

Data Modeling Project for MATH 7241

October 2020

Due date: Tuesday December 1, week after Thanksgiving.

Groups: if you wish you may collaborate in a group of at most two people. In this case each member of the group must make a substantial contribution to the project, and your project report must describe which contributions were made by each member.

Step 1: find a good data set!

Recommended source: UCI archive. Search for Time Series.

<https://archive.ics.uci.edu/ml/index.php>

Welcome to the UC Irvine Machine Learning Repository!

We currently maintain 394 data sets as a service to the machine learning community. You may [view all data sets](#) through our searchable interface. Our [old web site](#) is still available, for those who prefer the old format. For a general overview of the Repository, please visit our [About](#) page. For information about citing data sets in publications, please read our [citation policy](#). If you wish to donate a data set, please consult our [donation policy](#). For any other questions, feel free to [contact the Repository librarians](#). We have also set up a [mirror site](#) for the Repository.

Supported By:  In Collaboration With: 

Latest News:

04-04-2013: Welcome to the new Repository admins Kevin Bache and Moshe Lichman!
 03-01-2010: Note from donor regarding Netflix data
 10-16-2009: Two new data sets have been added.
 09-14-2009: Several data sets have been added.
 07-23-2008: Repository mirror has been set up.
 03-24-2008: New data sets have been added!
 06-25-2007: Two new data sets have been added: UJI Pen Characters, MAGIC Gamma Telescope







Featured Data Set: CMU Face Images












Task: Classification
 Data Type: Image
 # Instances: 640

This data consists of 640 black and white face images of people taken with varying pose (straight, left, right, up), expression (neutral, happy, sad, angry), eyes (wearing sunglasses or not), and size

Newest Data Sets:

- 08-28-2017:  Burst Header Packet (BHP) flooding attack on Optical Burst Switching (OBS) Network
- 07-23-2017:  Eco.hotel
- 07-23-2017:  Las Vegas Strip
- 07-20-2017:  Parkinson Disease Spiral Drawings Using Digitized Graphics Tablet
- 07-16-2017:  PM2.5 Data of Five Chinese Cities
- 07-16-2017:  Seline_Transactions_Dataset_Weekly
- 06-29-2017:  Data for Software Engineering Teamwork Assessment in Education Setting
- 05-30-2017:  chestnut - LARVIC
- 05-24-2017:  Epileptic Seizure Recognition

Most Popular Data Sets (hits since 2007):

- 1503112:  Zia
- 989310:  Adult
- 741287:  Wine
- 645208:  Car Evaluation
- 579500:  Breast Cancer Wisconsin (Diagnostic)
- 572635:  Forest Fires
- 542310:  Human Activity Recognition Using Smartphones
- 523473:  Heart Disease
- 516585:  Wine Quality

Search for a time series:



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Browse Through: 75 Data Sets

Table View List View

Default Task	Name	Data Type	Default Task	Attribute Types	# Instances	# Attributes	Year
Classification (16) Regression (21) Clustering (24) Other (10)	UCI Activities of Daily Living (ADL) Recognition Using Binary Sensors	Multivariate, Sequential, Time-Series	Classification, Clustering		2747		2013
Attribute Type Categorical (0) Numerical (83) Mixed (7)	UCI Activity Recognition from Single Chest-Mounted Accelerometer	Univariate, Sequential, Time-Series	Classification, Clustering	Real			2014
Data Type - Unlabeled Multivariate (308) Univariate (16) Sequential (40) Time-Series (75) Text (0) Domain Theory (22) Other (0)	UCI Activity Recognition system based on Multisensor data fusion (ARMI)	Multivariate, Sequential, Time-Series	Classification	Real	42040	6	2016
Area Life Sciences (0) Physical Sciences (8) C.S./Engineering (36) Social Sciences (0) Business (8) Games (0) Other (13)	UCI Air Quality	Multivariate, Time-Series	Regression	Real	9208	15	2016
# Attributes Less than 10 (18) 10 to 100 (20) Greater than 100 (26)	UCI Air quality	Multivariate, Time-Series	Regression	Real	9208	15	2016
# Instances Less than 100 (0) 100 to 1000 (15) Greater than 1000 (40)	UCI Amazon Access Samples	Time-Series, Domain Theory	Regression, Clustering, Causal Discovery		30000	20000	2011
	UCI Appliances energy prediction	Multivariate, Time-Series	Regression	Real	10735	29	2017
	UCI Australian Sign Language signs	Multivariate, Time-Series	Classification	Categorical, Real	6650	15	1999
	UCI Australian Sign Language signs (High Quality)	Multivariate, Time-Series	Classification	Real	2505	22	2002

Select one time series:



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Air Quality Data Set

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Abstract: Contains the responses of a gas multisensor device deployed on the field in an Italian city. Hourly responses averages are recorded along with gas concentrations references from a certified analyzer.

Data Set Characteristics:	Multivariate, Time-Series	Number of Instances:	9358	Area:	Computer
Attribute Characteristics:	Real	Number of Attributes:	15	Date Donated:	2016-03-23
Associated Tasks:	Regression	Missing Values?	Yes	Number of Web Hits:	131942

Source:

Severio De Vito ([severio.de_vito@enea.it](#)), ENEA - National Agency for New Technologies, Energy and Sustainable Economic Development

Data Set Information:

The dataset contains 9358 instances of hourly averaged responses from an array of 5 metal oxide chemical sensors embedded in an Air Quality Chemical Multisensor Device. The device was located on the field in a significantly polluted area, at road level within an Italian city. Data were recorded from March 2004 to February 2005 (one year) representing the longest freely available recordings of on field deployed air quality chemical sensor devices responses. Ground Truth hourly averaged concentrations for CO, Non Methane Hydrocarbons, Benzene, Total Nitrogen Oxides (NOx) and Nitrogen Dioxide (NO2) were provided by a co-located reference certified analyzer. Evidence of cross-sensitivities as well as both concept and sensor drifts are present as described in De Vito et al., Sens. And Act. 5, Vol. 129,2,2008 (citation required) eventually affecting sensors concentration estimation capabilities. Missing values are tagged with -200 value. The dataset can be used exclusively for research purposes. Commercial purposes are fully excluded.

Attribute Information:

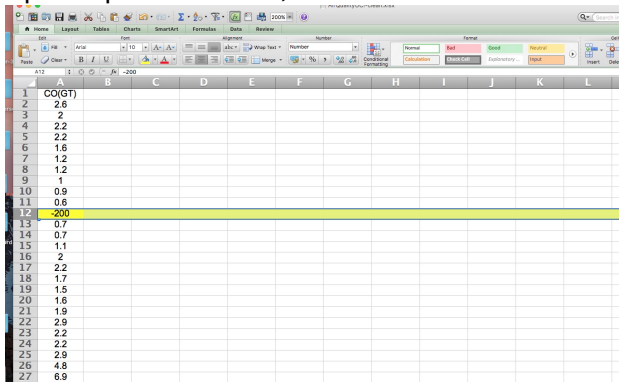
- 0 Date (DD/MM/YYYY)
- 1 Time (HH-MM-SS)
- 2 True hourly averaged concentration CO in mg/m³ (reference analyzer)
- 3 PT08.S1 (Sn oxide) hourly averaged sensor response (nominally CO targeted)
- 4 True hourly averaged overall Non Methane Hydrocarbons concentration in microg/m³ (reference analyzer)
- 5 True hourly averaged Benzene concentration in microg/m³ (reference analyzer)
- 6 PT08.S2 (Iridia) hourly averaged sensor response (nominally NMHC targeted)
- 7 True hourly averaged NOx concentration in ppb (reference analyzer)
- 8 PT08.S3 (tungsten oxide) hourly averaged sensor response (nominally NOx targeted)
- 9 True hourly averaged NO2 concentration in microg/m³ (reference analyzer)
- 10 PT08.S4 (tungsten oxide) hourly averaged sensor response (nominally NO2 targeted)

Step 2: download and clean the data set to prepare for modeling. For example, remove unnecessary data, correct 'error' entries etc

Raw data set:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
	Date	Time	DOY(Y)	PTM (T) (OZ)	MAK(CO)	OWK(WT)	PTM (S) (H) (C)	MAK(CO)	OWK(WT)	PTM (S) (H) (C)	MAK(CO)	OWK(WT)	PTM (S) (H) (C)	MAK(CO)	OWK(WT)	PTM (S) (H) (C)	MAK(CO)	OWK(WT)	PTM (S) (H) (C)
1	2/10/04	18:30:00	2.8	1300	192	10.9	1249	908	1295	102	1850	1258	13.8	48.9	8.17578				
2	2/10/04	18:30:00	2.8	1300	112	8.4	955	103	1114	82	1558	1075	13.3	43.7	8.17580				
3	2/10/04	20:30:00	2.2	1632	88	8.2	989	125	1140	104	1888	1076	11.8	44.5	8.17620				
4	2/10/04	21:30:00	2.2	1738	40	9.3	949	112	1382	102	1864	1075	11.5	45.2	8.17667				
5	2/10/04	22:30:00	1.8	1272	31	8.5	836	101	1203	106	1860	1112	11.2	58.8	8.17688				
6	2/10/04	23:30:00	1.2	1187	28	4.7	750	89	1317	86	1363	996	11.2	58.2	8.17688				
7	2/10/04	0:00:00	1.2	1188	31	3.6	880	82	1482	87	1333	733	11.3	48.8	8.17683				
8	2/10/04	1:00:00	1	1138	31	3.3	925	82	1483	86	1333	733	11.3	48.2	8.17682				
9	2/10/04	2:00:00	0.9	1094	28	2.3	987	45	1579	80	1278	507	10.7	58.7	8.17688				
10	2/10/04	3:00:00	0.8	1037	19	1.3	987	45	1579	80	1278	507	10.7	58.7	8.17688				
11	2/10/04	4:00:00	0.8	1037	19	1.3	987	45	1579	80	1278	507	10.7	58.7	8.17688				
12	2/10/04	5:00:00	0.7	1068	8	1.1	912	19	1918	28	1197	448	10.1	48.8	8.17688				
13	2/10/04	6:00:00	0.7	1068	16	1.6	912	39	1738	40	1217	472	10.9	48.8	8.17683				
14	2/10/04	7:00:00	1.1	1148	29	2.2	987	98	1490	82	1338	735	10.2	58.8	8.17417				
15	2/10/04	8:00:00	1.1	1200	84	8.2	955	116	1738	102	1517	1102	10.8	47.4	8.17688				
16	2/10/04	9:00:00	2.2	1301	87	9.5	960	129	1579	104	1883	1028	10.5	48.8	8.17691				
17	2/10/04	10:30:00	1.7	1233	77	6.3	927	112	1218	98	1443	895	10.8	48.8	8.17681				
18	2/10/04	11:30:00	1.5	1179	45	5.0	762	85	1288	82	1382	871	10.3	57.8	8.17580				
19	2/10/04	12:30:00	1.8	1208	81	8.2	774	704	1351	86	1471	884	10.8	48.8	8.17681				
20	2/10/04	13:30:00	1.9	1288	63	7.3	889	148	1182	102	1537	879	6.3	74.4	8.03001				
21	2/10/04	14:30:00	1.9	1311	194	10.5	1038	207	1483	108	1758	1037	6.3	81.1	8.03136				
22	2/10/04	15:30:00	2.2	1312	79	8.8	955	186	1682	128	1847	1496	6.3	79.8	8.03178				
23	2/10/04	16:30:00	2.8	1301	186	8.3	925	103	1738	131	1887	1517	6.3	81.1	8.03188				
24	2/10/04	17:30:00	2.8	1301	186	10.2	930	243	1658	105	1718	1164	6.8	8.8	8.03188				
25	2/10/04	18:30:00	4.8	1587	387	20.9	1719	281	789	107	2083	1496	10.3	84.2	8.03005				
26	2/10/04	19:30:00	4.8	1587	387	20.9	1719	281	789	107	2083	1496	10.3	84.2	8.03005				
27	2/10/04	20:30:00	8.1	1483	481	24.0	1484	381	814	188	2191	1884	8.8	87.8	8.03133				
28	2/10/04	21:30:00	8.1	1483	481	27.8	1488	381	887	188	2157	1882	8.1	84.2	8.03178				
29	2/10/04	22:30:00	1.5	805	81	4.7	740	94	1325	85	1333	827	8.2	84.2	8.03005				
30	2/10/04	23:30:00	1.5	805	81	4.7	740	94	1325	85	1333	827	8.2	84.2	8.03005				
31	2/10/04	0:00:00	1.7	1300	98	5.9	808	122	1294	87	1379	818	8.3	88.5	8.03408				
32	2/10/04	1:00:00	1.8	1344	103	6.4	826	133	1247	86	1382	882	10.7	58.7	8.03408				
33	2/10/04	2:00:00	1.4	888	40	4.1	718	82	1385	81	1374	882	7.1	81.8	8.03218				
34	2/10/04	3:00:00	1.8	889	21	1.8	834	207	1483	108	1758	1037	6.3	81.1	8.03481				
35	2/10/04	4:00:00	-0.8	827	12	1.1	908	21	1883	22	1134	384	6.1	88.5	8.03248				
36	2/10/04	5:00:00	-1.8	847	7	1.3	912	30	1885	44	1185	487	6.1	88.5	8.03233				
37	2/10/04	6:00:00	-2.8	871	26	1.3	912	48	1885	44	1185	487	6.8	88.5	8.03248				
38	2/10/04	7:00:00	-1.8	1307	33	6.8	750	109	1887	104	1887	1484	6.8	48.5	8.03218				
39	2/10/04	8:00:00	-0.8	1345	200	11.9	829	187	1887	104	1887	1484	6.8	48.5	8.03218				
40	2/10/04	9:00:00	-0.8	1345	-200	22.1	1393	-200	787	-200	2058	1580	13.2	58.2	8.03661				
41	2/10/04	10:30:00	1.7	1388	188	10.8	987	143	1887	104	1887	1484	6.8	48.5	8.03218				
42	2/10/04	11:30:00	2.7	1388	188	10.8	987	143	1887	104	1887	1484	6.8	48.5	8.03218				
43	2/10/04	12:30:00	2.5	1252	146	10.0	970	163	1888	105	1933	1603	10.1	34.5	8.03661				
44	2/10/04	13:30:00	2.5	1252	146	10.0	970	163	1888	105	1933	1603	10.1	34.5	8.03661				
45	2/10/04	14:30:00	2.8	1303	188	14.2	1322	188	1887	104	1887	1484	6.8	48.5	8.03218				
46	2/10/04	15:30:00	2.8	1303	188	14.2	1322	188	1887	104	1887	1484	6.8	48.5	8.03218				
47	2/10/04	16:30:00	2.4	1274	133	10.7	1041	105	1887	105	1910	1604	10.3	34.5	8.03661				
48	2/10/04	17:30:00	1.9	1315	133	14.8	1041	105	1887	105	1910	1604	10.3	34.5	8.03661				
49	2/10/04	18:30:00	8.8	1626	240	18.2	1486	212	821	148	1887	1484	6.8	48.5	8.03218				
50	2/10/04	19:30:00	8.8	1626	240	18.2	1486	212	821	148	1887	1484	6.8	48.5	8.03218				

Clean it up: keep one column, remove error entries:



The screenshot shows an Excel spreadsheet with a single column of data. The data is as follows:

	A	B	C	D	E	F	G	H	I	J	K	L
1	CO(GT)											
2	2.6											
3	2											
4	2.2											
5	2.2											
6	1.6											
7	1.2											
8	1.2											
9	1											
10	0.9											
11	0.6											
12	-200											
13	0.7											
14	0.7											
15	1.1											
16	2											
17	2.2											
18	1.7											
19	1.5											
20	1.6											
21	1.9											
22	2.9											
23	2.2											
24	2.2											
25	2.9											
26	4.8											
27	6.9											

The cell containing -200 in row 12 is highlighted in yellow, indicating it is an error entry.

Step 3: map your data into a Markov chain. To do this, you must choose the states for your model. Each entry in the time series should map into a unique state.

In this example, we choose a 9-state model, with the states $\{1, 2, \dots, 9\}$. Map each entry into a state by rounding to the nearest integer.

File Home Layout Tables Charts SmartArt Formulas Data Review View 100% W

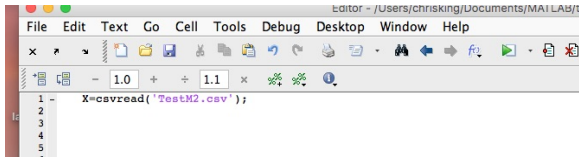
Font: Arial, Size: 10, Bold, Italic, Underline, Text Color, Background Color, Alignment: Left, Center, Right, Justify, Merge, Number: General, Conditional Formatting: Normal, Bad, Calculation, Blank Cell

Formula Bar: C2 =ROUND(A2,0)

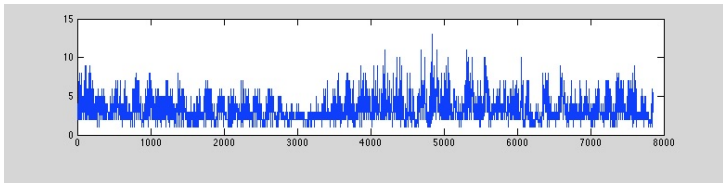
	A	B	C	D	E	F	G	H	I
1	CO(GT)		Rounded						
2	2.6		3						
3	2		2						
4	2.2		2						
5	2.2		2						
6	1.6		2						
7	1.2		1						
8	1.2		1						
9	1		1						
10	0.9		1						
11	0.6		1						
12	0.7		1						
13	0.7		1						
14	1.1		1						
15	2		2						
16	2.2		2						
17	1.7		2						
18	1.5		2						
19	1.6		2						
20	1.9		2						
21	2.9		3						
22	2.2		2						
23	2.2		2						
24	2.9		3						
25	4.8		5						
26	6.9		7						

Step 4: transfer the time series to a platform for analysis, eg Excel, Matlab, R etc.

For example, here we import the spreadsheet into Matlab:

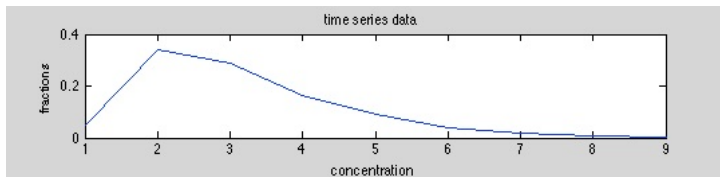


and here is the complete time series:



Step 5: compute the occupation frequencies for each state, and turn this into a probability distribution. This is the empirical distribution of your chain.

Empirical distribution from time series: fraction of time spent in each state



Step 6: compute the frequencies of jumps between each pair of states. Divide by the occupation frequency at each state so that the total jump probability out of each state is 1. This is your transition matrix.

Transition matrix from time series:

```
Command Window
File Edit Debug Desktop Window Help
New to MATLAB? Watch this Video, see Demos, or read Getting Started.

Trans2 =

Columns 1 through 7

    0.6393    0.3532    0.0050    0.0025         0         0         0
    0.0540    0.7504    0.1507    0.0317    0.0110    0.0015    0.0008
    0.0009    0.2129    0.5973    0.1443    0.0356    0.0058    0.0018
         0    0.0297    0.3143    0.4425    0.1572    0.0414    0.0133
         0    0.0029    0.1225    0.3098    0.3429    0.1614    0.0490
         0    0.0031    0.0404    0.2112    0.2888    0.2360    0.1553
         0         0    0.0132    0.1060    0.2384    0.2914    0.1589
         0         0    0.0161    0.0484    0.2258    0.2097    0.1935
         0         0         0    0.0323    0.0323    0.1935    0.1290

Columns 8 through 9

         0         0
         0         0
    0.0009         0
    0.0016         0
    0.0072    0.0014
    0.0404    0.0248
    0.1258    0.0596
    0.1774    0.0806
    0.1935    0.1935

fx >> |
```

Step 7: find the stationary vector of your transition matrix. In case it is not unique, find all stationary vectors.

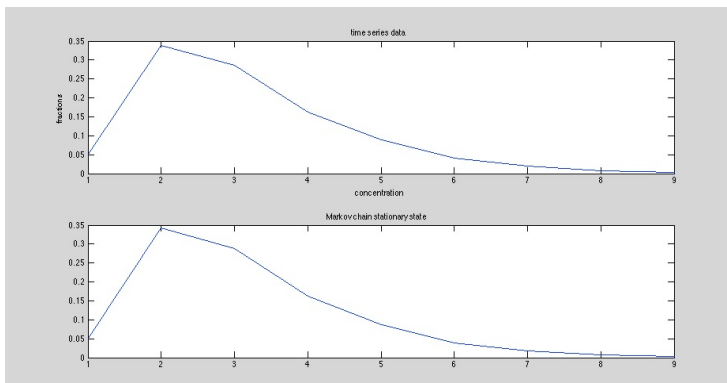
Stationary distribution of Markov chain:

```
ans =  
    0.0522    0.3425    0.2879    0.1623    0.0869    0.0397    0.0180    0.0069    0.0034
```

f_X >>

Step 8: compare the empirical distribution of the data set and the stationary distribution of your chain. Note any similarities!

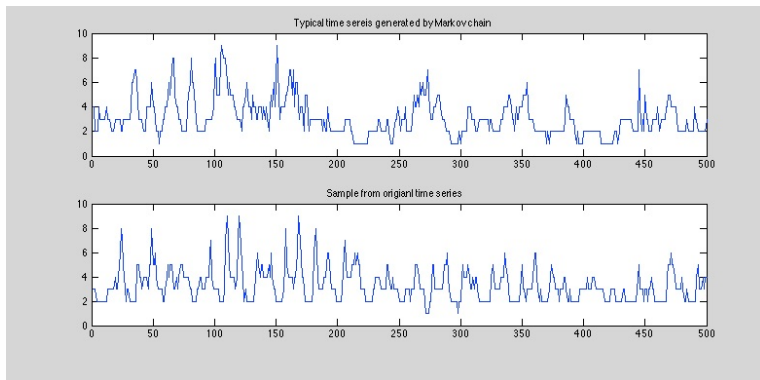
Empirical distribution from time series compared to the stationary distribution of chain:



Step 10:

Build a simulation of the Markov chain, using the transition matrix that you computed in Step 6. Generate a typical time series using your simulation, and compare with the original time series. Does it look like a good model?

Compare simulation of the Markov chain with original time series:



Step 11: Compare your simulation with the original time series using the autocorrelation function. Given a time series X_1, X_2, \dots, X_N , let \bar{X} be the average, then for $k = 0, 1, 2, \dots$ define

$$R(k) = \frac{\sum_{i=1}^{N-k} (X_i - \bar{X}) (X_{i+k} - \bar{X})}{\sum_{i=1}^N (X_i - \bar{X})^2}$$

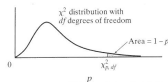
Compute the autocorrelation $R(0), R(1), R(2), \dots$ for the original time series and for the time series you generated in Step 10. Does it look like they describe the same series?

Step 12: Compare your simulation with the original time series using a goodness of fit test for the 2-step transition probabilities. Namely, let \widehat{p}_{ij} be the transition matrix that you computed in Step 6 above. Do the same kind of calculation on the original time series to get the frequency of going from each state i to each state j in *two steps*. Call this frequency N_{ij} , and let $N_i = \sum_j N_{ij}$. Compare these frequencies with the 2-step frequencies computed using \widehat{p}_{ij} , that is

$$M_{ij} = N_i q_{ij} = N_i \sum_k \widehat{p}_{ik} \widehat{p}_{kj}$$

Use a goodness of fit test to compare these at the 5% significance level for each state i (see notes on ‘Goodness of Fit Test’) and decide if the Markov chain $\{q_{ij}\}$ is a good model for the 2-step transitions of the data set.

Step 13: write a report (maximum 7 pages) explaining how you carried out the above steps, including: source and nature of raw data set, how it was cleaned, choice of states for Markov chain, empirical distribution, transition matrix, stationary distribution, comparison of empirical and stationary distributions, autocorrelation function, goodness of fit test. At the end of your report, answer this question: 'do you consider that the Markov chain method produces a good model for this time series? explain your answer'.

Table A.3 Upper and Lower Percentiles of χ^2 Distributions

df	0.010	0.025	0.050	0.10	0.90	0.95	0.975	0.99
1	0.000157	0.000982	0.00393	0.0158	2.706	3.841	5.024	6.635
2	0.0201	0.0506	0.103	0.211	4.605	5.991	7.378	9.210
3	0.115	0.216	0.352	0.584	6.251	7.815	9.348	11.345
4	0.297	0.484	0.711	1.064	7.779	9.488	11.143	13.277
5	0.554	0.831	1.145	1.610	9.236	11.070	12.832	15.086
6	0.872	1.237	1.635	2.204	10.645	12.592	14.449	16.812
7	1.239	1.690	2.167	2.833	12.017	14.067	16.013	18.475
8	1.646	2.180	2.733	3.490	13.362	15.507	17.535	20.090
9	2.088	2.700	3.325	4.168	14.684	16.919	19.023	21.666
10	2.558	3.247	3.940	4.865	15.987	18.307	20.483	23.209
11	3.053	3.816	4.575	5.578	17.275	19.675	21.920	24.725
12	3.571	4.404	5.226	6.304	18.549	21.026	23.336	26.217
13	4.107	5.009	5.892	7.042	19.812	22.362	24.736	27.688
14	4.660	5.629	6.571	7.790	21.064	23.685	26.119	29.141
15	5.229	6.262	7.261	8.547	22.307	24.996	27.488	30.578
16	5.812	6.908	7.962	9.312	23.542	26.296	28.845	32.000
17	6.408	7.564	8.672	10.085	24.769	27.587	30.191	33.409
18	7.015	8.231	9.390	10.865	25.989	28.869	31.526	34.805
19	7.633	8.907	10.117	11.651	27.204	30.144	32.852	36.191
20	8.260	9.591	10.851	12.443	28.412	31.410	34.170	37.566
21	8.897	10.283	11.591	13.240	29.615	32.671	35.479	38.932
22	9.542	10.982	12.338	14.041	30.813	33.924	36.781	40.289
23	10.196	11.688	13.091	14.848	32.007	35.172	38.076	41.638
24	10.856	12.401	13.848	15.659	33.196	36.415	39.364	42.980
25	11.524	13.120	14.611	16.473	34.382	37.652	40.646	44.314
26	12.198	13.844	15.379	17.292	35.563	38.885	41.923	45.642
27	12.879	14.573	16.151	18.114	36.741	40.113	43.194	46.963
28	13.565	15.308	16.928	18.939	37.916	41.337	44.461	48.278
29	14.256	16.047	17.708	19.768	39.087	42.557	45.722	49.588
30	14.953	16.791	18.493	20.599	40.256	43.773	46.979	50.892
31	15.655	17.539	19.281	21.434	41.422	44.985	48.232	52.191
32	16.362	18.291	20.072	22.271	42.585	46.194	49.480	53.486
33	17.073	19.047	20.867	23.110	43.745	47.400	50.725	54.776
34	17.789	19.806	21.664	23.952	44.903	48.602	51.966	56.061