_2 & Age_2 & Bed_2 & Bath_2 & Cars_2 & Park_2 & Cen.Air_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & Ar_n & F_n & Age_n & Bed_n & Bath_n & Cars_n & Park_n & Cen.Air_n \end{bmatrix} \qquad b = \begin{bmatrix} SP_1 \\ SP_2 \\ \vdots \\ SP_n \end{bmatrix}$$

$$x = \begin{bmatrix} x_0 & x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 & x_8 \end{bmatrix}^T$$

$$\boxed{\ln(SP) = x_0 + x_1 \ln(SF) + x_2\,Floor + x_3\,Age + x_4\,Cars + x_5\,Bed + x_6\,Bath + x_7\,CenAir + x_8\,Park} \Rightarrow$$

$$A = \begin{bmatrix} 1 & \ln(Ar_1) & F_1 & Age_1 & Bed_1 & Bath_1 & Cars_1 & Park_1 & Cen.Air_1 \\ 1 & \ln(Ar_2) & F_2 & Age_2 & Bed_2 & Bath_2 & Cars_2 & Park_2 & Cen.Air_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \ln(Ar_n) & F_n & Age_n & Bed_n & Bath_n & Cars_n & Park_n & Cen.Air_n \end{bmatrix} \qquad b = \begin{bmatrix} \ln SP_1 \\ \ln SP_2 \\ \vdots \\ \ln SP_n \end{bmatrix}$$

$$x = \begin{bmatrix} x_0 & x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 & x_8 \end{bmatrix}^T$$

2.1 Data Processing:

The data collected included a variety of properties such as condominiums, studios, loft, etc. in a number of different localities. It is essential to remove such unwanted data so that we have only condominiums, located in zip codes 60611 and 60619. Furthermore, facilities provided like TV-Cable, Fire Suppression, CO detectors, etc. were ignored. Finally, the outliers were weeded out (as they adversely affect the accuracy of the model) using the following statistical scheme[1]:

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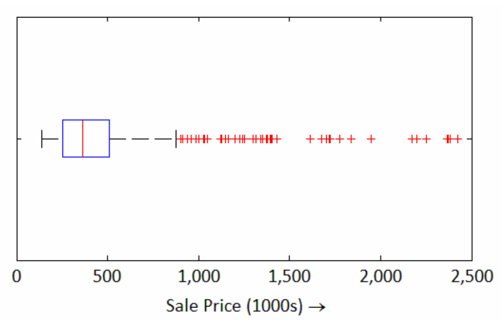
[1] Tukey, John (1977), *Exploratory Data Analysis*, Addison-Wesley

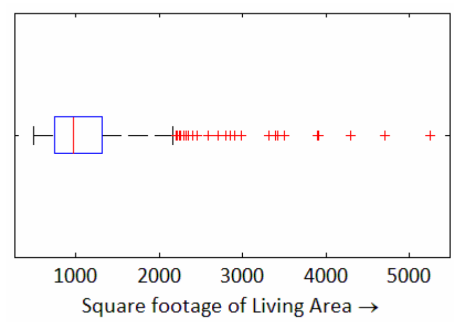
1. Compute 25th and 75th percentile for each parameter X_{25} & X_{75}
2. Inter-quartile Range is calculated as: $r = X_{75} - X_{25}$
3. Remove data which lies 1.5 times r below X_{75} or 1.5 times above X_{75} is classified as outlier, i.e. select $x \in [X_{25} - 1.5\,r,\, X_{75} + 1.5\,r]$

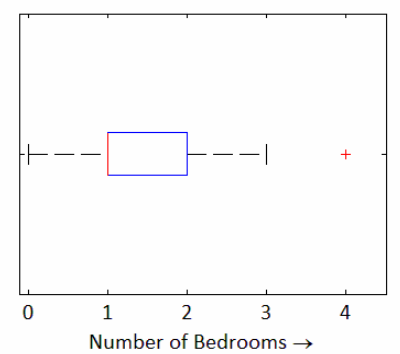
The table below describes the aforementioned scheme:

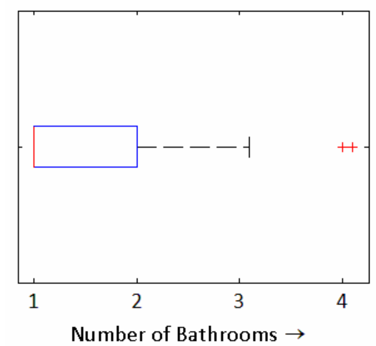
	Bed Rooms	Bath Rooms	Living Area (sf)	Sales Price ($)	SP/LvAr ($/sf)	Year Built	# of Cars	Unit Floor Level
MAX	5	4.10	5246.00	2,426,606	645.26	2006	2	63
MIN	0	1	500	140,000	200	1918	0	2
Upper Limit	3.5	3.5	2179.75	892,800	542.262	1998.5	1	69.5
Lower Limit	0.5	0.5	453.25	127,200	285.694	1983.5	1	0.5

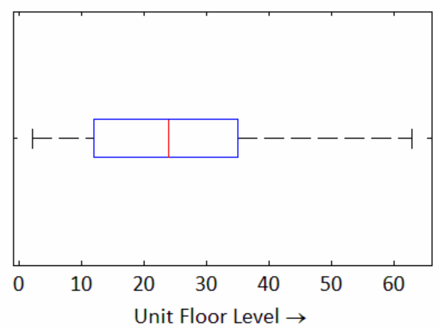
Box plots for selected variables are given below (showing 25th, 50th, 75th quartiles and outliers):

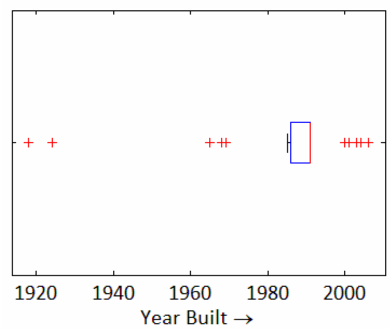












Section 3 – Solving the Least squares regression problem(s)

Three major methods were discussed in class – Normal Equation Method, Orthogonal Methods and Singular Value Decomposition. In normal equation method, the residual r is computed as $b - A.\,x$ which is minimized when it is normal to the span(A). Therefore, $A^T \cdot r = 0 \quad \Rightarrow \quad x = \left(A^T A\right)^{-1} A^T b$

For orthogonal method, householder transformation was used: $Hu = \left(I - 2\frac{vv^T}{v^T v}\right)u = u - \left(2\frac{v^T u}{v^T v}\right)v$

Finally, singular value decomposition was also employed: $x = \sum_{\sigma_i \neq 0} \frac{u_i^T b}{\sigma_i} v_i$, where $A = U \Sigma V^T$

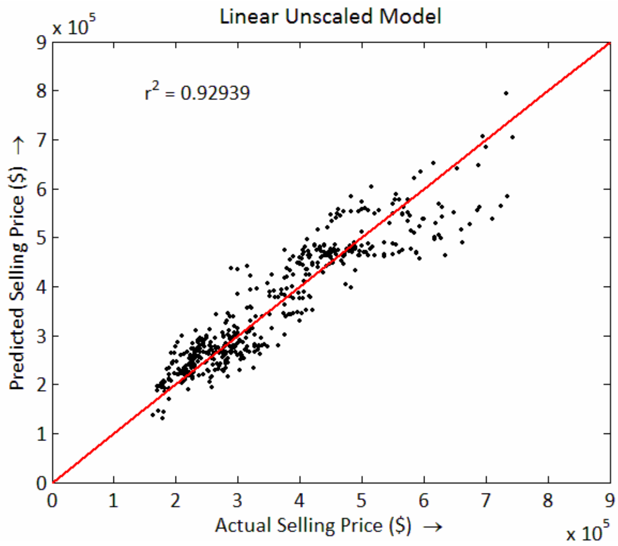
Numerical conditioning of least squares regression can be computed as: $cond(A) = \| A \|_2 \cdot \| A^+ \|_2$,

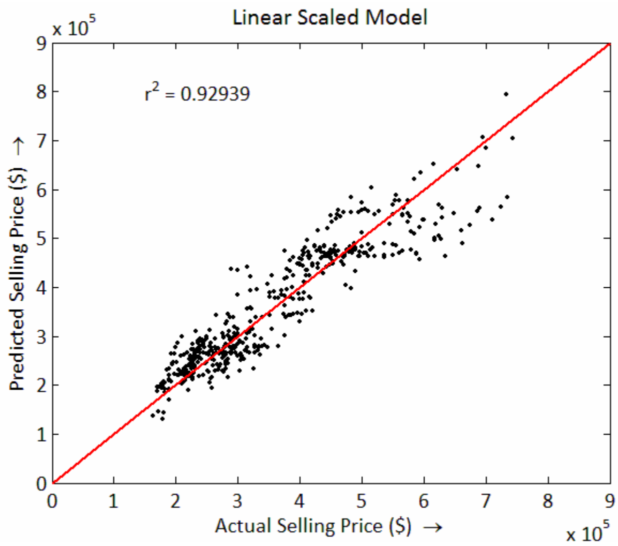
where the pseudo inverse of A is computed as, $A^+ = \left(A^T A\right)^{-1} A^T$. If A is rank deficient then A^+ does not exist and condition number is defined to be ∞. Therefore, it is essential to check whether A is rank deficient before attempting to solve for x^*. A large condition number implies that the problem is highly sensitive and solution is not reliable i.e. small residual does not imply accurate solution.

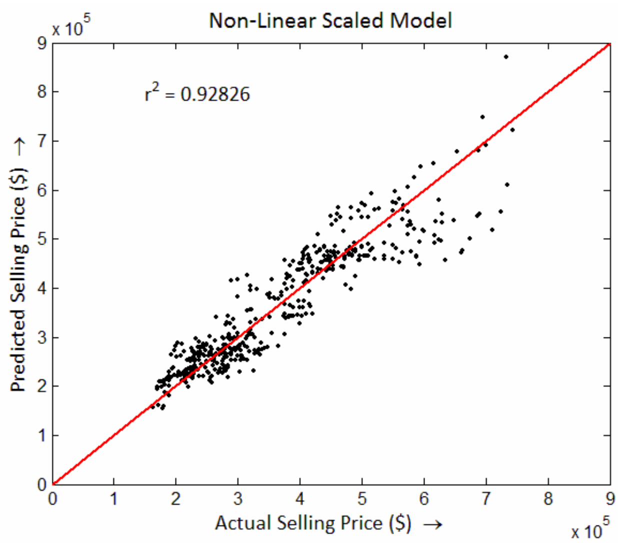
For the linear case, the condition number was found to be ~6000 and the residual ~10^6. This obviously means that the error in solution is 100% (values of b are in order of 10^6). Such a large residual was thought to be because of the difference in orders between explanatory variables. Therefore, the larger variables were scaled to [0, 1] using:

$$area_i = \frac{Area_i}{2000}, \quad floor_i = \frac{Floor_i}{64}, \quad age_i = \frac{Age_i}{100}$$

The condition number after scaling was reduced drastically to ~40 and the residual was about 10. Finally the scaled variables were used for the non linear (exponential) model; and predicted versus actual sales price were plotted for each:


Linear Unscaled Model
$r^2 = 0.92939$
Predicted Selling Price ($) →
Actual Selling Price ($) →
x 10^5
0 1 2 3 4 5 6 7 8 9


Linear Scaled Model
$r^2 = 0.92939$
Predicted Selling Price ($) →
Actual Selling Price ($) →
x 10^5
0 1 2 3 4 5 6 7 8 9


Non-Linear Scaled Model
$r^2 = 0.92826$
Predicted Selling Price ($) →
Actual Selling Price ($) →
x 10^5
0 1 2 3 4 5 6 7 8 9

MATLAB OUTPUT

```
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Linear Unscaled Model

 Condition Number of A for regression is: 6376.1639

 Cond# is ||A||.||A_pseudo_inv||

 The system is poorly conditioned!
 Warning: Small Residual does not imply Accurate Solution!!!

Residual computed using Normal Equations is: 1070125.8437

Residual computed using Orthog. (Householder) transformation is:
1070125.8437

Residual (MIN) computed using Singular Value Decomposition is:
1070125.8437


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Linear Scaled Model

 Condition Number of A for regression is: 40.0833

Residual computed using Normal Equations is: 10.7013

Residual computed using Orthog. (Householder) transformation is:
10.7013

Residual (MIN) computed using Singular Value Decomposition is: 10.7013


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NonLinear Scaled Model

 Condition Number of A for regression is: 354.9697

Residual computed using Normal Equations is: 2.7979

Residual computed using Orthog. (Householder) transformation is: 2.7979

Residual (MIN) computed using Singular Value Decomposition is: 2.7979
```

```
function RESIDUAL = NrmEqn(A,b)
    [ROWS, COLS] = size(A);          % Determine the dimension of matrix
    M = A' * A;                      % Solve A'*A*x = A'*b
    N = A' * b;
    COEFF = M \ N;
    RESIDUAL = norm(b - A*COEFF);
end
```

```
function RESIDUAL = Householder(A,b)
    [ROWS COLS] = size(A);                    % Determine the dimension of matrix
    for n = 1:COLS
        u = [zeros(n-1,1);A(n:ROWS,n)];       % u is the vector to be manipulated
        e = [zeros(n-1,1);eye(ROWS-n+1,1)];   % unit vector 'e'
        alpha = norm(u);                      % Extract only partial 'u'
        if u(n) > 0                           % ADD or SUBTRACT based on sign of u
            v = u + alpha * e;
        else
            v = u - alpha * e;
        end
        for k = 1:COLS                        % Adjust A and b accordingly
            H_A(:,k) = A(:,k) - 2*((v' * A(:,k))/(v' * v))*v;
            H_b = b - 2*((v' * b)/(v' * v))*v;
        end
        A = H_A;
        b = H_b;
    end
    A1 = H_A(1:COLS,:);
    b1 = H_b(1:COLS);
    COEFF = A1 \ b1;
    RESIDUAL = norm(b - A*COEFF);
end
```

```
function [RESIDUAL,COEFF] = SngValDcmp(A,b)
    [ROWS, COLS] = size(A);                 % Determine the dimension of matrix
    [U,S,V] = svd(A);                       % Get the singular values of A
    c = U' * b;
    for i = 1:COLS
        y(i,1) = c(i)/S(i,i);
    end
    COEFF = V * y;
    RESIDUAL = norm(b - A*COEFF);
end
```

```
% LinRgr.m
clear all; clc;
load work;

% Data Analysis...

figure;
plot(DATA(:,2),DATA(:,1),'k.');
ylabel('Selling Price ($)  \rightarrow');
xlabel('Unit Area (in square feet) \rightarrow');
title('Sales Price vs. Unit Area');
Rsq = corrcoef(DATA(:,2),DATA(:,1));
text(500,750000,sprintf('r^2 = %s',num2str(Rsq(1,2))));

figure;
plot(log(DATA(:,2)),log(DATA(:,1)),'k.');
ylabel('log(Selling Price)  \rightarrow');
xlabel('log(Unit Area) \rightarrow');
title('Log(Sales Price) vs. Log(Unit Area)');
Rsq = corrcoef(log(DATA(:,2)),log(DATA(:,1)));
text(6.4,13.5,sprintf('r^2 = %s',num2str(Rsq(1,2))));

figure;
plot(DATA(:,3),DATA(:,1),'k.');
ylabel('Selling Price ($)  \rightarrow');
xlabel('Floor Level  \rightarrow');
title('Sales Price vs. Unit Floor Level');
Rsq = corrcoef(DATA(:,3),DATA(:,1));
text(10,750000,sprintf('r^2 = %s',num2str(Rsq(1,2))));

figure;
plot(DATA(:,4),DATA(:,1),'k.');
ylabel('Selling Price ($)  \rightarrow');
xlabel('Age (in years) \rightarrow');
title('Sales Price vs. Age');
Rsq = corrcoef(DATA(:,4),DATA(:,1));
text(5,750000,sprintf('r^2 = %s',num2str(Rsq(1,2))));

% Computational Analysis...

                    % ----------------------------
                    %     Unscaled Linear model
                    % ----------------------------

[ROWS, COLS] = size(A);

if (rank(A) < COLS)     % Check whether the matrix is rank deficient!
    disp('A is Rank Deficient!!!');
end

A_psd_inv = inv(A' * A) * A';

RgrCndNum = norm(A)*norm(A_psd_inv);
disp(sprintf('----------------------'));
disp(sprintf('Linear Unscaled Model'));
disp(sprintf('\n Condition Number of A for regression is: %s',num2str(RgrCndNum)));
disp(sprintf('\n Cond# is ||A||.||A_pseudo_inv||'));

if RgrCndNum > 1.0e3
    disp(sprintf('\n The system is poorly conditioned!'));
    disp(sprintf(' Warning: Small Residual does not imply Accurate Solution!!!'));
end

Res_Nrm = NrmEqn(A,b);
Res_Hhd = Householder(A,b);
[Res_SVD,COEFF] = SngValDcmp(A,b);

disp(sprintf('\nResidual computed using Normal Equations is: %s',num2str(Res_Nrm)));
disp(sprintf('\nResidual computed using Orthog. (Householder) transformation is: %s',
    num2str(Res_Hhd)));
```

```
disp(sprintf('\nResidual (MIN) computed using Singular Value Decomposition is: %s',
    num2str(Res_SVD)));

y_act = b;
y_pred = A*COEFF;
figure;
plot(y_act,y_pred,'k.',0:1e5:9e5,0:1e5:9e5,'r','LineWidth',1.5);
axis([0 9.0e5 0 9.0e5]);
ylabel('Predicted Selling Price ($)  \rightarrow');
xlabel('Actual Selling Price ($)  \rightarrow');
title('Linear Unscaled Model');
Rsq = corrcoef(y_pred,y_act);
text(1.5e5,8e5,sprintf('r^2 = %s',num2str(Rsq(1,2))));

                    % ----------------------------
                    %     Scaled Linear model
                    % ----------------------------

b      = b * 1.0e-5;            % Selling price is in hundred thousand $
A(:,2) = A(:,2) / 2000;         % Unit area is normalized by 2000 sf
A(:,3) = A(:,3) / 64;           % Unit Floor Level is normalized by 64
A(:,4) = A(:,4) / 100;          % Age is normalized by 100 yrs

if (rank(A) < COLS)     % Check whether the matrix is rank deficient!
    disp('A is Rank Deficient!!!');
end

A_psd_inv = inv(A' * A) * A';

RgrCndNum = norm(A)*norm(A_psd_inv);
disp(sprintf('\n\n----------------------'));
disp(sprintf('Linear Scaled Model'));
disp(sprintf('\n Condition Number of A for regression is: %s',num2str(RgrCndNum)));

if RgrCndNum > 1.0e3
    disp(sprintf('\n The system is poorly conditioned!'));
    disp(sprintf(' Warning: Small Residual does not imply Accurate Solution!!!'));
end

Res_Nrm = NrmEqn(A,b);
Res_Hhd = Householder(A,b);
[Res_SVD,COEFF] = SngValDcmp(A,b);

disp(sprintf('\nResidual computed using Normal Equations is: %s',num2str(Res_Nrm)));
disp(sprintf('\nResidual computed using Orthog. (Householder) transformation is: %s',
    num2str(Res_Hhd)));
disp(sprintf('\nResidual (MIN) computed using Singular Value Decomposition is: %s',
    num2str(Res_SVD)));

y_act = b*1e5;
y_pred = A*COEFF*1e5;
figure;
plot(y_act,y_pred,'k.',0:1e5:9e5,0:1e5:9e5,'r','LineWidth',1.5);
axis([0 9.0e5 0 9.0e5]);
ylabel('Predicted Selling Price ($)  \rightarrow');
xlabel('Actual Selling Price ($)  \rightarrow');
title('Linear Scaled Model');
Rsq = corrcoef(y_pred,y_act);
text(1.5e5,8e5,sprintf('r^2 = %s',num2str(Rsq(1,2))));


                    % ----------------------------
                    % Non-Linear/Exponential model
                    % ----------------------------

b      = log(b*1.0e5);            % Log Selling Price
A(:,2) = log(A(:,2)*2000);        % Log Square Footage; Retain other normalized variables

if (rank(A) < COLS)     % Check whether the matrix is rank deficient!
    disp('A is Rank Deficient!!!');
```

```
end

A_psd_inv = inv(A' * A) * A';

RgrCndNum = norm(A)*norm(A_psd_inv);
disp(sprintf('\n\n----------------------'));
disp(sprintf('\nNonLinear Scaled Model'));
disp(sprintf('\n Condition Number of A for regression is: %s',num2str(RgrCndNum)));


if RgrCndNum > 1.0e3
    disp(sprintf('\n The system is poorly conditioned!'));
    disp(sprintf(' Warning: Small Residual does not imply Accurate Solution!!!'));
end

Res_Nrm = NrmEqn(A,b);
Res_Hhd = Householder(A,b);
[Res_SVD,COEFF] = SngValDcmp(A,b);

disp(sprintf('\nResidual computed using Normal Equations is: %s',num2str(Res_Nrm)));
disp(sprintf('\nResidual computed using Orthog. (Householder) transformation is: %s',
    num2str(Res_Hhd)));
disp(sprintf('\nResidual (MIN) computed using Singular Value Decomposition is: %s',
    num2str(Res_SVD)));

y_act = exp(b);
y_pred = exp(A*COEFF);
figure;
plot(y_act,y_pred,'k.',0:1e5:9e5,0:1e5:9e5,'r','LineWidth',1.5);
axis([0 9.0e5 0 9.0e5]);
ylabel('Predicted Selling Price ($)  \rightarrow');
xlabel('Actual Selling Price ($)  \rightarrow');
title('Non-Linear Scaled Model');
Rsq = corrcoef(y_pred,y_act);
text(1.5e5,8e5,sprintf('r^2 = %s',num2str(Rsq(1,2))));
```

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-200-068-1025	415.778	938	27	24	1	1	1	0	1
17-10-200-068-1081	458.190	873	34	24	1	1	1	0	1
17-10-200-068-1101	384.193	1822	37	24	1	2	2.1	0	1
17-10-200-068-1106	377.747	1456	37	24	1	1	1.1	0	1
17-10-200-681-1380	419.463	1490	41	24	1	1	1.1	0	1
17-10-200-681-2090	481.100	873	50	24	1	1	1	0	1
17-10-210-681-1210	373.315	1484	50	24	1	1	1.1	0	1
17-10-200-068-1217	469.645	873	51	24	1	1	1.1	0	1
17-10-200-068-1250	495.283	1484	55	24	1	1	1.1	0	1
17-10-203-029-1024	272.308	650	11	40	1	1	1	0	1
17-10-203-027-1048	267.692	650	13	40	1	1	1	0	1
17-10-203-027-1064	242.308	1300	15	40	1	2	2	0	1
17-10-203-027-1107	282.780	633	19	40	1	1	1	0	1
17-10-203-027-1128	283.133	830	21	40	1	1	1	0	1
17-10-203-027-1155	277.076	855	24	40	1	1	1	0	1
17-10-212-000-0000	353.591	933	3	3	1	1	1	0	1
17-10-212-000-0000	353.591	933	3	3	1	1	1	0	1
17-10-212-019-0000	364.309	933	3	3	1	1	1	0	1
17-10-212-000-0000	403.966	933	4	3	1	1	1	0	1
17-10-212-019-0000	427.631	1473	6	3	1	2	2.1	0	1
17-10-212-000-0000	410.397	933	6	3	1	1	1	0	1
17-10-212-000-0000	410.397	933	6	3	1	1	1	0	1
17-10-212-000-0000	414.671	933	7	3	1	1	1	0	1
17-10-212-000-0000	409.325	933	7	3	1	1	1	0	1
17-10-212-019-0000	432.905	933	8	3	1	1	1	0	1
00-00-171-021-2000	400.750	933	8	3	1	1	1	0	1
00-00-171-021-2000	400.750	933	8	3	1	1	1	0	1
17-10-212-000-0000	422.298	1314	8	3	1	2	2	0	1
17-10-219-001-0000	471.997	1257	16	18	1	2	2	0	1
17-10-219-001-0000	310.256	741	16	18	1	1	1	0	1
17-10-219-001-0000	399.377	642	16	18	1	0	1	0	1
00-00-171-021-9001	334.049	1257	16	18	0	2	2	0	0
17-10-219-001-0000	326.947	642	17	18	0	0	1	0	0
17-10-219-001-0000	321.321	1257	17	18	1	2	2	0	1
00-00-171-021-9001	356.702	741	17	18	1	1	1	0	1
00-00-171-021-9001	379.757	741	17	18	1	1	1	0	1
17-10-219-001-0000	419.568	741	17	18	0	1	1	0	0
00-00-171-021-9001	334.049	1257	17	18	0	2	2	0	0
17-10-219-001-0000	390.187	642	17	18	1	1	1	0	1
00-00-171-021-9001	443.769	642	17	18	1	0	1	0	1
17-10-219-001-0000	330.062	642	18	18	0	0	1	0	0
00-00-171-021-9001	318.138	1257	18	18	1	2	2	0	1
00-00-171-021-9001	379.757	741	18	18	1	1	1	0	1
00-00-171-021-9001	299.190	741	18	18	0	1	1	0	0
00-00-171-021-9001	401.713	642	18	18	1	0	1	0	1
00-00-171-021-9001	353.427	642	18	18	1	0	1	0	1
00-00-171-021-9001	357.677	1257	18	18	1	2	2	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
00-00-171-021-9001	345.639	642	19	18	1	0	1	0	1
00-00-171-021-9001	318.138	1257	19	18	0	2	2	0	0
17-12-190-010-0000	314.980	741	19	18	1	1	1	0	1
00-00-171-021-9001	305.938	741	19	18	0	1	1	0	0
00-00-171-021-9001	330.453	1257	19	18	1	2	2	0	1
00-00-171-021-9001	369.626	642	19	18	1	0	1	0	1
00-00-171-021-9001	283.956	642	19	18	0	0	1	0	0
00-00-171-021-9001	390.958	741	19	18	1	1	1	0	1
00-00-171-021-9001	345.744	1257	19	18	1	2	2	0	1
00-00-171-021-9001	397.040	642	19	18	0	0	1	0	0
00-00-171-021-9001	333.178	642	20	18	0	0	1	0	0
17-10-219-001-0000	361.098	1257	20	18	0	2	2	0	0
00-00-171-021-9001	318.138	1257	20	18	0	2	2	0	0
00-00-171-021-9001	379.907	642	20	18	1	0	1	0	1
00-00-171-021-9001	315.115	1257	20	18	0	2	2	0	0
00-00-171-021-9001	358.234	1257	20	18	1	2	2	0	1
17-10-219-001-0000	315.109	642	20	18	1	0	1	0	1
00-00-171-021-9001	340.966	642	21	18	1	0	1	0	1
17-10-219-001-0000	361.098	1257	21	18	0	2	2	0	0
00-00-171-021-9001	319.703	741	21	18	0	1	1	0	0
17-10-219-001-0000	393.715	1257	21	18	1	2	2	0	1
17-10-219-001-0000	333.178	642	21	18	1	0	1	0	1
00-00-171-021-9001	374.781	1257	21	18	2	2	2	0	1
17-10-219-001-0000	505.171	1257	21	18	1	2	2	0	1
00-00-171-021-9001	354.256	1257	21	18	1	2	2	0	1
17-10-219-001-0000	319.470	642	21	18	1	0	1	0	1
17-10-219-001-0000	336.293	642	22	18	0	0	1	0	0
17-10-219-001-0000	413.683	1257	22	18	1	2	2	0	1
17-10-219-001-0000	328.481	1257	22	18	1	2	2	0	1
17-10-219-001-0000	340.966	642	22	18	1	0	1	0	1
17-10-219-001-0000	336.293	642	22	18	1	0	1	0	1
17-10-219-001-0000	375.418	1257	22	18	1	2	2	0	1
17-10-219-001-0000	330.947	1257	22	18	1	2	2	0	1
17-10-219-001-0000	323.988	642	22	18	1	0	1	0	1
00-00-171-021-9001	322.912	1257	23	18	1	2	2	0	1
17-10-219-001-0000	308.232	741	23	18	1	1	1	0	1
00-00-171-021-9001	376.383	741	23	18	0	1	1	0	0
00-00-171-021-9001	427.128	1257	23	18	1	2	2	0	1
17-10-219-001-0000	323.988	642	23	18	1	0	1	0	1
17-10-219-001-0000	339.408	642	23	18	1	0	1	0	1
17-10-219-001-0000	323.988	642	23	18	1	0	1	0	1
17-10-219-001-0000	354.984	642	24	18	0	0	1	0	0
17-10-219-001-0000	340.621	741	24	18	0	1	1	0	0
17-10-219-001-0000	364.280	1257	24	18	1	2	2	0	1
17-10-219-001-0000	323.988	642	24	18	1	0	1	0	1
17-10-219-001-0000	339.408	642	24	18	1	0	1	0	1
00-00-171-021-9001	372.235	1257	24	18	0	2	2	0	0

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-219-001-0000	378.408	741	24	18	0	1	1	0	0
17-10-219-001-0000	330.947	1257	24	18	1	2	2	0	1
17-10-219-001-0000	356.542	642	24	18	1	0	1	0	1
17-10-219-001-0000	305.251	1257	25	18	0	2	2	0	0
17-10-219-001-0000	393.927	741	25	18	1	1	1	0	1
17-10-219-001-0000	357.518	1257	25	18	1	2	2	0	1
00-00-171-021-9001	467.697	1257	25	18	1	2	2	0	1
17-10-219-001-0000	328.349	642	25	18	1	0	1	0	1
00-00-171-021-9001	393.925	642	26	18	1	0	1	0	1
00-00-171-021-9001	349.960	1257	26	18	1	2	2	0	1
00-00-171-021-9001	391.228	741	26	18	0	1	1	0	0
00-00-171-021-9001	363.087	1257	26	18	1	2	2	0	1
17-10-219-001-0000	328.349	642	26	18	1	0	1	0	1
17-10-219-001-0000	324.185	1257	26	18	1	2	2	0	1
17-10-219-001-0000	363.968	741	26	18	0	1	1	0	0
17-10-219-001-0000	467.697	1257	26	18	1	2	2	0	1
17-10-219-001-0000	328.349	642	26	18	1	0	1	0	1
17-10-219-001-0000	329.150	741	27	18	0	1	1	0	0
17-10-219-001-0000	403.262	1257	27	18	1	2	2	0	1
17-10-219-001-0000	428.193	642	27	18	1	0	1	0	1
17-10-219-001-0000	328.349	642	27	18	1	0	1	0	1
17-10-219-001-0000	337.132	645	28	18	1	0	1	0	1
17-10-219-001-0000	389.204	741	28	18	0	1	1	0	0
17-10-219-001-0000	384.964	1257	28	18	1	2	2	0	1
17-10-219-001-0000	417.290	642	28	18	1	0	1	0	1
17-10-219-001-0000	318.380	642	28	18	1	0	1	0	1
17-10-219-001-0000	328.719	1257	28	18	1	2	2	0	1
17-10-219-001-0000	442.510	741	28	18	0	1	1	0	0
00-00-171-021-9001	445.426	1257	28	18	2	2	2	0	1
17-10-219-001-0000	332.866	642	28	18	1	0	1	0	1
17-10-219-001-0000	347.574	1257	29	18	0	2	2	0	0
17-10-219-001-0000	343.995	741	29	18	0	1	1	0	0
17-10-219-001-0000	332.866	642	29	18	1	0	1	0	1
17-10-219-001-0000	318.540	642	29	18	1	0	1	0	1
17-10-219-001-0000	361.893	1257	29	18	1	2	2	0	1
17-10-219-001-0000	368.421	741	29	18	0	1	1	0	0
17-10-219-001-0000	295.794	642	30	18	0	0	1	0	0
17-10-219-001-0000	322.196	1257	30	18	1	2	2	0	1
17-10-219-001-0000	309.785	1257	30	18	0	2	2	0	0
17-10-219-001-0000	394.590	1257	30	18	2	2	2	0	1
17-10-219-001-0000	332.866	642	30	18	1	0	1	0	1
17-10-219-001-0000	295.794	642	30	18	1	0	1	0	1
17-10-219-001-0000	449.483	1257	30	18	1	2	2	0	1
17-10-219-001-0000	381.782	1257	30	18	1	2	2	0	1
17-10-219-001-0000	447.908	741	30	18	0	1	1	0	0
17-10-219-001-0000	340.016	1257	30	18	1	2	2	0	1
17-10-219-001-0000	332.866	642	30	18	1	0	1	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-219-001-0000	345.639	642	31	18	0	0	1	0	0
17-10-219-001-0000	331.663	1257	31	18	0	2	2	0	0
17-10-219-001-0000	403.374	741	31	18	1	1	1	0	1
17-10-219-001-0000	435.981	642	31	18	1	0	1	0	1
17-10-219-001-0000	351.869	642	31	18	1	0	1	0	1
17-10-219-001-0000	389.737	1257	31	18	1	2	2	0	1
17-10-219-001-0000	447.908	741	31	18	0	1	1	0	0
17-10-219-001-0000	461.337	1257	31	18	1	2	2	0	1
17-10-219-001-0000	351.551	1257	32	18	0	2	2	0	0
17-10-219-001-0000	408.910	1257	32	18	1	2	2	0	1
17-10-219-001-0000	378.600	1257	32	18	1	2	2	0	1
17-10-219-001-0000	351.869	642	32	18	1	0	1	0	1
17-10-219-001-0000	344.551	1257	32	18	1	2	2	0	1
17-10-219-001-0000	345.639	642	33	18	0	0	1	0	0
17-10-219-001-0000	330.072	1257	33	18	0	2	2	0	0
17-10-219-001-0000	321.727	741	33	18	0	1	1	0	0
17-10-219-001-0000	386.555	1257	33	18	1	2	2	0	1
17-10-219-001-0000	420.405	642	33	18	1	0	1	0	1
17-10-219-001-0000	351.869	642	33	18	1	0	1	0	1
17-10-219-001-0000	386.555	1257	33	18	1	2	2	0	1
00-00-171-021-9001	437.470	1257	33	18	0	2	2	0	0
17-10-219-001-0000	355.529	1257	34	18	0	2	2	0	0
17-10-219-001-0000	408.772	741	34	18	1	1	1	0	1
17-10-219-001-0000	375.034	741	34	18	0	1	1	0	0
17-10-219-001-0000	325.696	1257	34	18	1	2	2	0	1
17-10-219-001-0000	337.227	642	34	18	1	0	1	0	1
17-10-219-001-0000	351.869	642	34	18	1	0	1	0	1
17-10-219-001-0000	389.539	1257	34	18	1	2	2	0	1
17-10-219-001-0000	344.551	1257	34	18	1	2	2	0	1
17-10-219-001-0000	375.418	1257	35	18	0	2	2	0	0
17-10-219-001-0000	408.097	741	35	18	1	1	1	0	1
00-00-171-021-9001	411.217	1257	35	18	1	2	2	0	1
17-10-219-001-0000	359.657	642	35	18	1	0	1	0	1
17-12-190-010-0000	351.869	642	35	18	1	0	1	0	1
17-10-219-001-0000	451.282	741	35	18	0	1	1	0	0
17-10-219-001-0000	355.529	1257	36	18	0	2	2	0	0
17-10-219-001-0000	408.097	741	36	18	1	1	1	0	1
17-10-219-001-0000	398.650	741	36	18	0	1	1	0	0
17-10-219-001-0000	383.373	1257	36	18	1	2	2	0	1
17-10-219-001-0000	351.869	642	36	18	1	0	1	0	1
17-10-219-001-0000	441.970	741	36	18	0	1	1	0	0
17-10-219-001-0000	349.085	1257	36	18	1	2	2	0	1
17-10-219-001-0000	341.745	642	36	18	1	0	1	0	1
17-10-219-001-0000	400.875	1257	37	18	0	2	2	0	0
17-10-219-001-0000	398.650	741	37	18	0	1	1	0	0
17-10-219-001-0000	397.693	1257	37	18	1	2	2	0	1
17-10-219-001-0000	435.981	642	37	18	1	0	1	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-219-001-0000	301.713	642	37	18	1	0	1	0	1
17-10-219-001-0000	337.788	1257	37	18	1	2	2	0	1
17-10-219-001-0000	458.704	741	37	18	0	1	1	0	0
17-10-219-001-0000	376.518	741	37	18	0	1	1	0	0
00-00-171-021-9001	384.885	1257	37	18	0	2	2	0	0
17-10-219-001-0000	425.078	642	37	18	1	0	1	0	1
17-10-219-001-0000	380.986	1257	38	18	0	2	2	0	0
17-10-219-001-0000	395.239	741	38	18	0	1	1	0	0
17-10-219-001-0000	363.484	1257	38	18	1	2	2	0	1
17-10-219-001-0000	435.981	642	38	18	1	0	1	0	1
17-10-219-001-0000	301.713	642	38	18	1	0	1	0	1
17-10-219-001-0000	337.788	1257	38	18	1	2	2	0	1
17-10-219-001-0000	451.282	741	38	18	0	1	1	0	0
17-10-219-001-0000	349.085	1257	38	18	1	2	2	0	1
17-10-219-001-0000	435.981	642	38	18	1	0	1	0	1
17-10-219-001-0000	380.986	1257	39	18	0	2	2	0	0
17-10-219-001-0000	456.005	741	39	18	1	1	1	0	1
17-10-219-001-0000	462.753	741	39	18	0	1	1	0	0
17-10-219-001-0000	437.470	1257	39	18	1	2	2	0	1
17-10-219-001-0000	443.769	642	39	18	1	0	1	0	1
17-10-219-001-0000	354.984	642	40	18	1	0	1	0	1
17-10-210-010-0000	367.462	1257	40	18	0	2	2	0	0
17-10-219-001-0000	403.374	741	40	18	0	1	1	0	0
17-10-219-001-0000	405.648	1257	40	18	1	2	2	0	1
17-10-219-001-0000	304.673	642	40	18	1	0	1	0	1
17-10-219-001-0000	361.893	1257	41	18	0	2	2	0	0
17-10-219-001-0000	330.634	741	41	18	0	1	1	0	0
17-10-219-001-0000	388.146	1257	41	18	1	2	2	0	1
17-10-219-001-0000	437.539	642	41	18	1	0	1	0	1
17-10-219-001-0000	426.969	1257	41	18	1	2	2	0	1
17-10-219-001-0000	357.916	1257	42	18	0	2	2	0	0
17-10-219-001-0000	442.212	642	45	18	1	0	1	0	1
17-10-219-001-0000	358.100	642	45	18	1	0	1	0	1
17-10-219-001-0000	421.346	1635	45	18	1	3	2.1	0	1
17-10-219-001-0000	491.763	1257	49	18	1	2	2	0	1
17-10-219-001-0000	427.873	757	50	18	1	1	1	0	1
17-10-219-001-0000	411.258	1590	52	18	1	3	2.1	0	1
17-10-219-001-0000	428.193	642	53	18	1	0	1	0	1
17-10-219-001-0000	389.252	642	54	18	1	0	1	0	1
17-10-219-001-0000	460.262	642	55	18	1	0	1	0	1
00-00-171-021-9001	465.394	1257	56	18	1	2	2	0	1
17-10-219-001-0000	431.849	741	56	18	1	1	1	0	1
17-10-219-001-0000	451.558	642	56	18	1	0	1	0	1
17-10-219-001-0000	428.193	642	56	18	0	0	1	0	0
17-10-222-007-1474	490.654	642	57	18	1	0	1	0	1
17-10-219-001-0000	370.657	1980	58	18	1	3	2.1	0	1
17-10-219-001-0000	461.018	1257	60	18	1	2	2	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-214-016-1851	354.545	1100	5	41	1	1	1	1	1
17-10-214-016-1850	363.636	1100	5	41	1	1	1	1	1
17-10-214-016-1844	368.182	1100	5	41	1	1	1	1	1
07-10-214-016-1842	340.909	1100	5	41	0	1	1	1	0
17-10-214-016-1821	379.545	1100	7	41	1	1	1	1	1
17-10-214-016-1794	349.091	1100	8	41	1	1	1	1	1
17-10-214-016-1781	377.273	1100	9	41	1	1	1	1	1
17-10-214-016-1771	460.340	706	9	41	1	1	1	1	1
17-10-214-016-1685	362.727	1100	14	41	1	1	1	1	1
17-10-214-016-1667	369.091	1100	15	41	1	1	1	1	1
17-10-214-016-1657	429.178	706	16	41	0	1	1	1	0
17-10-214-016-1578	340.909	1,100	20	41	0	1	1	1	0
17-10-214-016-1502	455.172	1450	25	41	1	2	2	1	0
17-10-214-016-1485	396.552	1450	26	41	1	2	2	1	1
17-10-214-016-1469	409.655	1450	28	41	0	2	2	1	0
17-10-214-012-0000	413.793	1450	29	41	1	2	2	1	1
17-10-214-016-1435	489.655	1450	30	41	1	2	2	1	1
17-10-214-016-1322	347.222	1440	40	41	1	2	2	0	0
17-10-214-016-1316	447.586	1450	40	41	1	2	2	1	1
17-10-214-016-1302	414.533	1445	41	41	0	2	2	1	0
17-10-214-016-1251	391.034	1450	46	41	0	2	2	1	1
17-10-214-016-1242	434.483	1,450	47	41	1	2	2	1	1
17-10-214-016-1237	475.862	1450	47	41	1	2	2	1	1
17-10-214-016-1229	479.720	1430	48	41	1	2	2	1	1
17-10-214-016-1213	500.000	1450	49	41	1	2	2	1	1
17-10-214-016-1183	353.636	1100	52	41	0	1	1	1	0
17-10-214-016-1119	368.182	1100	57	41	1	1	1	1	1
17-10-214-016-1118	368.182	1100	57	41	1	1	1	1	1
17-10-214-016-1083	381.818	1100	60	41	1	1	1	1	1
17-10-214-016-1074	345.000	1100	61	41	0	1	1	1	0
17-10-214-018-1066	390.909	1100	62	41	0	1	1	1	0
17-10-214-016-1059	412.409	1100	62	41	1	1	1	1	1
17-10-211-024-1041	462.329	1460	12	6	1	2	2	0	0
17-10-211-024-1044	367.660	1107	13	6	1	1	1.1	0	1
17-10-211-024-1061	352.638	1744	15	6	1	2	2	0	1
17-10-211-024-1063	466.390	1324	15	6	1	2	2	0	1
17-10-211-013-0000	474.320	1324	17	6	1	2	2	0	1
17-10-211-024-1110	460.803	1046	20	6	1	1	1.1	0	1
17-10-211-013-0000	453.677	1047	25	6	1	1	1.1	0	1
17-10-211-021-1039	277.995	1127	4	91	1	1	1	0	1
17-10-211-021-1107	238.542	1200	4	91	0	1	1	0	0
17-10-211-021-1123	337.838	1110	4	91	1	2	1	0	1
17-10-211-021-1017	295.735	1055	6	91	0	2	1	0	0
17-10-211-021-1029	284.250	1073	6	91	0	1	1	0	0
17-10-211-021-1041	255.319	1128	6	91	1	1	1	0	1
17-10-202-063-1009	279.563	1556	2	85	1	2	1.1	0	1
17-10-202-063-1017	264.566	1682	3	85	1	2	1.1	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-202-062-1011	260.909	1100	3	85	1	1	1	0	1
17-10-202-083-1022	286.207	1450	5	85	1	1	1.1	0	1
17-10-202-063-1116	319.444	1800	12	85	1	2	1.1	0	1
17-10-219-027-1040	344.000	500	4	18	1	0	1	0	1
17-10-219-027-1053	368.276	725	4	18	1	1	1	0	1
17-10-219-027-1054	348.000	750	4	18	1	1	1	0	1
17-10-292-711-2300	302.667	750	4	18	1	1	1	0	1
17-10-219-027-1076	408.000	750	5	18	1	1	1	0	1
17-10-219-027-1125	294.643	1400	7	18	1	2	2	0	1
17-10-219-027-1129	368.750	800	8	18	1	1	1	0	1
17-10-219-027-1167	346.667	750	10	18	1	1	1	0	1
17-10-219-027-1169	321.250	800	10	18	1	1	1	0	1
17-10-219-027-1174	344.231	650	10	18	1	1	1	0	1
17-10-219-027-1180	435.000	800	10	18	1	1	1	0	1
17-10-219-027-1182	406.667	750	10	18	1	1	1	0	1
17-10-219-029-1189	409.333	750	11	18	1	1	1	0	1
17-10-219-027-1213	405.629	1208	12	18	1	2	2	0	1
17-10-219-027-1221	355.172	725	12	18	1	1	1	0	1
17-10-219-027-1222	448.000	750	12	18	1	1	1	0	1
17-10-219-027-1223	360.000	500	12	18	0	0	1	0	0
17-10-219-027-1444	358.000	500	3	18	0	0	1	0	0
17-10-219-027-1460	383.448	725	3	18	0	1	1	0	0
17-10-219-027-1126	327.160	810	4	18	2	1	1	0	1
17-10-219-027-1539	326.000	500	7	18	0	0	1	0	0
17-10-219-027-1542	341.667	1200	8	18	1	2	2	0	1
17-10-219-027-1551	390.819	806	8	18	1	1	1	0	1
00-09-348-930-0000	389.630	675	8	18	1	1	1	0	1
17-10-219-027-1565	372.727	825	9	18	1	1	1	0	1
17-10-219-021-1571	349.256	806	9	18	1	1	1	0	1
17-10-219-027-1572	393.210	810	9	18	0	1	1	0	0
17-10-210-027-1573	356.250	640	9	18	1	1	1	0	1
17-10-219-027-1587	420.690	725	10	18	1	1	1	0	1
17-10-219-027-1592	452.854	806	10	18	1	1	1	0	1
17-10-219-027-1603	398.667	750	11	18	1	1	1	0	1
17-10-219-027-1629	344.000	1250	12	18	1	2	2	0	1
17-10-223-033-1008	286.624	628	5	8	1	0	1	0	1
17-10-223-033-1042	301.587	630	8	8	1	0	1	0	1
17-10-223-031-1048	302.611	651	9	8	1	0	1	0	1
17-10-223-033-1051	323.077	975	9	8	1	1	1	0	1
17-10-223-033-1060	321.045	651	10	8	1	0	1	0	1
17-10-223-033-1020	306.924	1401	11	8	1	2	2	0	1
17-10-223-033-1083	312.803	1445	12	8	1	2	2	0	1
17-10-223-033-1084	329.493	651	12	8	1	0	1	0	1
17-10-223-033-1094	317.935	920	12	8	1	1	1	0	1
17-10-223-033-1099	334.197	965	13	8	1	1	1	0	1
17-10-223-033-1106	312.500	920	13	8	2	1	1	0	1
17-10-223-033-1220	317.647	1445	16	8	1	2	2	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-223-033-1141	309.783	920	16	8	1	1	1	0	1
17-10-223-033-1070	389.008	1401	20	8	1	2	2	0	1
00-00-171-021-8003	311.419	1445	21	8	1	2	2	0	1
17-10-223-033-1199	318.339	1445	23	8	1	2	2	0	1
17-10-223-033-1050	397.924	1445	25	8	1	2	2	0	1
17-10-223-033-1239	374.359	975	26	8	1	1	1	0	1
17-10-223-033-1244	342.561	1445	26	8	1	2	2	0	1
17-10-218-003-1234	347.826	920	26	8	1	1	1	0	1
17-10-223-033-1259	333.910	1445	28	8	2	2	2	0	1
17-10-223-033-1268	364.706	1445	28	8	1	2	2	0	1
17-10-223-033-1280	319.723	1445	29	8	1	2	2	0	1
17-10-223-033-1280	352.941	1445	29	8	2	2	2	0	1
17-10-223-033-1288	364.767	965	30	8	1	1	1	0	1
17-10-223-033-1294	306.667	975	30	8	1	1	1	0	1
17-10-223-033-1325	411.849	1401	33	8	2	2	2	0	1
17-10-223-033-1399	403.283	1401	35	8	2	2	2	0	1
17-10-223-033-1356	380.184	651	36	8	0	0	1	0	0
17-10-223-033-1357	342.550	651	36	8	0	0	1	0	0
17-10-223-033-1358	371.429	1400	36	8	1	2	2	0	1
17-10-223-033-1392	362.519	651	39	8	1	0	1	0	0
17-10-223-033-1431	393.782	965	42	8	1	1	1	0	1
17-10-223-031-4370	391.304	920	42	8	1	1	1	0	1
17-10-223-033-1438	341.969	965	42	8	1	1	1	0	1
17-10-223-033-1441	334.869	651	43	8	1	0	1	0	1
17-10-223-033-1050	353.303	651	44	8	1	0	1	0	1
17-10-223-033-1456	383.420	965	44	8	0	1	1	0	0
17-10-227-033-1467	401.554	965	45	8	1	1	1	0	1
17-10-223-033-1473	337.895	950	45	8	1	1	1	0	1
17-10-223-033-1475	403.571	1400	46	8	0	2	2	0	0
17-10-223-033-1484	387.543	1,445	46	8	2	2	2	0	1
17-10-223-033-1513	353.303	651	49	8	0	0	1	0	0
17-10-223-033-1531	382.609	920	50	8	1	1	1	0	1
12-35-551-234-7000	405.530	651	51	8	1	0	1	0	1
17-10-223-033-1547	392.857	1400	52	8	2	2	2	0	1
17-10-223-033-1548	402.174	920	52	8	1	1	1	0	1
17-10-223-033-1552	357.143	1400	52	8	0	2	2	0	0
17-10-223-033-1555	390.217	920	53	8	2	1	1	0	1
17-10-223-033-1587	355.000	1000	55	8	2	1	1	0	1
17-10-223-033-1589	352.507	678	56	8	1	0	1	0	1
00-00-171-021-8003	393.241	651	57	8	1	0	1	0	1
17-10-223-033-1601	360.983	651	57	8	1	0	1	0	1
17-10-223-033-1602	410.714	1400	57	8	1	2	2	0	1
17-10-200-065-1003	285.194	1648	6	44	1	2	2.1	0	1
17-10-200-065-1152	303.398	1648	21	44	1	2	2.1	0	1
17-10-200-065-1269	296.925	943	32	44	1	1	1.1	0	1
17-10-200-065-1287	283.333	600	34	44	1	0	1	0	1
17-10-200-651-3180	299.046	943	35	44	1	1	1	0	1

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
00-00-171-022-1004	483.559	1370	7	5	1	1	2	0	1
17-10-221-082-0000	456.204	1370	8	5	1	2	2	0	1
17-10-221-000-0000	452.555	1370	27	5	1	2	2	0	1
17-10-221-082-1011	383.048	1227	8	9	1	1	1.1	0	1
17-10-221-082-1076	438.367	1225	21	9	1	1	1.1	0	1
17-10-221-079-1078	415.648	1227	21	9	1	1	1.1	0	1
17-10-221-082-1078	385.493	1227	21	9	1	1	1.1	0	1
17-10-221-082-1081	406.122	1225	22	9	1	1	1.1	0	1
17-10-209-025-1606	326.531	980	3	23	1	1	1	0	1
17-10-209-025-1585	396.923	650	3	23	1	0	1	0	1
17-10-209-025-1013	283.333	900	5	23	0	1	1	1	0
17-10-209-025-1020	353.750	800	5	23	0	1	1	0	0
17-10-209-025-1033	371.212	594	6	23	1	1	1	0	1
17-10-209-025-1046	307.448	725	6	23	1	1	1	1	1
17-10-209-025-1048	241.667	1200	6	23	1	2	2	1	1
17-10-209-025-1535	315.000	600	7	23	1	1	1	0	1
17-10-209-025-1062	295.833	600	7	23	1	0	1	1	1
17-10-209-025-1080	361.667	600	8	23	1	1	1	1	1
17-10-209-025-1088	307.500	800	8	23	1	1	1	1	0
17-10-209-025-1090	345.000	700	8	23	1	1	1	1	1
17-10-209-025-1101	303.125	800	9	23	1	1	1	1	1
17-10-209-025-1135	316.667	600	10	23	1	0	1	0	0
17-10-209-025-1100	331.429	700	10	23	1	1	1	0	1
17-10-209-025-1145	346.939	784	10	23	1	1	1	0	1
17-10-209-025-1153	302.500	600	11	23	1	0	1	1	0
17-10-209-025-1160	312.500	800	11	23	1	1	1	1	1
17-10-209-025-1165	315.909	1100	11	23	1	2	2	1	1
17-10-209-025-1181	346.250	800	12	23	1	1	1	1	1
17-10-209-025-1193	301.020	784	12	23	1	1	1	1	1
17-10-209-002-0000	283.333	600	12	23	0	0	1	1	0
17-10-209-025-1210	339.333	750	14	23	1	1	1	1	1
17-10-209-025-1214	262.500	800	14	23	1	1	1	1	1
17-10-209-025-1236	374.286	700	15	23	1	1	1	1	1
17-10-209-025-1320	316.667	600	19	23	1	1	1	0	1
17-10-209-025-1335	320.833	1200	19	23	1	2	2	0	1
17-10-209-025-1346	304.569	788	20	23	1	1	1	0	1
17-10-209-025-1355	301.200	1250	20	23	1	2	2	1	1
17-10-209-025-1378	322.581	775	21	23	1	1	1	1	1
17-10-209-025-1380	308.707	735	21	23	1	1	1	1	1
17-10-209-025-1424	290.625	800	23	23	1	1	1	1	1
17-10-209-025-1429	290.909	1100	23	23	1	2	2	1	1
17-10-209-025-1442	315.355	788	24	23	1	1	1	1	0
17-10-209-025-1471	308.765	753	25	23	1	1	1	0	0
17-10-209-025-1478	326.531	735	25	23	1	1	1	0	1
17-10-209-025-1501	312.500	784	26	23	1	1	1	0	1
17-10-209-025-1514	330.000	800	27	23	1	1	1	0	1
17-10-209-025-1528	260.870	1150	28	23	0	2	2	1	0

Property ID # (PIN)	$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
17-10-209-025-1556	308.333	600	29	23	1	0	1	1	1
17-10-208-014-1043	292.727	1650	7	23	1	2	2	0	1
17-10-208-014-1039	336.364	1650	11	23	1	2	2	0	1
17-10-208-014-1029	312.121	1650	21	23	1	2	2	0	1
17-10-208-014-1015	354.545	1650	35	23	1	2	2	0	1
17-10-208-014-1060	341.298	1109	35	23	1	1	1.1	0	1
17-10-208-014-1151	321.799	1445	35	23	1	2	2	0	1
17-10-208-014-1006	360.606	1650	44	23	1	2	2	0	1
17-10-208-014-1140	349.481	1445	46	23	1	2	2	0	1
17-10-203-028-1014	237.647	850	5	40	0	1	1	0	0
17-10-203-028-1037	237.143	875	8	40	1	1	1	0	0
17-10-203-028-1043	244.571	875	9	40	0	1	1	0	0
17-10-203-028-1049	225.714	875	10	40	0	1	1	0	0
17-10-203-028-1057	220.571	875	12	40	1	1	1	0	0
17-10-203-028-1068	264.706	850	14	40	1	1	1	0	1
17-10-203-028-1071	281.538	650	14	40	0	1	1	0	0
17-10-203-028-1108	228.571	875	20	40	0	1	1	0	0
17-10-203-028-1130	285.185	675	24	40	0	1	1	0	0
17-10-203-028-1141	232.000	875	26	40	0	1	1	0	0
17-10-208-017-1375	313.333	1200	5	19	1	2	2	0	1
17-10-208-017-1367	354.444	900	5	19	1	1	1	0	1
17-10-208-017-1363	323.750	800	6	19	1	1	1	0	1
17-10-208-017-1363	343.750	800	6	19	1	1	1	0	1
17-10-208-017-1352	321.429	700	7	19	0	1	1	0	0
17-10-208-017-1344	335.000	800	8	19	1	1	1	0	1
17-10-208-017-1321	371.429	700	10	19	1	1	1	0	1
17-10-208-017-1320	360.000	800	10	19	1	1	1	0	1
17-10-208-017-1317	355.556	900	10	19	1	1	1	0	1
17-10-208-017-1298	365.000	1200	12	19	1	2	2	0	1
17-10-208-017-1317	326.667	900	13	19	1	1	1	0	1
17-10-208-017-1261	355.714	700	16	19	1	1	1	0	1
17-10-208-017-1260	350.000	800	16	19	1	1	1	0	1
17-10-208-017-1248	343.750	1200	17	19	1	2	2	0	1
17-10-208-017-1238	341.667	1200	18	19	1	2	2	0	1
17-10-208-017-1255	368.750	1200	22	19	1	2	2	0	1
17-10-208-017-1183	409.375	800	24	19	1	1	1	0	0
17-10-208-017-1182	397.143	700	24	19	1	1	1	0	1
17-10-208-001-0521	365.000	800	25	19	1	1	1	0	1
17-10-208-017-1168	374.167	1200	25	19	1	2	2	0	1
17-10-208-017-1119	346.250	800	27	19	1	1	1	0	1
17-10-208-017-1133	408.750	800	29	19	1	1	1	0	1
17-10-208-017-1129	356.250	800	29	19	1	1	1	0	1
17-10-208-017-1111	338.571	700	31	19	0	1	1	0	0
17-10-208-017-1109	393.750	800	31	19	1	1	1	0	1
17-10-208-017-1106	389.944	900	32	19	1	1	1	0	1
17-10-208-017-1097	294.444	900	32	19	1	1	1	0	1
17-10-208-017-1256	441.111	900	35	19	1	1	1	0	1

Property ID # (PIN)	\$/sf	Area (sf)	UFL	Age (yr)	# Cars	Bed	Bath	Cen. Air (NO = 1)	Park
00-01-710-202-1058	384.387	775	36	19	1	1	1	0	1
00-01-710-202-1058	379.355	775	38	19	1	1	1	0	1
17-10-208-017-1051	375.000	800	38	19	1	1	1	0	1
17-10-208-017-1046	387.097	775	39	19	1	1	1	0	1
17-10-208-017-1045	354.839	775	39	19	1	1	1	0	1
17-10-208-017-1023	386.111	1800	43	19	1	3	2	0	1
17-10-208-017-1019	413.333	1800	43	19	2	3	2	0	1
17-10-208-017-1009	458.065	775	45	19	1	1	1	0	1

DATA ANALYSIS	\$/sf	Area
X_{75}	398.650	1257
X_{25}	327.000	700
MAX	505.171	1980
MIN	220.571	500
IQR = X_{75} - X_{25}	71.650	557
HI: $X_{75} + 1.5 \times IQR$	506.126	2092.5
LOW: $X_{25} - 1.5 \times IQR$	219.525	-135.5
HI > MAX	TRUE	TRUE
LOW < MIN	TRUE	TRUE