34_log_freq_model_of_lex_dec

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0.1 The log-frequency model of lexical decision

In previous notebooks, we introduced a model for participant in a simple lexical decision task. That model was sufficient introduce how we simulate interaction with the environment, but it was too simplistic in its assumptions about memory since memory retrievals were not dependent on any parameters of the retrieved word.

In this and following notebooks, we improve on that model by incorporating the ACT-R model of declarative memory we just introduced.

We start with the discussion of basic properties of word frequency and the way to model lexical decision while keeping these properties in mind. We then construct several ACT-R models that simulate lexical-decision tasks and whose retrieval is dependent on parameters of the retrieved word.

One very robust parameter affecting latencies and accuracies in lexical decision tasks is frequency (Whaley, Charles P. 1978. Word-nonword classification time. *Journal of Verbal Learning and Verbal Behavior* 17:143–154).

Frequency effects have been found not just in lexical decision tasks, but in many if not all tasks that involve some kind of lexical processing:

- Forster, Kenneth I. 1990. *Lexical processing*. The MIT Press.
- Monsell, Stephen. 1991. The nature and locus of word frequency effects in reading. In *Basic processes in reading: Visual word recognition*, ed. D. Besner and G. W. Humphreys, 148–197. Hillsdale, NJ: Erlbaum.

These frequency effects have a specific functional form: since Howes, Davis H, and Richard L Solomon (1951) (Visual duration threshold as a function of word-probability. *Journal of experimental psychology* 41), it is accepted that lexical access can be well approximated as a log-function of frequency.

Modeling lexical access in terms of log-frequency provides a good, but not perfect, fit to the data.

Murray, Wayne S, and Kenneth I Forster. 2004. Serial mechanisms in lexical access: the rank hypothesis. *Psychological Review* 111:3, 721-756 studied the role of frequency in detail and identified various issues with the log-frequency model. The data consisted of collected responses and response times in a lexical decision task using words from 16 frequency bands, summarized in the table below.

- example words in the table are based on the *Corpus of Contemporary American English* (COCA; http://corpus.byu.edu/coca/, specifically the list available at http://www.wordfrequency.info/files/entriesWithoutCollocates.txt, which lists frequencies of words of 450 million words total (as of March 7, 2017).
- the chosen example word was one of the closest one to the mean frequency listed in the same row, but these were not the words used in the actual experiment: Murray & Forster (2004) controlled for other parameters, e.g., word length, while manipulating word frequency.

Frequency bands of words used in Murray and Forster (2004) (Exp. 1); frequency reported in number of tokens per 1 million words:

Group	Frequency range	Mean frequency	Latency (ms)	Accuracy (%)	Example word
1	315–197	242.0	542	97.22	guy
2	100–85	92.8	555	95.56	somebody
3	60–55	57.7	566	95.56	extend
4	42–39	40.5	562	96.3	dance
5	32–30	30.6	570	96.11	shape
6	24–23	23.4	569	94.26	besides
7	19	19.0	577	95	fit
8	16	16.0	587	92.41	dedicate
9	14-13	13.4	592	91.67	robot
10	12–11	11.5	605	93.52	tile
11	10	10.0	603	91.85	between
12	9	9.0	575	93.52	precedent
13	7	7.0	620	91.48	wrestle
14	5	5.0	607	90.93	resonate
15	3	3.0	622	84.44	seated
16	1	1.0	674	74.63	habitually

Using the RT latencies from Murray & Forster (2004), let us build a log-frequency model and evaluate the discrepancies between the predictions of the model and the data.

- we first store the data in two variables `freq` (mean frequency) and `rt` (reaction time / latency; measured in s).

[1]:
```
import matplotlib.pyplot as plt
plt.style.use('seaborn')
import seaborn as sns

import numpy as np
import pandas as pd

import pymc3 as pm
```

[2]:
```
freq = np.array([242, 92.8, 57.7, 40.5, 30.6, 23.4, 19,
                 16, 13.4, 11.5, 10, 9, 7, 5, 3, 1])
rt = np.array([542, 555, 566, 562, 570, 569, 577, 587,
```

```
                 592, 605, 603, 575, 620, 607, 622, 674])/1000
accuracy = np.array([97.22, 95.56, 95.56, 96.3, 96.11, 94.26,
                     95, 92.41, 91.67, 93.52, 91.85, 93.52,
                     91.48, 90.93, 84.44, 74.63])/100
```

We can now build a Bayesian model, very similar to the one for the exponential model of forgetting we built before:

[3]:
```
log_freq_model = pm.Model()
with log_freq_model:
    # priors
    intercept = pm.Normal('intercept', mu=0, sd=300)
    slope = pm.Normal('slope', mu=0, sd=300)
    sigma = pm.HalfNormal('sigma', sd=300)
    # likelihood
    mu = pm.Deterministic('mu', intercept + slope*np.log(freq))
    observed_rt = pm.Normal('observed_rt', mu=mu, sd=sigma, observed=rt)
```

```
INFO (theano.gof.compilelock): Waiting for existing lock by process '3682' (I am
process '45872')
INFO (theano.gof.compilelock): To manually release the lock, delete
/home/ady/.theano/compiledir_Linux-5.8--generic-x86_64-with-
glibc2.29-x86_64-3.8.5-64/lock_dir
```

[4]:
```
with log_freq_model:
    trace = pm.sample(draws=5000, tune=15000, n_init=200000, cores=4)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (4 chains in 4 jobs)
NUTS: [sigma, slope, intercept]
```

```
<IPython.core.display.HTML object>
```

```
Sampling 4 chains for 15_000 tune and 5_000 draw iterations (60_000 + 20_000
draws total) took 19 seconds.
```

We can now plot the estimates of the log-frequency model:

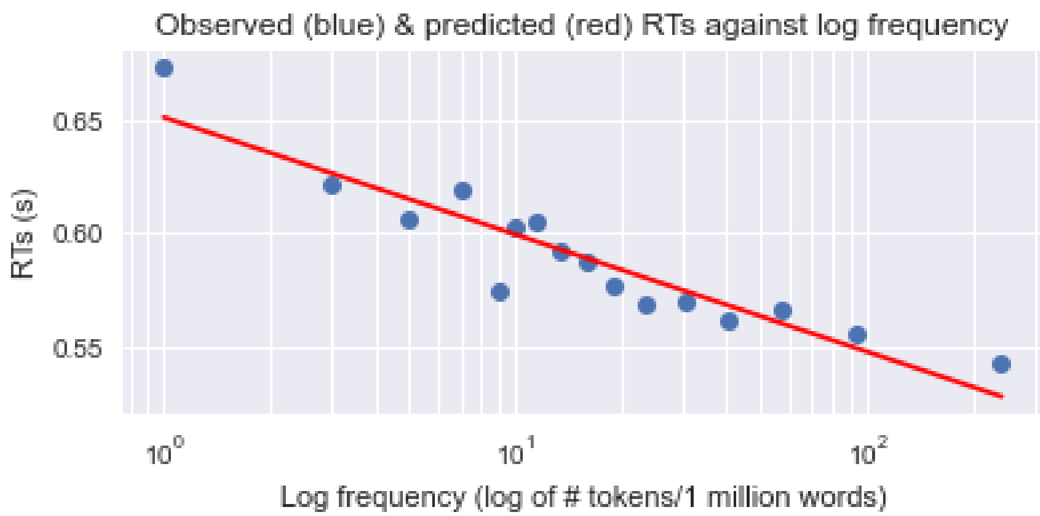
[5]:
```
mu = trace["mu"]
```

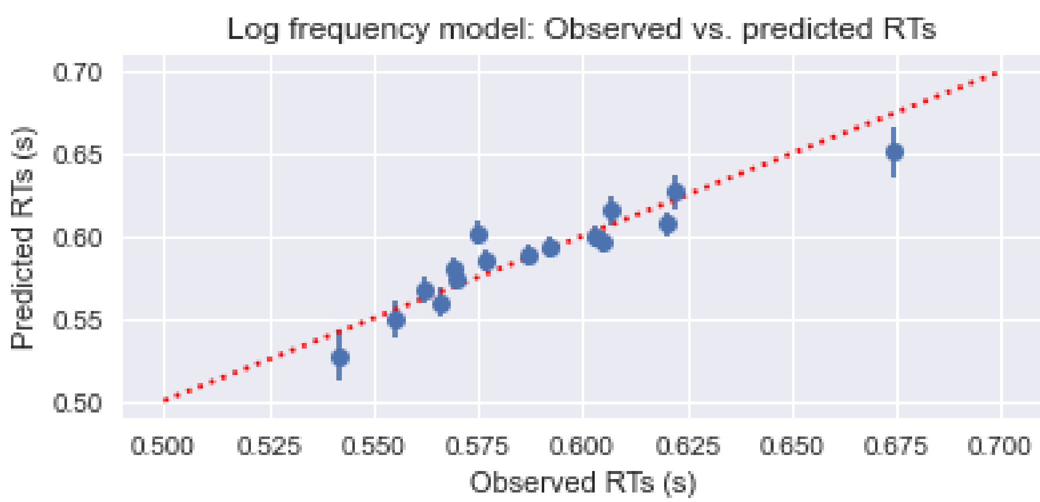
[6]:
```
import arviz as az
```

[7]:
```
fig, (ax1, ax2) = plt.subplots(ncols=1, nrows=2)
fig.set_size_inches(5.5, 5.5)

# plot 1
ax1.plot(freq, rt, marker='o', linestyle='')
ax1.plot(freq, mu.mean(axis=0), color='red', linestyle='-')
```

```python
ax1.set_title('Observed (blue) & predicted (red) RTs against log frequency')
ax1.set_xlabel('Log frequency (log of # tokens/1 million words)')
ax1.set_xscale('log', base=10) # or just ax1.set_xscale('log')
ax1.set_ylabel('RTs (s)')
ax1.grid(b=True, which='minor', color='w', linewidth=1.0)

# plot 2
yerr=[mu.mean(axis=0)-az.hdi(mu)[:,0],
      az.hdi(mu)[:,1]-mu.mean(axis=0)]

ax2.errorbar(rt, mu.mean(axis=0), yerr=yerr, marker='o', linestyle='')
ax2.plot(np.linspace(0.5, 0.7, 10), np.linspace(0.5, 0.7, 10),
         color='red', linestyle=':')
ax2.set_title('Log frequency model: Observed vs. predicted RTs')
ax2.set_xlabel('Observed RTs (s)')
ax2.set_ylabel('Predicted RTs (s)')
ax2.grid(b=True, which='minor', color='w', linewidth=1.0)

plt.tight_layout(pad=0.5, w_pad=0.2, h_pad=1.9);
```

```
/usr/local/lib/python3.8/dist-packages/arviz/stats/stats.py:493: FutureWarning:
hdi currently interprets 2d data as (draw, shape) but this will change in a
future release to (chain, draw) for coherence with other functions
  warnings.warn(
```





- the log-frequency model gets the middle values right, but it tends to underestimate the amount of time needed to access words in the extreme frequency bands,
  - both low frequency (associated with high RTs)
  - and high frequency (associated with low RTs)

Next, we model frequency effects in ACT-R as practiced memory retrieval, which is commonly assumed to be a power function of time in the same way that memory performance is.

```
[ ]:
```