UPC - Complex and Social Networks

Lab4: Non-linear regression on dependency trees

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1 Introduction

2 Results

Language	0	1	2	3	1+	2+	3+	4	4+	5	5+
Arabic	9.52	0.66	0.66	0.72	0.66	0.66	0.66	0.68	0.68	0.65	0.66
Basque	2.75	0.45	0.45	0.49	0.45	0.45	0.45	0.46	0.46	0.45	0.45
Catalan	7.73	0.53	0.53	0.55	0.53	0.53	0.53	0.53	0.53	0.53	0.53
Chinese	1.28	0.35	0.34	0.36	0.34	0.34	0.34	0.37	0.35	0.34	0.34
Czech	4.86	0.65	0.64	0.68	0.94	0.64	0.64	0.67	0.66	0.63	0.63
English	6.22	0.70	0.69	0.72	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Greek	7.16	0.57	0.57	0.62	0.57	0.57	0.57	0.58	0.58	0.57	0.57
Hungarian	4.75	1.09	1.09	1.20	1.09	1.10	1.09	1.25	1.15	1.09	1.09
Italian	5.98	0.53	0.53	0.58	0.53	0.52	0.53	0.54	0.54	0.53	0.53
Turkish	3.13	0.55	0.55	0.60	0.54	0.55	0.54	0.56	0.56	0.54	0.54

Table 1: Residual standard error for every model and language

Language	0	1	2	3	1+	2+	3+	4	4+	5	5+
Arabic	30174	8238	8217	9013	8220	8207	8278	8535	8439	8183	8221
Basque	14267	3608	3581	4112	3584	3582	3590	3738	3733	3583	3585
Catalan	104292	23473	23406	24856	23358	23480	23462	23593	23595	23433	23435
Chinese	180870	40240	38009	44305	38436	37332	37258	44946	40632	37921	37781
Czech	150242	49676	49033	51950	68101	48876	48759	50654	50616	48049	48270
English	121969	39929	39448	41178	39315	39364	39420	39323	39276	39287	39367
Greek	19992	5096	5070	5550	5071	5083	5096	5202	5199	5073	5075
Hungarian	38251	19382	19367	20608	19380	19407	19388	21121	20009	19370	19372
Italian	26584	6511	6451	7252	6438	6423	6489	6677	6652	6428	6430
Turkish	30859	9937	9810	10901	9759	9799	9722	10116	10111	9794	9784

Table 2: AIC for every model and language

Language	0	1	2	3	1+	2+	3+	4	4+	5	5+
Arabic	21991.4	55.0	34.7	830.4	37.0	24.3	95.7	352.2	255.8	0.0	37.7
Basque	10685.9	27.6	0.0	531.3	3.0	0.8	8.7	157.3	152.0	1.9	3.9
Catalan	80934.9	115.8	48.5	1498.2	0.0	122.1	104.3	235.7	237.4	75.5	77.5
Chinese	143612.3	2982.4	750.8	7046.6	1178.0	73.6	0.0	7688.2	3373.6	662.6	522.9
Czech	102192.8	1627.0	983.2	3900.6	20051.5	827.1	710.0	2604.2	2567.0	0.0	220.5
English	82693.4	653.3	172.4	1901.9	39.2	88.4	144.3	47.2	0.0	11.4	91.2
Greek	14921.4	25.3	0.0	479.9	1.1	12.9	26.0	131.6	129.0	2.4	4.4
Hungarian	18883.8	14.4	0.0	1241.0	12.7	39.4	20.8	1753.7	641.3	2.6	4.6
Italian	20160.4	87.4	27.9	828.8	14.4	0.0	65.1	253.6	228.8	4.6	6.6
Turkish	21137.2	214.9	88.5	1179.0	37.4	77.2	0.0	393.5	389.1	72.3	61.6

Table 3: Difference in AIC with best model for every language

Language	N	μ_n	σ_n	μ_x	σ_x
Arabic	4108	27	20.6	2.17	0.93
Basque	2933	11	6.5	1.96	0.69
Catalan	15053	26	13.6	2.32	0.70
Chinese	54238	6	3.3	1.44	0.48
Czech	25037	16	10.7	2.02	0.87
English	18779	24	11.2	3.05	0.90
Greek	2951	23	14.4	2.20	0.81
Hungarian	6424	22	12.6	3.88	1.78
Italian	4144	18	13.3	1.97	0.77
Turkish	6030	11	8.3	1.84	0.82

Table 4: Basic information

	Model																						
Language	1	2		3		1+		2+			3+			4	4+		5			5+			
	b	a	b	a	c	b	d	a	b	d	a	c	d	a	a	d	a	b	c	a	b	c	d
Arabic	0.34	0.7	0.36	1.6	0.01	0.34	-0.06	0.52	0.41	0.32	-3.1	-0.02	4.1	0.73	0.63	0.32	0.83	0.29	0.0021	1.1	0.22	0.0028	-0.21
Basque	0.42	0.67	0.46	1.3	0.032	0.44	-0.094	0.61	0.48	0.088	-3.3	-0.044	4	0.87	0.83	0.086	0.7	0.43	0.0022	0.7	0.43	0.0022	0
Catalan	0.35	0.72	0.37	1.7	0.012	0.35	-0.025	0.87	0.33	-0.15	-2.6	-0.03	3.6	0.75	0.75	0.012	0.8	0.32	0.0017	0.8	0.32	0.0017	0
Chinese	0.38	0.6	0.5	1.1	0.048	0.45	-0.15	0.26	0.71	0.51	-3.8	-0.037	4.5	0.83	0.64	0.35	0.73	0.36	0.0087	0.43	0.51	0.0048	0.33
Czech	0.36	0.62	0.44	1.5	0.016	-72	2	0.23	0.66	0.58	19	0.0029	-18	0.79	0.75	0.093	0.82	0.28	0.0085	1.1	0.21	0.01	-0.22
English	0.46	0.95	0.37	2.2	0.014	0.42	0.3	0.96	0.39	-0.16	-3.4	-0.04	4.5	1	1.1	-0.2	0.91	0.39	-0.00091	64	0.012	0.00021	-64
Greek	0.35	0.71	0.38	1.6	0.014	0.36	-0.1	0.57	0.41	0.18	-3	-0.028	3.9	0.76	0.73	0.089	0.73	0.37	0.00045	0.73	0.37	0.00045	0
Hungarian	0.59	0.61	0.61	2.4	0.021	0.6	-0.13	0.61	0.61	0.1	-11	-0.015	12	1.4	2.1	-2.3	0.59	0.63	-0.00075	0.59	0.63	-0.00075	0
Italian	0.35	0.63	0.41	1.5	0.015	0.36	-0.13	0.46	0.46	0.32	-3	-0.026	3.9	0.74	0.69	0.15	0.77	0.31	0.0034	0.77	0.31	0.0034	0
Turkish	0.41	0.69	0.43	1.3	0.029	0.44	-0.16	0.55	0.49	0.2	-3.7	-0.036	4.4	0.85	0.88	-0.061	0.63	0.5	-0.0032	0.56	0.53	-0.0038	0.092

Table 5: Calculated parameters for every model and language

3 Discussion

3.1 Heteroscedasticity

Solving Heteroscedasticity After we noted that the data was not homoscedastic. We tried aggregating the data and calculating models that data. This didn't turn out well. First we had a lot of trouble with choosing the right starting values (more than when using the original data). And after we succeeded getting a working model it appeared that the approximation was really bad, see plots in Figure 11, especially compared to the models on the original data.

The aggregated data was hard to approximate, mainly because it consisted of less than 100 points, which makes it a very sparse dataset. When we looked at the best models for this language, we noted that simpler models were strongly preferred because the RSS was a lot lower and thus the amount of parameters had a higher influence on the AIC.

Also the aggregated data gave 1 weight for every vertex, this means that a vertex with

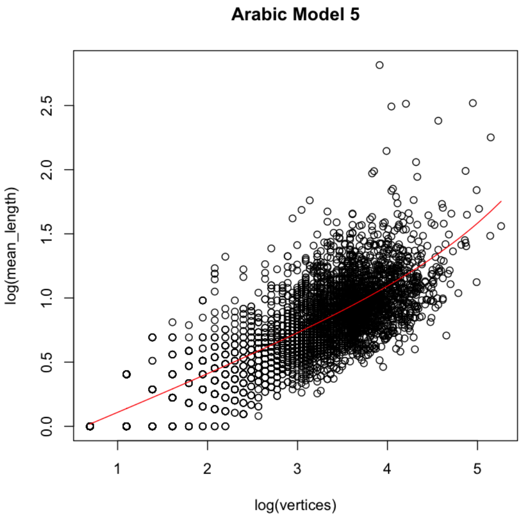


Figure 1: The best model in a log-log plot for Arabic

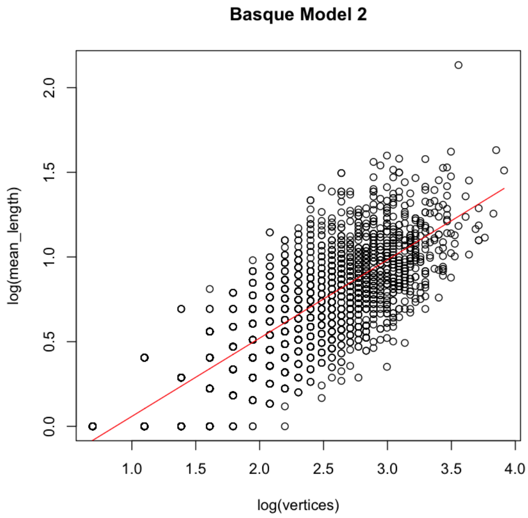


Figure 2: The best model in a log-log plot for Basque

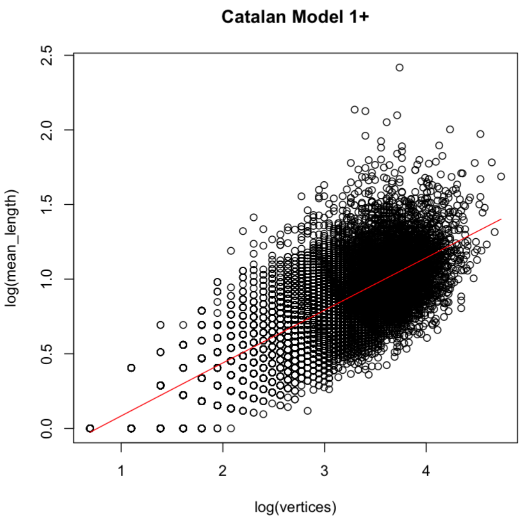


Figure 3: The best model in a log-log plot for Catalan

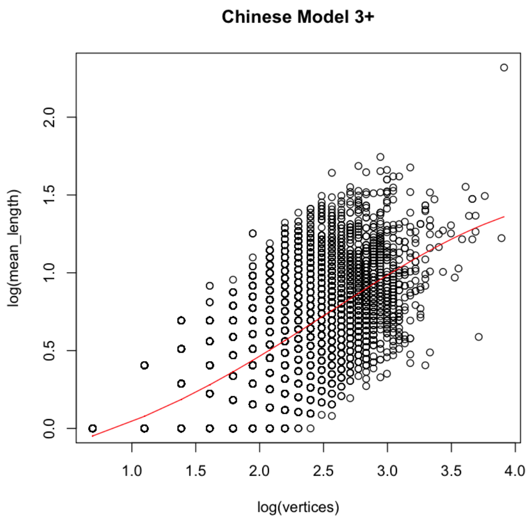


Figure 4: The best model in a log-log plot for Chinese

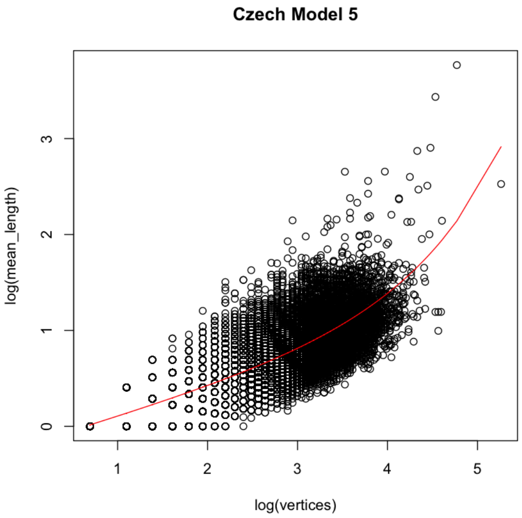


Figure 5: The best model in a log-log plot for Czech

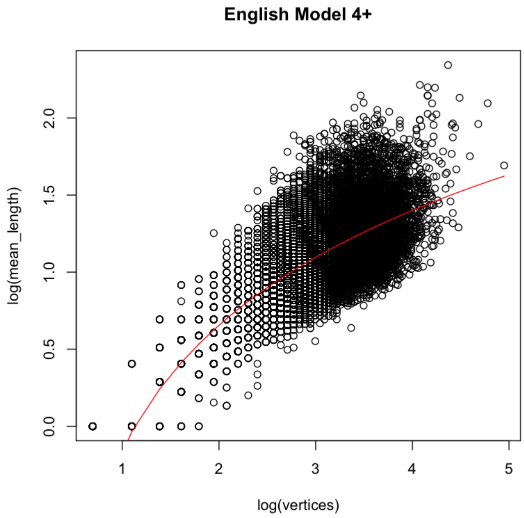


Figure 6: The best model in a log-log plot for English

Figure 7: The best model in a log-log plot for Greek

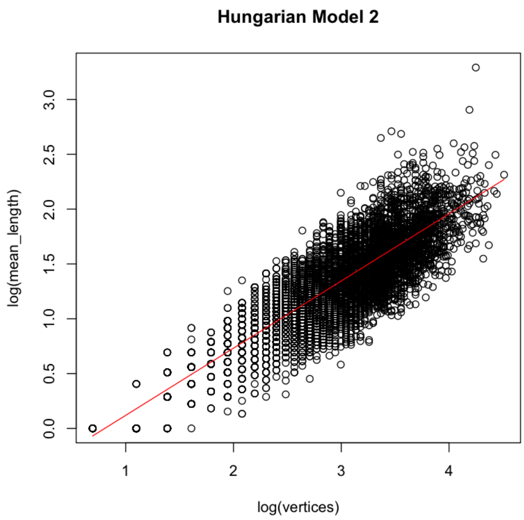


Figure 8: The best model in a log-log plot for Hungarian

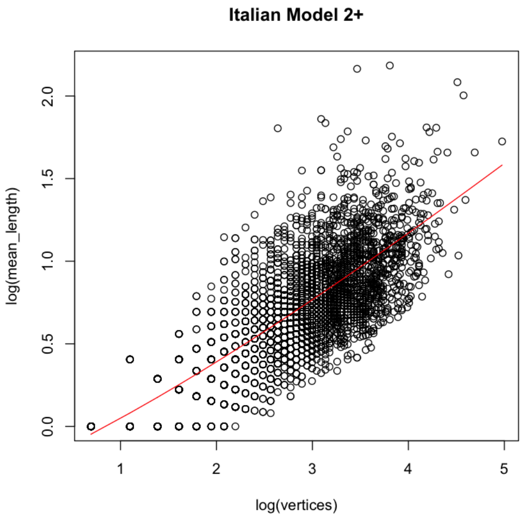


Figure 9: The best model in a log-log plot for Italian

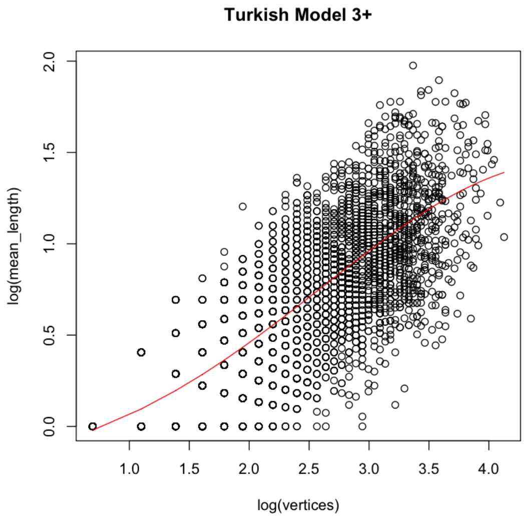


Figure 10: The best model in a log-log plot for Turkish

length 5 will count for as much as a vertex with length 113, while the first one might have appeared more than 100 more than the second one. This makes the data very vulnerable for outliers. To solve this, we could add weights when calculating the non-linear model, but we ran out of time to do so.

Because of all these problems we decided not to work with the aggregated data, but with the original data.

3.2 Languages and their best models

We note in all the plots of the best model that we get a best model that nicely fits the model. In the first image of Figure 11 we can even see that most models give a reasonably good fit. This is expected, as lots of models resemble each other.

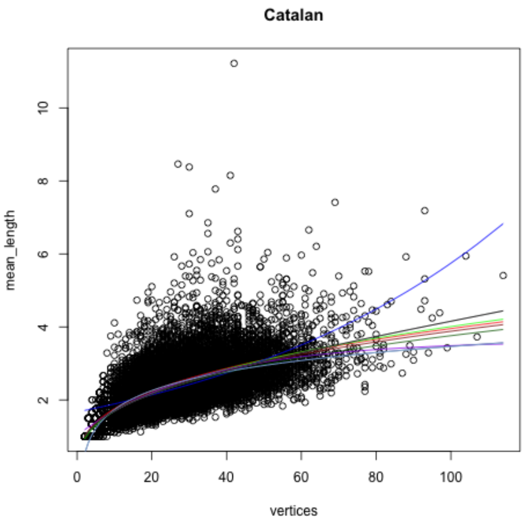
We notice immediately that the best model differs for different languages. For example, the two languages with the lowest μ_n and lowest μ_x: Turkish and Chinese both prefer model 3+. While no other languages prefers this model, nor model 3.

Depending on the language, also models $1+, 2, 2+, 4+$ and 5 get selected as a model.

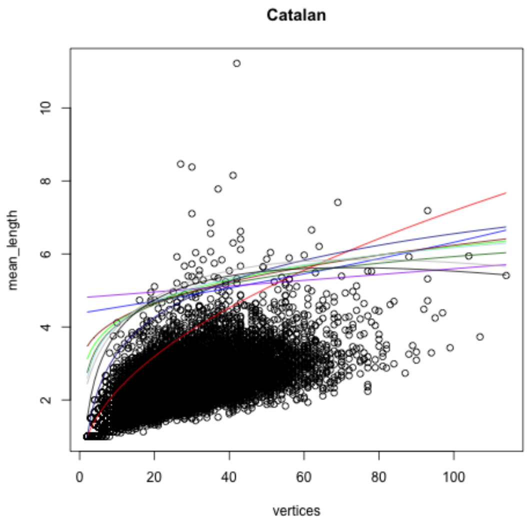
We also noticed that, for most languages (except Catalan, Chinese and Turkish) model 5 is very close to the best result.

3.3 Conclusions

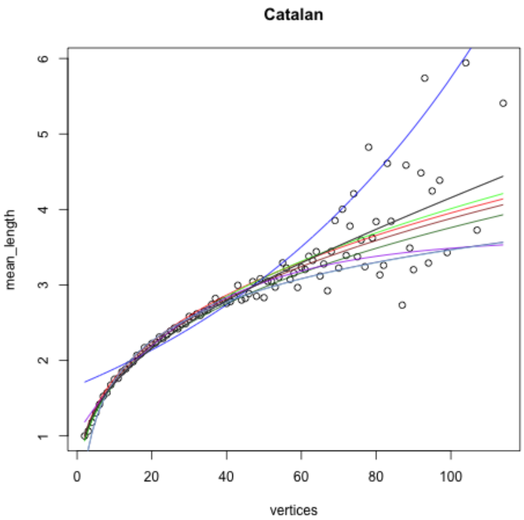
So we can conclude that a combination of model 5 and model 3+ would lead to good best fits for all models. We also note that probably model 5+ alone would be sufficient as well, but then we would have to tune the starting values a lot better and solve some



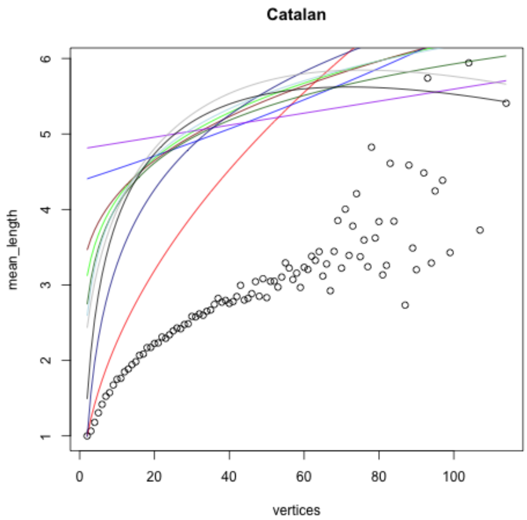
Models based on data plotted against data



Models based on aggregated data plotted against data



Models based on data plotted against aggregated data



Models based on aggregated data plotted against aggregated data

Figure 11: A comparison between the models based on the aggregated data against models based on our original data

extra issues.

We can also conclude that for some languages the model for the mean length of the edges of the dependency tree as a function of the number of words significantly differs from the models for other languages.

To finish we found that we have found a model with a good fit for every language.

4 Methods

We employed several methods for finding starting values. If there was no additive term, a linear approximation was usually sufficient. When there was an additive term, this usually wasn't. So we mainly did some manual search, using the expand.grid and nls2 functions. Once a starting value was found, it usually worked for a lot of languages.
When evaluating the mean data, we could evaluate a grid every time before starting, to get better results.
To automate the process, we used selfstarters.

After we find good starting values for the original data for almost every language and model, a few errors remained. To solve these, we adapted the maximum iterations for the model and also the tolerance and the minFactor. At last we set warnOnly True, so that we could fully automate the calculation of the best model and didn't have to worry about these errors. Running all models for all languages we get 2 errors (for model 5+) and we consider this acceptable.